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AN ARTIFICIAL INTELLIGENCE-BASED FRAMEWORK FOR CONCEPTUAL COST ESTIMATION IN CONSTRUCTION PROJECTS

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SUMMARY: *Conceptual cost estimation plays a critical role in the early planning stage of construction projects by supporting budgeting, feasibility assessment, and strategic decision-making before detailed project information becomes available. However, conventional estimation approaches often rely on expert judgment, historical experience, and limited project information, which may reduce estimation accuracy, consistency, and transparency. Although Artificial Intelligence (AI) has increasingly been applied to conceptual cost estimation, existing studies remain fragmented across datasets, input parameters, feature engineering techniques, AI algorithms, validation approaches, and performance evaluation metrics. Therefore, this study proposes a structured framework for AI-based conceptual cost estimation grounded in a PRISMA-based systematic literature review supported by ASReview. The framework was developed through the analysis of 28 studies identified in Scopus and Web of Science for the period from 2005 to 2026 and selected through a systematic screening process. The selected studies were then analyzed through quantitative descriptive analysis of publication trends, publication types, and publisher distribution, followed by qualitative template analysis of problem definition, datasets, input parameters, feature selection, modeling approaches, data analysis techniques, and model evaluation. The findings reveal substantial variation in methodological practices and highlight several limitations in the existing literature, including limited emphasis on conceptual-stage cost estimation, restricted dataset diversity, inconsistent validation procedures, and limited integration of heterogeneous data sources. Based on these findings, a seven-step conceptual framework for AI-based conceptual cost estimation is proposed to provide a structured and systematic approach to develop, validate, and implement AI-based conceptual cost estimation models. Overall, the proposed framework synthesizes the existing literature into a structured workflow for AI-based conceptual cost estimation and provides methodological guidance for future model development, validation, and practical implementation. As a literature-derived framework, it supports more transparent and consistent conceptual cost estimation and provides a basis for further validation through expert evaluation and application to construction projects.*

KEYWORDS: *artificial intelligence (AI), conceptual cost estimation, construction management, cost estimation framework, review.*

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1. INTRODUCTION

The construction project life cycle comprises sequential phases, including planning, design, construction, and operations, that guide a project from inception to completion and ensure that each phase contributes effectively to achieving overall project goals (T. Wang & Chen, 2023). Cost estimation plays a critical role in establishing initial budgets and planning resource allocation; however, early-stage estimation remains challenging because limited scope definition and insufficient data often lead to inaccurate predictions and budget deviations, highlighting the need for more reliable estimation methods (Tayefeh Hashemi et al., 2020). At the same time, industry analyses indicate that AI is becoming increasingly important in construction because of its potential to improve estimation accuracy, forecasting performance, and early-stage planning while achieving cost savings of approximately 10-15% (Ragan, 2025). It is also identified as a key driver of digital transformation, with potential to accelerate design optioneering, reduce uncertainty in conceptual estimates, and enhance project predictability (Meisels et al., 2025).

AI refers to computational systems that analyze data, learn from patterns, and perform tasks such as pattern recognition, decision-making, and problem-solving (Duan et al., 2019). In recent years, AI-assisted approaches have gained prominence in construction cost estimation, using large datasets and models to improve accuracy, efficiency, and adaptability (Shamim et al., 2025). Furthermore, AI has introduced new opportunities for enhancing cost estimation during the early planning stages, where limited information often constrains traditional methods (Ottaviani et al., 2024). Common AI methods such as Machine Learning (ML) and Deep Learning (DL) have emerged as powerful tools capable of processing large and complex datasets, identifying hidden patterns, and generating predictive insights from historical project data (Shamim et al., 2025). Unlike conventional approaches, AI-based methods can reduce reliance on manual interpretation of historical data and subjective judgment by identifying systematic patterns and adapting to different project types and sizes (Matel et al., 2022). These technologies can improve early-stage construction cost estimation by generating more accurate and consistent predictions under limited information conditions while supporting data-driven decision-making during project planning (Shamim et al., 2025). As construction organizations increasingly adopt digital project delivery environments, conceptual cost estimation is evolving from a standalone expert task into an information-technology-enabled process embedded within BIM-based workflows, digital twins, and data-driven decision-support systems, reinforcing the need for structured guidance on how AI-based estimation models are developed and integrated into these environments.

Recent reviews have contributed meaningfully to understanding how AI supports cost estimation, yet the existing body of work reveals several areas that remain open for deeper investigation. For example, Ayinla et al. (2023) reviewed AI applications in cost estimation and organized their findings under four groups of techniques: ANN, CBR, regression models, and DNNs. However, their search string did not include terms related to the conceptual phase, and AI methods such as deep learning and natural language processing were not included in the search terms. Some studies offer taxonomies that link various ML techniques to construction applications, yet they often stop short of focusing on a specific cost estimation phase or detailing model verification techniques (Karadimos & Anthopoulos, 2024). Ottaviani et al. (2024) focused on conceptual cost estimation but searched a single database using only "artificial intelligence" and "machine learning" as AI terms. Their review examined MLR, NN, SVM, kNN, RF, GB, RBF, CBR, and GA, and evaluated model performance using error-based metrics only, leaving opportunities for a more comprehensive assessment.

Bibliometric analyses have expanded knowledge of AI methods and validation approaches, although many are constrained by datasets centered primarily on building projects and do not fully address conceptual cost estimation at the project level (R. Wang et al., 2024). R. Wang et al. (2024) limited their review to building projects and covered different project stages, from planning to demolition. Their search did not include natural language processing, and their analysis of input variables combined conceptual, project, and construction cost estimates without examining feature selection techniques. More recent studies have emphasized the comparative performance of AI and traditional methods while still highlighting the need for a holistic and phase-specific synthesis (Shamim et al., 2025). In their multi-sector review, Shamim et al. (2025) compared the average accuracy of machine learning, deep learning, regression, and hybrid models across construction, healthcare, and manufacturing projects. However, their review did not focus on a specific construction project phase and did not systematically examine input parameters or feature selection. Most recently, Abuzaid et al. (2026) conducted a PRISMA-based review of AI applications in preconstruction cost estimation and proposed an AI-Expert

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Integration Framework. Their framework was presented as a conceptual approach that emphasizes expert integration, validation, and explainability, rather than providing detailed methodological guidance for each stage of model development. In addition, although AI techniques were mapped across four broad project categories, input variables were only listed for individual studies and were not classified by project type, and feature selection was not analyzed as a separate dimension.

Taken together, existing reviews provide broad overviews of AI-based construction cost estimation but offer limited targeted and systematic synthesis of AI techniques, input requirements, feature selection approaches, validation metrics, methodological procedures, and application contexts specific to conceptual cost estimation. In particular, input parameters have not been classified by project type, and stage-by-stage methodological guidance for developing AI-based conceptual cost estimation models remains limited. This gap is consequential because the conceptual stage is where cost estimates carry the greatest decision-making weight, establishing budgets, feasibility judgments, and go/no-go decisions, yet it is also where the least project information is available. Findings from recent reviews centered on detailed-stage estimation do not transfer to these conditions because the input parameters, data availability, and accuracy expectations differ fundamentally. In the absence of a phase-specific synthesis, researchers develop models with inconsistent variables, validation procedures, and reporting practices, which impede cumulative progress and cross-study comparison, while practitioners lack evidence-based guidance on the techniques, inputs, and performance evaluation practices reported in the literature when design information is minimal. In practice, owners, developers, and public agencies depend on conceptual estimates to authorize capital budgets, validate project feasibility, and compare alternative project options before detailed design information becomes available (El Asmar et al., 2011; Ottaviani et al., 2024). Estimators and preconstruction teams, however, must select modeling approaches without evidence-based guidance on which input parameters are observable at the conceptual stage (Elmousalami, 2020), how different AI techniques have been applied to early-stage datasets and how their performance has been evaluated, leaving these decisions dependent on individual judgment and experience (Tayefeh Hashemi et al., 2020; Valentini et al., 2017). A systematic, conceptual-stage-specific synthesis is therefore a prerequisite for both methodological standardization in research and credible AI adoption in early project planning.

To address these needs, this study conducts a PRISMA-guided systematic review of AI-based conceptual cost estimation at the project level, covering publications from 2005 to 2026 identified through Scopus and Web of Science and screened using ASReview, a machine-learning-assisted screening tool. The included studies are analyzed through a two-stage design that combines quantitative descriptive analysis of publication patterns with qualitative template analysis of datasets, input parameters, feature-selection practices, modeling approaches, analytical techniques, and performance evaluation procedures. Accordingly, this study aims to characterize the current research landscape of AI-based conceptual cost estimation at the project level, identify the key requirements and methodological considerations for developing AI-based conceptual cost estimation models, and synthesize the identified practices and requirements into a framework for their development and implementation. The study's contributions are threefold: (i) it consolidates the fragmented evidence on AI-based conceptual cost estimation into a structured synthesis of input requirements, techniques, and validation practices organized by project type, including a classification of 36 input parameters across six categories and seven project types, (ii) it identifies systematic methodological gaps, including inconsistent validation procedures, limited dataset diversity, and incomplete reporting, that currently constrain cumulative research progress and industry adoption and finally, (iii) it translates these findings into a literature-derived, seven-step conceptual framework that organizes the decisions, data requirements, and evaluation criteria to be considered at each stage of developing an AI-based conceptual cost estimation model. Collectively, these contributions offer a methodological foundation for standardizing research practices and provide estimators and preconstruction teams with a structured basis for developing and evaluating AI-based approaches under the limited-information conditions of early project planning.

2. RESEARCH BACKGROUND

2.1 Construction cost estimation methods

Cost estimation methods vary across the construction project life cycle depending on the level of project definition and the reliability of available information. When project details are still scarce, estimators rely on conceptual estimation, which draws on data from similar completed projects. As the design matures, parametric estimation becomes feasible through statistical relationships between cost drivers and project characteristics, and once

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detailed quantities from the work breakdown structure are available, bottom-up estimation takes over (Barakchi et al., 2017; Shamim et al., 2025; Tayefeh Hashemi et al., 2020). A conceptual estimate is a rough-order forecast prepared before significant design information is available and with only a minimal scope definition (El Asmar et al., 2011). Within the conceptual stage itself, several techniques are commonly used, including order-of-magnitude, top-down, and analogous estimating, which combine historical project costs with the limited scope and design information available at this point to produce an early cost projection (AS Estimation and Consultants, 2026; Gerardi, 2026).

Conceptual cost estimation plays a critical role in early project decision-making. It supports preliminary feasibility assessment, establishes an initial budget, guides early design choices, and helps determine whether a project should move forward before detailed design information becomes available (Gerardi, 2026; Mase & Giali, 2026; Ottaviani et al., 2024). This role reflects the broader progression of construction cost estimates in detail and accuracy across the project life cycle, from conceptual, feasibility, preliminary, and budget estimates during planning and feasibility to progressively more detailed estimates during design, bidding, and construction. ASPE's five-level classification system formalizes this progression according to the level of detail and accuracy of each estimate, ranging from Level 1 (Order of Magnitude) to Level 5 (Bid Estimate). Conceptual estimating corresponds closely to Level 1, where design information is at its most limited and estimate accuracy is correspondingly at its lowest (Guimond, 2024). As additional project information becomes available, conceptual estimates are progressively replaced or refined by estimates that incorporate more detailed quantities, materials, labor, market rates, drawings, and eventually contractor pricing.

Within this early project environment, conventional conceptual estimating procedures rely heavily on historical project information and estimator judgment. Estimators use historical data from comparable projects together with the limited scope and design information available for the proposed project (Gerardi, 2026; Valentini et al., 2017). Quantities that can be reasonably measured at this stage are priced using historical unit costs, while items that cannot yet be quantified in detail are estimated through percentage-based allowances and contingency factors drawn from past projects. Before historical information is applied to a new project, estimators identify relevant previous projects, assess the applicability of their cost information, and adjust the historical data for inflation, location, and project-specific conditions (Gerardi, 2026). Consequently, the resulting estimate depends considerably on the estimator's experience and judgment in determining which historical information is applicable and how it should be adjusted for the characteristics of the new project.

Conventional conceptual estimating also involves several practical limitations. Limited scope definition and incomplete project information create substantial uncertainty at the conceptual stage, which contributes to the wide accuracy ranges associated with conceptual and Rough Order of Magnitude (ROM) estimates, often on the order of -50% to +50%. These ranges progressively narrow as project information and design details become available (AS Estimation and Consultants, 2026). The process also depends on the availability and applicability of historical data. This process can be difficult to standardize across projects because the selection and adjustment of historical information depend considerably on individual estimator experience and judgment. Conceptual cost estimation therefore remains constrained by limited scope definition, data deficiencies, and subjective estimation practices, making conventional estimation a resource-restricted, judgment-dependent, and time-consuming task (Gerardi, 2026).

The practical limitations of conventional procedures have contributed to growing interest in AI-based conceptual cost estimation. In addition to addressing the accuracy limitations associated with estimates developed under limited project information, AI-based approaches offer the potential to process and apply historical project data more systematically, reduce dependence on repeated manual data processing, and shorten the time required to develop conceptual estimates. Accordingly, the potential contribution of AI to conceptual cost estimation extends beyond predictive accuracy to the efficiency and consistency of the overall estimation process.

2.2 Current artificial intelligence applications in construction cost estimation

AI-based cost estimation approaches have gained increasing attention in the literature in recent years, with studies spanning various stages of construction projects. At the conceptual and early design stages, CBR models have been used to estimate façade system costs for high-rise buildings (Luong-Duc & Anh-Thong, 2024), while integrated approaches combining CBR, RF, and ANN have been shown to enhance the reliability of façade work

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cost predictions (Long & Anh, 2024). Ensemble models employing ANN and SVM have also demonstrated strong performance in estimating costs for floor structural frames (Juszczyk, 2020).

Within the design and planning stage, hybrid optimization techniques have been applied to balance strength, energy, and cost considerations in building material selection using fuzzy-based metaheuristic algorithms (Ronghui & Liangrong, 2022). ANNs have been used to assess the likelihood of time and cost overruns during planning (Al Mnaseer et al., 2023), and multi-technique hybrid models integrating neural networks, fuzzy logic, and genetic algorithms have provided highly accurate predictions of pile foundation costs (Deepa et al., 2025).

Along the bidding stage, NN-driven methods have supported contractors in estimating engineering service costs and improving bidding decisions (Matel et al., 2022). During project execution, ML models have been widely applied to predict cost overruns, with CatBoost identified as a particularly effective technique (Hamdan et al., 2024), while rework costs have been addressed using ensemble classification models (Mostofi et al., 2022). Risk-based frameworks using classification algorithms have also been used to predict completion-cost overrun ratios in ongoing projects (Turkyilmaz & Polat, 2024). In the operational stage, probabilistic DL approaches have been introduced to improve cost estimation for aged-housing renovation, offering practical decision-support tools for maintenance and refurbishment planning (J. Kim & Cha, 2022).

Recent studies demonstrate the strong potential of AI-based techniques to improve construction cost estimation across project phases. However, research at the conceptual stage remains limited in scope and primarily focuses on isolated components rather than project-level cost dynamics. At the same time, ongoing digital transformation, increased data availability, and growing expectations for early decision-making accuracy in the construction industry highlight the need for more comprehensive and industry-aligned AI-driven conceptual cost estimation approaches.

3. RESEARCH METHODOLOGY

This study employed a mixed-methods approach within a systematic literature review guided by the PRISMA framework to examine AI-based conceptual cost estimation in construction. Figure 1 presents the overall research methodology adopted in this study, which consists of three main stages: (i) data collection, (ii) data analysis, including quantitative and qualitative analyses, and (iii) development of the AI-based conceptual cost estimation framework, and each stage is detailed as follows.

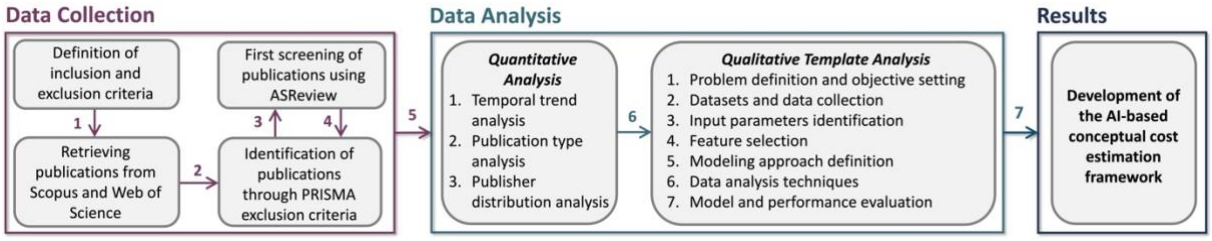


Figure 1: Research flowchart for the mixed-methods approach.

3.1 Data collection

The literature review process consisted of three main stages: identification of relevant literature, screening and eligibility assessment, and inclusion of relevant studies in the final review. These stages were conducted systematically in accordance with PRISMA principles to ensure transparency, consistency, and methodological rigor throughout the review process.

3.1.1 Identification of relevant literature

Following the PRISMA framework (Page et al., 2021), publications were retrieved from Scopus and Web of Science, two widely recognized databases that provide comprehensive coverage of high-quality and relevant scholarly research (Baas et al., 2020; Pranckutė, 2021; V. K. Singh et al., 2021). The eligibility criteria for selecting studies were based on several considerations. Only publications written in English were included, and the review encompassed journal articles, conference papers, and book chapters to ensure methodological and thematic diversity. The search timeframe spanned from 2005 to November 2026 to reflect the period during which AI-based

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tools began gaining traction in construction engineering and management. Studies were further selected based on their focus on AI applications in cost estimation during the early planning stages of construction projects. Moreover, the search strategy was developed using three main keyword categories: (i) *cost estimation terms*, including construction cost, cost estimation, cost management, cost prediction, cost forecast, conceptual estimate, and estimation; (ii) *project phase descriptors*, including pre-construction, schematic design, design stage, and early design; and (iii) *AI techniques*, including artificial intelligence (AI), machine learning (ML), deep learning (DL), and natural language processing (NLP). Keywords within each category were combined using the OR operator, while the categories themselves were connected using the AND operator, as follows: ("construction cost" OR "cost estimat*" OR "cost management" OR "cost predict*" OR "cost forecast*" OR "conceptual estimat*" OR "estimat*") AND ("pre-construction" OR "schematic design" OR "design stage" OR "early design") AND ("artificial intelligence" OR "AI" OR "machine learning" OR "ML" OR "deep learning" OR "DL" OR "natural language processing" OR "NLP"). This structured search logic ensured that all retrieved studies simultaneously addressed cost estimation, early-stage project planning, and AI-related methods. Following the guidelines for systematic reviews, broad search terms were used to identify as many relevant studies as possible (Lefebvre et al., 2025). Truncated cost terms such as "estimat*" were used to capture variations such as estimate, estimation, and estimating (Bramer et al., 2018). Specific project stage terms were combined with general terms such as "design stage" to identify studies using longer expressions such as "conceptual design stage". Specific AI algorithm names were not included in the search string because selecting terms based on prior knowledge may introduce bias (Grames et al., 2019). Therefore, general AI terms were used to cover different AI techniques. According to the initial search results, 437 papers were listed in the Scopus database and 289 papers were listed in the Web of Science database. Then, the two databases were combined, and 261 duplicate papers were removed. Overall, 465 papers were obtained after the identification phase in the PRISMA process.

3.1.2 Screening, selection and eligibility assessment

The screening process was supported by ASReview, a machine-learning-assisted review tool, to improve screening efficiency and prioritize relevant studies (Van De Schoot et al., 2021). The default ASReview LAB v2 configuration (ELAS-Ultra) was used without modification, with TF-IDF feature extraction, an SVM classifier, maximum query strategy, and balanced sampling. All retrieved records were uploaded and screened using the same keywords defined in the initial database query. Initial training inputs guided the screening process, although recommendations became less relevant as screening progressed. Studies were screened based on titles and abstracts and excluded if they addressed unrelated domains. Papers were included only if they aligned with construction engineering and management and contained keywords from each predefined category. In addition, to assess screening consistency, the second author independently reviewed a random 20% subsample of the records. Disagreements in the screening decisions were jointly reviewed by both authors based on the predefined inclusion and exclusion criteria, and final screening decisions were reached through discussion and consensus. Screening continued until all uploaded records had been reviewed; therefore, no early stopping rule was applied. Full-text eligibility decisions were jointly reviewed by both authors. This process yielded 69 relevant studies, of which eight were not accessible. The full-text screening phase further refined the selection, resulting in the exclusion of 33 papers based on relevance criteria. The excluded studies consisted of review articles (7), studies focusing on individual building components (5), papers addressing specific cost categories rather than early-stage estimation (14), and studies limited to service- or material-specific costs (7). Studies focusing on individual components and specific cost categories were excluded because the review examines AI-based conceptual cost estimation at the overall project level. These studies involve different units of analysis and typically use more detailed and specialized input parameters than those available during project-level conceptual estimation. Differences in parameter type, number, and level of detail may also influence the selection and performance of AI methods, limiting the direct applicability of these studies to the development of a project-level conceptual cost estimation framework.

3.1.3 Relevant studies included in the review

Following the completion of the full PRISMA screening process and the application of all predefined eligibility and exclusion criteria, a total of 28 studies were identified as suitable for inclusion in the final synthesis. The relatively small number of eligible studies suggests that, although AI applications in construction cost estimation are extensively published, studies that specifically address cost estimation at the conceptual, project-level stage remain scarce within the literature identified in this review. This scarcity indicates the phase-specific gap identified

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in this study and underscores the need for the structured synthesis undertaken here, consistent with PRISMA guidance, which states that the number of included studies should reflect the true size of the eligible evidence base rather than a predetermined target (Page et al., 2021).

These studies represent the most relevant and methodologically aligned contributions addressing AI-based cost estimation within the early planning stages of construction projects. The overall progression from initial identification to final inclusion is depicted in the PRISMA flow diagram presented in Figure 2, which documents each stage of the screening and exclusion process. With the final set of studies established, the subsequent section presents the detailed data analysis procedures used to examine methodological patterns, thematic insights, and emerging trends across the selected literature.

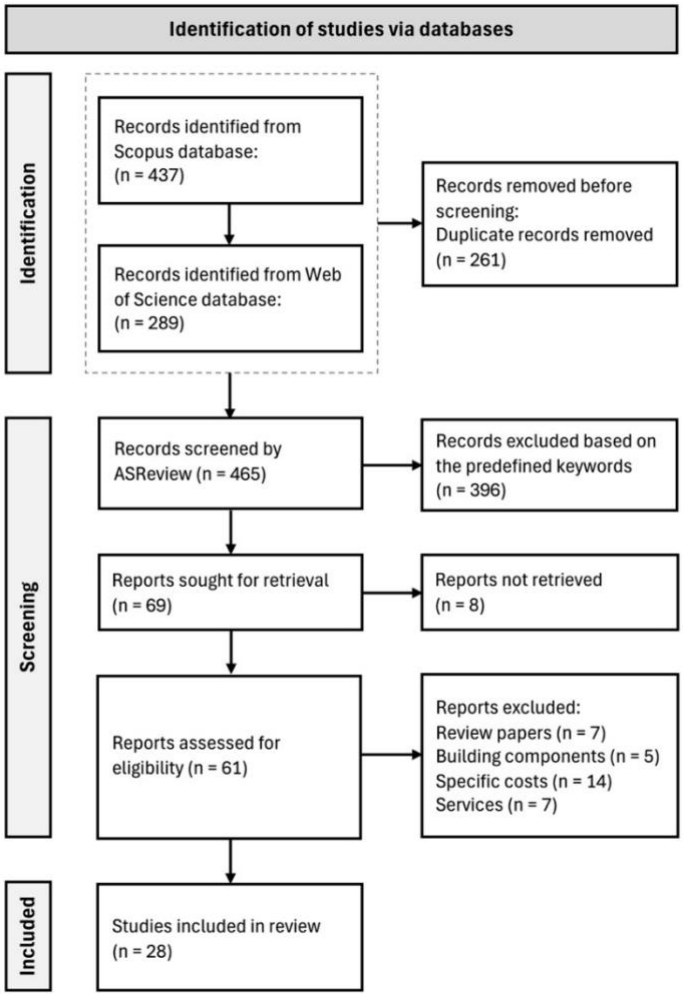


Figure 2: PRISMA flowchart of the study.

3.2 Data analysis

The data analysis systematically examined the methodological characteristics, analytical approaches, and insights of the 28 selected studies. It integrates quantitative descriptive techniques and qualitative template analysis to provide a comprehensive understanding of AI-based cost estimation in early-stage construction planning. In the first stage, quantitative descriptive analysis was conducted to map key characteristics of the selected studies. This involved examining publication year, publication type, and publisher distribution, following the descriptive approach outlined in previous research (Haneem et al., 2017). These patterns provided a contextual understanding of how interest in AI-based cost estimation has developed over time and across different scholarly outlets, and they offered a foundation for interpreting subsequent qualitative findings. This is followed by qualitative template analysis, a method that uses a predefined coding structure to organize and interpret qualitative data (King, 1998).

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An initial template was developed based on the study objectives and recurring methodological components, including dataset characteristics, input parameters, modeling approaches, and performance evaluation, and was iteratively refined to incorporate emerging themes. In addition, the included studies were reviewed in terms of dataset adequacy, validation procedure, reporting completeness, reproducibility, and potential overfitting. This assessment was based on the information reported in each study and was used to support the interpretation of the findings rather than to exclude studies.

3.3 AI-based cost estimation framework development

In the final stage, the findings from the quantitative and qualitative analyses are synthesized to develop a structured framework for AI-based conceptual cost estimation. This stage integrates the identified methodological components and patterns derived from the literature to define the key steps required for model development and application. The results of this synthesis are presented in the subsequent section.

4. RESULTS

4.1 Quantitative analysis of the selected studies

Understanding descriptive publication trends and the temporal distribution of studies provides insight into the development of research and the evolution of scholarly interest in an emerging field (Zhao et al., 2021). Figure 3 was developed by proportionally categorizing the 28 reviewed publications according to publication year, publication type, and publisher, where the horizontal dimensions in each section represent the relative distribution of studies across categories, and the numbers (#) indicate the number of publications in each category. The annual distribution of publications indicates a clear increase in interest in AI-based cost estimation, with no studies meeting the inclusion criteria prior to 2020. Publications rose from one study in 2020 to three in 2021 and four in 2022, declined to two in 2023, and peaked at eight studies in 2024. This was followed by four studies in 2025 and six studies in 2026, although the search for 2026 covered publications only up to November. Overall, this pattern reflects a rapid expansion of research activity in recent years.

In addition to temporal trends, publication types were also analyzed. Most studies were published as journal articles (n = 23), while conference papers (n = 4) and a single book chapter (n = 1) indicate more limited dissemination through alternative publication outlets. The distribution of publication outlets shows that ASCE and MDPI (n = 4 each) account for the highest number of studies, followed by IEEE and Taylor & Francis (n = 3 each) and CIB, Elsevier, Emerald, and Springer (n = 2 each), while single-study publishers were grouped under “Others” (n = 6). Overall, these patterns reflect the emerging and interdisciplinary nature of AI-based early-stage cost estimation research.



Figure 3: Distribution of publications by year, publication type, and publisher.

4.2 Qualitative template analysis of the selected studies

An initial data extraction table was developed before the detailed review of the selected studies. The table first included key parameters such as project type, data source, data analysis methods, and performance metrics. During the review process, differences in input parameters, feature analysis procedures, and modeling approaches were identified across studies depending on project scope and data availability. These observations led to the inclusion

of additional components, and the data extraction matrix was finalized for all 28 studies. The results of the qualitative template analysis are presented in Table 2 after the detailed explanation of each step, while the abbreviations used in the subsequent sections and Table 2 are provided in Appendix A. The insights derived from this analysis form the foundation for the proposed seven-step framework.

4.2.1 Step 1: Problem definition and objective setting

The first step in AI-based conceptual cost estimation involves clearly defining the estimation problem and objectives because early-stage projects are characterized by limited and uncertain information (G.-H. Kim et al., 2004). Clearly defined objectives ensure that the estimation process aligns with the intended decision-making context, such as feasibility assessment, schematic design planning, early budget forecasting, or AI model performance evaluation (Tayefeh Hashemi et al., 2020). Since conceptual and detailed estimates require different levels of data granularity and methodological rigor, objective definition directly influences the selection of AI techniques, data requirements, and modeling strategies (Shamim et al., 2025).

The specification of project type is equally important because transportation, residential, institutional, utility, bridge, and green building projects involve distinct engineering characteristics, cost structures, and cost drivers. When project categories are not clearly defined, AI models may rely on heterogeneous datasets that weaken predictive validity and reduce transferability to real-world applications (Guo & Li, 2021; Yi & Luo, 2024). Conversely, a well-defined project scope supports the identification of relevant cost factors, data sources, and modeling boundaries (Y.-M. Cheng, 2014). The literature also shows that AI-based methods are increasingly adopted during the conceptual phase because they can identify historical cost patterns and generate reliable predictions under limited design information (M.-Y. Cheng & Khasani, 2024; R. Wang et al., 2025). Together, these observations highlight the importance of establishing clear estimation objectives, project type, and decision boundaries before proceeding to later stages such as data selection, feature identification, model development, and performance evaluation.

4.2.2 Step 2: Datasets and data collection

Since early-stage estimation often involves limited and uncertain information, the datasets used in AI-based conceptual cost estimation models primarily rely on historical project data to identify cost patterns and influential cost drivers, demonstrating the increasing adoption of data-driven approaches in conceptual cost estimation, as summarized in Table 2. The identified studies utilized geographically diverse datasets, with frequent representation from the United States (Helaly et al., 2025; Karaca et al., 2020; Mohamed & Moselhi, 2022; Zhang, 2024), Iraq (Abbas & Aswed, 2024; Abd et al., 2024; Ali et al., 2022; Ghadbhan Abed et al., 2022), and China (Guo & Li, 2021; Tong et al., 2021; R. Wang et al., 2025). Additionally, the collected datasets also varied substantially by project type. Residential projects were the most frequently represented, followed by transportation projects, particularly road and highway systems, and general building projects. Institutional, bridge, and utility projects appeared less frequently, while only one study focused on green building projects. This distribution indicates that AI-based conceptual cost estimation research remains concentrated within limited project types, particularly residential, transportation and general building projects. The reviewed studies used diverse data sources, with government and institutional datasets being the most common because of their structured project records. Several studies also incorporated expert-based methods to supplement limited early-stage information. Overall, the findings highlight the methodological diversity of AI-based conceptual cost estimation research and the need for more standardized reporting practices and stronger alignment between project type, data source, and model development.

4.2.3 Step 3: Input parameters identification

Identifying input parameters is a fundamental step in AI-based conceptual cost estimation because the accuracy, interpretability, and reliability of models depend heavily on the systematic selection of variables representing project characteristics, external factors, site conditions, and project specifications (Elmousalami, 2020). According to the analysis of the identified studies, the distribution of input parameters across project types reveals both common and project-specific modeling priorities in AI-based conceptual cost estimation studies. Cost characteristics (total, labor, material, and unit costs), schedule characteristics (start date and total duration), project scope, structural dimensions, market conditions and project location appear as the most consistently utilized parameters across multiple project categories, indicating their fundamental importance in early-stage cost estimation regardless of project type. Residential and institutional building studies primarily emphasize

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architectural and MEP-related parameters. In contrast, bridge projects focus more heavily on structural characteristics, transportation intensity, and construction methods. Transportation infrastructure studies demonstrate a strong concentration on pavement properties, structural dimensions, number of lanes/spans, and geographical complexity. The green building study places greater emphasis on sustainability ratings, government incentives, and market conditions, whereas utility projects rely more heavily on site conditions, project delivery and schedule characteristics, and electrical and utility scope. Overall, the findings demonstrate that while several core parameters are consistently applied across project categories, the selection of input variables is strongly shaped by project-specific engineering characteristics, operational requirements, and cost drivers. Table 1 presents the input parameters identified in the reviewed studies together with their corresponding references, organized by project type and parameter categories.

Table 1: Identified input parameters from the reviewed studies.

	Input Parameters	Project Type*						
		B	**R**	**I**	**GB**	**BR**	**T**	**U**
Project Attributes	Cost characteristics	[8], [14]	[2], [13], [15], [16], [19]	[6], [9]	[18]	[1],	[4], [12]	
	Schedule characteristics	[14], [22]		[6], [17]		[1]	[5], [12]	[11],
	Project delivery method	[22]						[11],
	Project owner	[27]		[24]				
	Construction method					[1],		[23]
	Functional classification	[22], [27]	[13], [16], [28]	[24]		[1]	[3], [4], [7]	[23]
	Technical complexity	[14], [26]					[4], [7]	[23]
	Project scope	[8], [14], [22], [27]	[10]			[1]	[3], [4], [5], [7]	[23]
External	Market conditions	[14], [22], [27]	[25], [28]	[6], [24]	[18]		[4], [5]	[23]
	Demographic trends		[2]		[18]		[5]	
	Transportation intensity					[1],		
	Government incentives				[18]			
	Force majeure	[14], [22]						
Site	Project location	[22], [27]	[15], [28]	[24]		[1],	[5], [7]	[11],
	Site area	[8], [14], [27]	[10]	[6]				
	Geographical complexity	[22], [27]	[25]			[1]	[3], [5]	[11],
Architectural	Total floor area	[8], [14], [22], [26],	[2], [10], [13], [15], [16],	[6], [17]				
	Building height	[8], [26], [27]	[2], [10], [25]	[17]				
	Number of floors	[8], [14], [22], [27]	[2], [10], [16], [25]	[6], [9],				
	Number of units	[26]	[16], [19], [28]	[9]				
	Number of special facilities	[26], [27]	[2], [10], [16], [25]	[6]				
	Interior finish level		[2], [13], [19], [28]	[9]				
	Building envelope type		[2], [19], [25]	[17]				
	Sustainability ratings				[18]			
Engineering	Structural type	[26], [27]	[2]	[17]		[1],		
	Foundation type	[26]	[2]	[6], [9]				
	Structural materials		[15], [19]		[18]	[1],		[11]
	Structural dimensions	[14]	[10]	[9]		[1],	[3], [4], [5], [7],	[11],
	Structural quantities		[10], [19], [28]	[9], [24]		[1]	[4], [12]	
	Number of lanes/spans					[21]	[3], [4], [7]	
	Pavement properties						[3], [5]	
MEP	Electrical scope		[2]	[9]				[23]
	HVAC scope		[2], [28]	[9]				
	Fire system scope		[2]					
	Water supply scope		[2], [25]	[9]				
	Utility scope							[11]

*B: Building, BR: Bridge, GB: Green Building, I: Institutional, R: Residential, T: Transportation, U: Utility

References: [1] Karaca et al. (2020), [2] Guo & Li (2021), [3] Suneja et al. (2021), [4] Tong et al. (2021), [5] Ghadbhan Abed et al. (2022), [6] Ali et al. (2022), [7] Mohamed & Moselhi (2022), [8] U. Park et al. (2022), [9] Aguinaldo & Silva (2023), [10] D. Park & Yun (2023), [11] Abbas & Aswed (2024), [12] Abd et al. (2024), [13] Aquino et al. (2024), [14] Cheng & Khasani (2024), [15] Sadick et al. (2024), [16] Saeidlou & Ghadiminia (2024), [17] Yi & Luo (2024), [18] Zhang (2024), [19] Abu-Mahfouz et al. (2025), [20] Bansal et al. (2025), [21] Helaly et al. (2025), [22] R. Wang et al. (2025), [23] Abuzaid, Bashir, Al-Shihabi, et al. (2026), [24] Alrasheed et al. (2026), [25] Arce Fernández et al. (2026), [26] Jiang et al. (2026), [27] Jo et al. (2026), [28] Vincy & Kanaga (2026)

Compared with conventional conceptual estimating procedures, the parameters identified in Table 1 represent many of the project attributes, site conditions, and external factors that are traditionally considered through estimator experience and professional judgment. In conventional practice, these factors inform the assessment of project conditions and the adjustments applied to historical cost information when developing an estimate for a new project. In AI-based conceptual cost estimation, these factors are explicitly defined as input parameters and incorporated into the modeling process to evaluate their relationships with project cost. The variation across project types further indicates that parameter relevance depends on the specific characteristics and cost drivers of each project category. Accordingly, the proposed framework provides a systematic approach for identifying and incorporating these factors into conceptual cost estimation rather than relying primarily on experience-based assessment. This integration maintains the practical considerations of conventional conceptual estimating while providing a data-driven basis for determining how project-specific factors are represented in AI-based cost estimation models. However, the practical use of these input parameters also depends on their relevance to the project type and their availability at the conceptual stage. Architectural parameters, including total floor area, building height, and number of floors, were frequently used in building, residential, and institutional projects, whereas engineering parameters were more prominent in bridge, transportation, and utility projects (Table 1). In contrast, MEP-related parameters were mainly used in residential and institutional projects and appeared only to a limited extent in utility projects, indicating a more restricted application across the reviewed project types. Therefore, input variable selection requires consideration of both the cost drivers relevant to the specific project and the information realistically available when the conceptual estimate is developed.

4.2.4 Step 4: Feature selection

Feature selection improves the accuracy, efficiency, and interpretability of AI-based conceptual cost estimation models by identifying the most relevant variables and reducing challenges associated with high-dimensional data (Tang et al., 2014). The reviewed studies demonstrate diverse feature-selection strategies tailored to project characteristics and data structure in AI-based conceptual cost estimation. These strategies include filter-based methods such as PCC and GRA, embedded methods such as LASSO and XGBoost-based importance measures, and dimensionality-reduction methods such as PCA to reduce dimensionality, eliminate redundant variables, and identify influential cost drivers. In addition, post-hoc explanation and other feature analysis approaches, including SHAP, sensitivity analysis, fuzzy logic algorithms, and F-AHP, are applied to evaluate feature importance, improve interpretability, and refine variable selection. The reviewed studies also incorporate expert knowledge- and literature-based approaches to identify contextually relevant and methodologically consistent cost drivers in AI-based conceptual cost estimation models.

4.2.5 Step 5: Modeling approach definition

AI-based conceptual cost estimation research demonstrates four main methodological orientations identified in the reviewed studies. The most common approach focuses on performance comparison, where multiple AI models are evaluated based on predictive accuracy, reliability, and efficiency. A second approach emphasizes the application or effectiveness of a single AI method within a specific project context. Other studies adopt hybrid approaches by integrating multiple AI techniques to improve prediction performance and robustness, while some additionally compare hybrid models against individual or alternative approaches to evaluate their relative advantages. Overall, performance comparison remains the dominant methodological orientation, whereas single-method and hybrid approaches indicate opportunities for broader methodological development in conceptual cost estimation research, with hybrid approaches appearing more frequently in recent studies.

4.2.6 Step 6: Data analysis techniques

Data analysis techniques, particularly supervised machine learning, play a central role in AI-based conceptual cost estimation by identifying patterns and relationships within complex construction datasets to support predictive modeling and improve decision-making accuracy (Shetty et al., 2022). Analytical approaches in AI-based conceptual cost estimation include linear modeling techniques such as OLS, MLR, Ridge Regression, Bayesian Ridge, LASSO, and Elastic Net Regression to model cost relationships and address multicollinearity or variable sparsity. Tree-based and ensemble methods, including RF, Extra Trees, GB, XGBoost, LightGBM, CatBoost, and AdaBoost, were also widely adopted because of their ability to capture nonlinear relationships and improve predictive robustness. Kernel-based and instance-based methods such as SVM, SVR, GPR, and KNN were utilized to model nonlinear cost behavior, improve generalization performance, quantify predictive uncertainty, and

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generate predictions from historical project similarities. Neural network approaches, including ANN, MLP, and BPNN, and deep learning approaches such as DNN were also applied to capture complex nonlinear cost relationships. Probabilistic approaches such as Bayesian networks were also applied to represent uncertainty and dependencies among cost drivers (Abuzaid, Bashir, Al-Shihabi, et al., 2026). Complementing numerical approaches, NLP techniques, including transformer-based models such as DistilBERT, also demonstrated emerging potential for extracting cost-related insights from textual project information when structured data were limited or unavailable. Finally, hybrid and metaheuristic-integrated models combined multiple computational techniques, including ensemble, optimization-enhanced, and stacked learning approaches, to improve prediction accuracy, robustness, and adaptability in AI-based conceptual cost estimation. In addition, a recent study used automated machine learning (AutoML) to compare multiple algorithms systematically within a single workflow (Jo et al., 2026).

4.2.7 Step 7: Model and performance evaluation

Evaluating the performance of AI-based cost estimation models requires a rigorous and multifaceted assessment strategy, as no single metric can fully capture the predictive behavior, stability, and generalizability of a model (Nastoska et al., 2025). In the reviewed studies, error-based evaluation metrics, including MAPE, MAE, RMSE, NRMSE, MedAE, MSE, MPE, MER, RER, and MSRE, were employed in 25 studies to measure prediction accuracy and assess the distributional characteristics and reliability of estimation errors in AI-based conceptual cost estimation models for early-stage decision-making contexts. Goodness-of-fit metrics, including R^2, R, WI, and RI, were employed in the reviewed studies to evaluate how effectively AI-based conceptual cost estimation models capture observed data patterns, explain variance, and represent structural relationships in construction cost data. Additional performance metrics included F1-score, confusion matrices, accuracy ratio, prediction ratio, error rate, efficiency ratio, TAP, and AA. F1-score and confusion matrices were used for classification-based evaluation, whereas AA and TAP were reported as measures of prediction accuracy. Overall, the reviewed studies demonstrate that effective evaluation of AI-based conceptual cost estimation models requires the use of multiple complementary metrics aligned with model type, data characteristics, and estimation objectives to ensure robust and reliable performance assessment.

The reviewed studies covered diverse project types and utilized datasets from multiple countries and data sources. Various feature analysis methods, modeling strategies, and AI techniques, including machine learning, deep learning, NLP-based, ensemble, and hybrid approaches, were identified across the studies, while performance evaluation relied on multiple complementary metrics to assess prediction accuracy and model reliability. Within individual studies that compared multiple methods on the same dataset, hybrid or optimization-enhanced models frequently outperformed the tested standalone alternatives. However, differences in datasets, project characteristics, preprocessing procedures, validation procedures, and metrics prevent direct performance comparison across studies. Table 2 presents the overall results of the qualitative template analysis and the key findings identified across the reviewed studies.

Table 2: Qualitative template analysis of the reviewed studies.

Reference	Project Type*	Data Source	Feature Analysis	Modeling Approach	Data Analysis Methods	Performance Metrics	Results
Karaca et al. (2020)	BR	Government agency	BVT	Performance comparison	ANN, MLP, AIE	MAPE	ANN achieved the lowest MAPE
Guo & Li (2021)	R	Institutional database	PCC	Performance comparison	SVM, BPNN, RF	R^2, MSE, MAE	SVM showed the highest R^2 value
Suneja et al. (2021)	T	Government agency	Not specified	Single method	DNN	TAP, RMSE, MAPE	DNN achieved a TAP of 63.7%
Tong et al. (2021)	T	Industry	GRA	Performance comparison	GRA+LASSO, LASSO, OLS	MAPE	GRA+LASSO achieved the lowest MAPE
Ghadbhan Abed et al. (2022)	T	Government agency	Not specified	Performance comparison	RR, LASSO, KNN, RF	RMSE, MAPE, R^2	RR showed the highest R^2 value

Reference	Project Type*	Data Source	Feature Analysis	Modeling Approach	Data Analysis Methods	Performance Metrics	Results
Ali et al. (2022)	I	Survey	XGBoost	Performance comparison	XGBoost+SVM, XGBoost+RF, XGBoost+ANN	R^2, RMSE, MAE, MAPE, Nash, WI	XGBoost+RF showed the highest R^2 value
Mohamed & Moselhi (2022)	T	Literature	Literature	Performance comparison	ANN, SVM, RF	MAPE	ANN achieved the lowest MAPE in cost estimation
U. Park et al. (2022)	B	Public dataset	PCC	Hybrid method and performance comparison	RF+SVM+CatBoost (BDT), ANN, LR, SVR, AdaBoost, XGBoost, LightGBM, CatBoost	RMSE, R^2	RF+SVM+CatBoost (BDT) showed the highest R^2 value
Aguinaldo & Silva (2023)	I	Government agency	SA	Single method	ANN	R, MSE	ANN achieved an R value of 0.999 and an MSE of 0.053
D. Park & Yun (2023)	R	Government agency	PCC	Single method	DNN	MER, RER, MSE	MER reduced to 20.82%
Abbas & Aswed (2024)	U	Government agency	Expert judgement	Single method	ANN	MPE, AA, RMSE, MAPE	ANN achieved a MAPE of 1.5% and an AA of 98.5%
Abd et al. (2024)	T	Not specified	Literature	Performance comparison	Basic ANN, ANN+R Controller, ANN+RMSE Controller, ANN+R & RMSE Controllers, optimized ANN	RMSE, R	Optimized ANN showed the highest R
Aquino et al. (2024)	R	Survey	FLA	Single method	ANN	MSE, MAPE, F1-score, confusion matrix	ANN achieved an F1-score of 0.95 and an accuracy of 0.96
Cheng & Khasani (2024)	B	Literature	PCA, LASSO	Performance comparison	LSMBM, LSSVM, RF, BPNN, DT, KNN, SVM, LR with PCA/LASSO	RMSE, MAE, MAPE, R, R^2, RI	LSMBM+PCA achieved the lowest MAPE
Sadick et al. (2024)	R	Institutional database	Literature	Single method	DistilBERT	F1-score, confusion matrix	DistilBERT achieved an F1-score of 0.79 and an accuracy of 0.79
Saeidlou & Ghadimini a (2024)	R	Public dataset	Not specified	Performance comparison	DNN, SVM, LR	R^2, RMSE, MAE, MAPE	DNN achieved the lowest MAPE
Yi & Luo (2024)	I	Industry	SHAP	Performance comparison	AI-CCECA (DNN based model) and other methods developed in the literature	Accuracy ratio, prediction ratio, error rate, efficiency ratio	AI-CCECA showed the highest accuracy ratio
Zhang (2024)	GB	Institutional database	Not specified	Hybrid method	LR+ANN+RF+XGBoost+LGBoost + NGBoost	RMSE, MSE, MAE	The proposed model showed low prediction errors
Abu-Mahfouz et al. (2025)	R	Survey	F-AHP	Single method	ANN	RMSE, MAPE, R^2	ANN achieved a MAPE of 3%

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Reference	Project Type*	Data Source	Feature Analysis	Modeling Approach	Data Analysis Methods	Performance Metrics	Results
Bansal et al. (2025)	U	Survey	SHAP	Hybrid method and performance comparison	LR, LASSO, ENR, RF, XGBoost, GPR, GPR+XGBoost	R^2	GPR+XGBoost achieved highest R^2
Helaly et al. (2025)	BR	Industry reports	Not specified	Performance comparison	OLS, LASSO, Ridge, RF, GB, XGBoost	R^2, MAPE, MAE, Med AE, RMSE	XGBoost achieved the lowest MAPE
R. Wang et al. (2025)	B	Industry	PCC, SHAP	Hybrid method and performance comparison	BPNN, DBO+BPNN, GA+BPNN, PSO+BPNN	R^2, R, MAPE, MAE, MSE, MSRE, RMSE	DBO+BPNN achieved the lowest MAPE
Abuzaid, Bashir, Al-Shihabi, et al. (2026)	U	Industry	Expert judgement	Performance comparison	BN, MLR, RF	MAE, RMSE, MAPE, R^2	MLR showed the highest R^2; RF achieved the lowest MAPE
Alrasheed et al. (2026)	I	Industry	SA	Single method	ANN	MAPE, R^2	ANN achieved a MAPE of 0.72%
Arce Fernández et al. (2026)	R	Government agency	PCC	Performance comparison	XGBoost, RF, MLR, MLP	MAE, MSE, RMSE, MAPE, R^2	RF showed the highest R^2 value
Jiang et al. (2026)	B	Not specified	GRA, SHAP	Hybrid method and performance comparison	XGBoost+LightGBM (CCBSN-BO), RF, XGBoost, LightGBM, LASSO, SVM	R^2, MAPE	CCBSN-BO achieved the lowest MAPE
Jo et al. (2026)	B	Government agency	Feature importance	Performance comparison	AutoML: XGBoost, GBR, ETR, RF, LightGBM, AB, LASSO, LLAR, Ridge, BR, OMP	RMSE, NRMSE, MAE, MAPE, MSE	XGBoost achieved the lowest NRMSE
Vincy & Kanaga (2026)	R	Not specified	SA	Hybrid method and performance comparison	RF+XGBoost+LightGBM+MLP (stacked), XGBoost, MLP, RF, Ridge, LASSO	MAPE, MAE, R^2	Hybrid stacked ensemble achieved the lowest MAPE

*B: Building, BR: Bridge, GB: Green Building, I: Institutional, R: Residential, T: Transportation, U: Utility

Although the reviewed studies collectively demonstrate the growing applicability of AI to conceptual cost estimation, several consistent patterns emerge across the literature. The existing literature remains concentrated in a limited number of project sectors, with residential projects emerging as the most frequently investigated project type, followed by transportation, building, and institutional projects. Bridge and utility projects remain underrepresented, whereas green building projects are the least represented. However, recent studies have begun to address underrepresented sectors, including power-sector utility projects (Abuzaid, Bashir, Al-Shihabi, et al., 2026). Consequently, the current evidence base has largely been established within a limited range of construction domains, which may restrict the transferability of existing AI models to projects with different characteristics and cost drivers. This limitation is further reinforced by the widespread reliance on government agencies, institutional databases, and industry-specific datasets rather than publicly available benchmark datasets. As a result, independent validation and cross-study comparisons remain challenging.

The reviewed studies also reveal notable differences in the selection of conceptual-stage input variables. Architectural parameters represented the most frequently adopted input category, particularly in building, residential, and institutional projects, where total floor area, number of floors, and building height were commonly incorporated. Project attribute and engineering parameters were also widely used across multiple project types,

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especially cost characteristics, project scope, structural dimensions, and structural materials. Recent studies also incorporated external economic indices, such as construction cost indices (Abuzaid, Bashir, Al-Shihabi, et al., 2026; Jo et al., 2026), and project owner characteristics (Alrasheed et al., 2026; Jo et al., 2026) as input parameters. In contrast, MEP-related variables appeared in only a limited number of studies and were largely confined to residential, institutional, and utility projects, while transportation studies primarily emphasized pavement properties and number of lanes/spans, and bridge studies focused on structural characteristics. These variations demonstrate that the selection of input variables remains highly project-specific and that a standardized set of conceptual-stage input parameters for AI-based conceptual cost estimation has yet to be established.

Substantial variation was also observed in feature analysis techniques, modeling approaches, data analysis methods, model evaluation, and performance reporting. Feature analysis ranged from conventional statistical techniques, including Pearson Correlation Coefficient (PCC), Principal Component Analysis (PCA), and Grey Relational Analysis (GRA), to explainable AI techniques such as SHAP and XGBoost-based feature importance, whereas several studies did not explicitly report a feature analysis method. Notably, studies that adopted SHAP used industry, survey-based, or unspecified data sources (Bansal et al., 2025; Jiang et al., 2026; R. Wang et al., 2025; Yi & Luo, 2024). These sources typically include larger and less standardized sets of parameters, which may increase the need for model interpretability. In contrast, studies using government, institutional, or public datasets predominantly relied on simpler statistical techniques, such as PCC (Guo & Li, 2021; D. Park & Yun, 2023; U. Park et al., 2022), or did not report a formal feature analysis method. In addition, a recent study introduced expert-based predictor selection through a Delphi process (Abuzaid, Bashir, Al-Shihabi, et al., 2026). Among nonlinear AI techniques, Random Forest (RF) was the most frequently adopted, followed by Artificial Neural Network (ANN), XGBoost, and Support Vector Machine (SVM), likely because these techniques can capture nonlinear relationships between project parameters and cost without requiring strong assumptions about data distribution. This capability is particularly relevant to conceptual cost estimation, where the available project information is often limited and heterogeneous. Recent studies also demonstrated a growing tendency toward hybrid and ensemble approaches that combined multiple AI techniques with optimization algorithms and feature selection methods, including PCA, LASSO, DBO, GA, and PSO, to improve predictive performance. The frequent performance advantage of hybrid and ensemble approaches is consistent with the general logic of ensemble learning, where combining multiple algorithms can reduce prediction variance and offset the limitations of individual methods, particularly when relationships between project characteristics and cost are complex. This may explain why hybrid and ensemble models frequently outperformed standalone algorithms, although the best-performing combinations varied across the reviewed studies. Although performance comparison was the dominant modeling approach, the number and selection of baseline models differed considerably across studies.

Performance evaluation also exhibited considerable variation across the reviewed studies. MAPE, RMSE, MAE, R^2, and MSE were the most frequently reported evaluation metrics, whereas several studies adopted additional application-specific measures, including NRMSE, TAP, Nash coefficient (Nash), Willmott Index (WI), Accuracy (AA), MER, RER, F1-score, confusion matrix, prediction ratio, accuracy ratio, efficiency ratio, and MSRE. ANN, DNN, SVM, RF, and XGBoost-based regression models were primarily evaluated using MAPE, RMSE, MAE, and R^2, whereas DistilBERT and ANN-based classification models employed F1-score, confusion matrix, and accuracy-related metrics. This distinction reflects differences in the underlying prediction task, as regression-oriented studies require performance metrics appropriate for evaluating continuous cost outputs, whereas classification-oriented studies require metrics appropriate for evaluating categorical outcomes. Within individual case studies, ANN-based models were most frequently reported as the best-performing approach. However, several recent studies demonstrated that hybrid and ensemble models, including XGBoost+RF, RF+SVM+CatBoost, LSMBM+PCA, GPR+XGBoost, DBO+BPNN, XGBoost+LightGBM (CCBSN-BO), and stacked RF+XGBoost+LightGBM+MLP, achieved better predictive performance than conventional AI models under their respective datasets and evaluation settings. Since these comparisons were conducted within individual studies using different datasets, preprocessing procedures, baseline models, and evaluation settings, the reported performance advantages of hybrid and ensemble models should not be generalized across all contexts.

Beyond their observed frequency and performance, the identified AI techniques also differ in their practical characteristics. Neural network-based techniques such as ANN and DNN can capture nonlinear relationships between project characteristics and cost but are generally associated with limited interpretability and greater susceptibility to overfitting when applied to small datasets. In comparison, tree-based methods, including Random Forest and XGBoost, which are among the most frequently adopted techniques, generally require less data

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preprocessing and provide feature importance measures that facilitate model interpretation. More complex approaches introduce an additional trade-off between predictive performance and practical implementation. Hybrid and ensemble approaches demonstrated performance advantages over standalone methods in several reviewed studies; however, their integration of multiple algorithms and modeling procedures can increase implementation complexity and limit the interpretability of the overall model. A temporal pattern can be observed in the adoption of explainable AI techniques and, to a lesser extent, hybrid modeling approaches. Explainable AI techniques such as SHAP were not used in studies published before 2024 and appeared only in studies published from 2024 onward (Bansal et al., 2025; Jiang et al., 2026; R. Wang et al., 2025; Yi & Luo, 2024). The recent adoption of these techniques reflects greater attention to model interpretability. More complex modeling approaches were also applied in several recent studies (Bansal et al., 2025; R. Wang et al., 2025; Zhang, 2024). Their increased application also reflects a gradual transition toward more complex modeling approaches. This trend continued in 2026, with studies adopting hybrid and stacked ensemble models (Jiang et al., 2026; Vincy & Kanaga, 2026) and automated machine learning (Jo et al., 2026). In contrast, dataset size and the selection of performance metrics did not show a clear trend over the reviewed period. MAPE, RMSE, and R^2 remained the most frequently reported metrics. Dataset sizes varied considerably across both earlier and more recent studies without a consistent increase over time, ranging from 7 (Bansal et al., 2025) to 63,899 (Sadick et al., 2024) observations in earlier studies and from 28 (Alrasheed et al., 2026) to approximately 100,000 (Vincy & Kanaga, 2026) observations in studies published in 2026. Overall, interpretability and modeling complexity have received greater attention in recent studies, whereas other methodological practices have shown less consistent changes over the reviewed period.

The variation in the best-performing models across the reviewed studies further indicates that no single algorithm consistently outperformed others under all conditions. The reviewed studies can also be grouped based on modeling pipeline complexity, ranging from studies applying a single method to those comparing multiple standalone algorithms or employing hybrid or ensemble approaches. Part of this variation may be associated with differences in project type, data source, and feature analysis practices, which influence the input variables used in the models and the ability of different algorithms to capture relationships between project characteristics and cost. However, neither dataset size nor the number of input parameters appears to consistently distinguish between comparative studies in which a combination of algorithms performed best and those in which a single algorithm performed best. Studies reporting a combination of algorithms as best-performing used datasets ranging from 7 (Bansal et al., 2025) to 775 (U. Park et al., 2022) observations, with one study using approximately 100,000 projects (Vincy & Kanaga, 2026), and between 1 and 10 input parameters (as categorized in Table 1), whereas comparative studies reporting a single algorithm as best-performing used datasets ranging from 56 (Mohamed & Moselhi, 2022) to 1,660 (Ghadbhan Abed et al., 2022) observations and between 4 and 14 input parameters. The ranges observed among these comparative studies show substantial overlap between the two groups. Studies that evaluated only a single method were not included in this comparison because no within-study determination of a best-performing modeling approach could be made. Based on the reviewed studies, the conditions under which more complex pipelines provide a meaningful advantage therefore cannot be clearly identified. In particular, the reviewed evidence does not indicate a dataset size threshold or a level of data heterogeneity beyond which hybrid or ensemble approaches consistently outperform simpler alternatives. Differences in preprocessing procedures, such as the treatment of outliers, normalization, and the handling of missing data, may also have influenced the reported performance of individual models. As discussed above, combining multiple algorithms may be more beneficial when the relationships between project characteristics and cost are complex and are not adequately captured by a single method; however, further evidence is needed to determine whether this advantage extends across different datasets and project contexts.

In addition, several reviewed studies did not report dataset size (Aguinaldo & Silva, 2023; Saeidlou & Ghadiminia, 2024; Yi & Luo, 2024; Zhang, 2024), which limits the assessment of this factor across the full evidence base. In contrast, all studies published in 2026 reported dataset size. Evaluation metric reporting also shows a modest association with the modeling approach. Studies in which a combination of algorithms performed best more frequently reported R^2, whereas studies in which a single algorithm performed best more frequently reported MAPE. Given the limited number of studies, this association provides an initial indication of differences in evaluation metric reporting between the two modeling approaches but requires further evidence to establish a consistent relationship. These findings suggest that model performance depends not only on the selected AI technique but also on dataset characteristics, feature selection strategies, and evaluation procedures. Therefore, the

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absence of standardized datasets, preprocessing procedures, validation procedures, and evaluation metrics continues to limit objective comparison across studies and hinders cumulative knowledge development in AI-based conceptual cost estimation.

The quality assessment showed that the reliability of the evidence varies considerably across the reviewed studies. Dataset size was one of the main differences. Some studies developed models using a very small number of projects, such as 7 (Bansal et al., 2025), 18 (Abbas & Aswed, 2024), 23 (Aquino et al., 2024), and 28 (Alrasheed et al., 2026), while others used several hundred or more observations (Ghadbhan Abed et al., 2022; Jo et al., 2026; Karaca et al., 2020; Sadick et al., 2024; Vincy & Kanaga, 2026). Several studies also did not report the size of their dataset (Aguinaldo & Silva, 2023; Saeidlou & Ghadiminia, 2024; Yi & Luo, 2024; Zhang, 2024). Validation procedures were mostly internal. Some studies applied cross-validation (Abuzaid, Bashir, Al-Shihabi, et al., 2026; Ali et al., 2022; Arce Fernández et al., 2026; M.-Y. Cheng & Khasani, 2024; Jiang et al., 2026; Jo et al., 2026; Mohamed & Moselhi, 2022; D. Park & Yun, 2023; U. Park et al., 2022; Tong et al., 2021; Vincy & Kanaga, 2026), whereas others relied on a single train/test split (Abu-Mahfouz et al., 2025; Guo & Li, 2021; Helaly et al., 2025; Suneja et al., 2021; R. Wang et al., 2025). Only Jo et al. (2026) tested their model on independent projects from a later period.

These differences affect how the reported accuracy should be read. Very high accuracy values were reported in some of the smallest studies (Abbas & Aswed, 2024; Alrasheed et al., 2026; Aquino et al., 2024), and Alrasheed et al. (2026) stated that overfitting could not be ruled out. This pattern is consistent with evidence that performance estimates obtained from small samples with a single data split tend to be biased upward (Vabalas et al., 2019). In Bansal et al. (2025), the target cost was calculated from standard rates rather than observed project costs, which may also contribute to high accuracy. Reporting was uneven as well. Some studies did not report the data split ratio, preprocessing steps, or tuning procedures (Abd et al., 2024; Ali et al., 2022; Karaca et al., 2020; Yi & Luo, 2024). Reproducibility was the weakest aspect. Only a few studies used publicly available data or shared their code (Bansal et al., 2025; M.-Y. Cheng & Khasani, 2024; Sadick et al., 2024; Saeidlou & Ghadiminia, 2024; Zhang, 2024), and many relied on confidential data or did not include a data availability statement. Accordingly, the performance values in Table 2 should be interpreted as study-specific results rather than evidence of general model reliability, especially for studies with small datasets or limited reporting.

4.3 AI-based cost estimation framework

The proposed seven-step framework was developed through the qualitative template analysis conducted across the reviewed studies. During the analysis process, recurring methodological components, procedural patterns, and decision stages observed in AI-based conceptual cost estimation studies were systematically identified, compared, and categorized. These recurring elements were subsequently synthesized into seven interconnected stages representing the common methodological workflow adopted in the literature, as illustrated in Figure 4. The framework therefore reflects the consolidated methodological structure derived from the qualitative template analysis and provides a generalized roadmap for developing AI-based conceptual cost estimation models in construction projects. By systematically organizing fragmented methodological practices into a coherent structure, the framework contributes a more transparent, standardized, and implementation-oriented foundation for future AI-based conceptual cost estimation research and practice.

The framework is distinguished from generic machine-learning workflows by embedding conceptual-stage decision guidance at each step. Step 1 anchors the estimation objective to the decision context of the conceptual phase, where scope definition is minimal; Step 3 links input parameter selection to project type using the evidence consolidated in Table 1, enabling estimators to identify parameters observable before design development; Step 5 outlines the single, hybrid, and comparative modeling orientations reported in the literature and the trade-offs among them; and Step 7 maps error-based, goodness-of-fit, and classification metrics to model output types, as synthesized from the reviewed studies. Steps 4 and 7 allow the selection of one or more options, since several reviewed studies combined multiple feature selection techniques and performance metrics. Taken together, the seven stages establish a structured decision-support process for developing AI-based conceptual cost estimation models under limited-information conditions. The framework connects project definition, data suitability, variable availability, model selection, and evaluation into a coherent and traceable workflow. It therefore addresses a central limitation identified in the reviewed literature: methodological fragmentation across datasets, input parameters, analytical techniques, validation procedures, and reporting practices.

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The guidance embedded in the framework draws on two types of evidence, which should be distinguished when the framework is applied. The first type consists of empirical findings derived from the reviewed studies. These studies used datasets ranging from 7 (Bansal et al., 2025) to approximately 100,000 (Vincy & Kanaga, 2026) observations, and neither dataset size nor the number of input parameters consistently distinguished studies in which a combination of algorithms performed best from those in which a single algorithm performed best (Section 4.2). In addition, the performance advantages of hybrid and ensemble models were observed only within individual studies under their respective datasets, preprocessing procedures, and evaluation settings. Accordingly, the reviewed evidence does not establish a dataset size threshold or a level of data heterogeneity at which more complex modeling pipelines become preferable. The second type consists of general methodological guidance drawn from the broader machine learning literature rather than from the reviewed studies. For example, small datasets can produce overly optimistic performance estimates, and validation approaches such as nested cross-validation or independent train/test splits provide more reliable estimates in such cases (Vabalas et al., 2019). Similarly, combining multiple models can reduce the risk of relying on a single inadequate model (Dietterich, 2000), although the reviewed studies do not establish the conditions under which this advantage applies in conceptual cost estimation. Therefore, recommendations in the framework that concern dataset size, data heterogeneity, or model complexity should be interpreted as general methodological guidance that requires further empirical validation in conceptual cost estimation contexts.

The framework also offers value to both researchers and practitioners. For researchers, it provides a common structure for designing studies, reporting methodological decisions, and comparing findings across project types and modeling approaches. For practitioners, it provides a roadmap for determining whether available data are suitable, which variables can be used at the conceptual stage, which modeling orientations have been applied in comparable contexts and what trade-offs are associated with increasing model complexity, and how model outputs should be evaluated before being incorporated into budgeting or feasibility decisions. Rather than prescribing a single algorithm, dataset, or metric, the framework organizes the decisions that must be made and clarifies how those decisions should respond to project context and information availability. Accordingly, the framework should be interpreted as a literature-derived, evidence-informed, and adaptable conceptual structure rather than a rigid sequence of technical procedures. Its central contribution lies in translating fragmented methodological practices from the existing literature into a construction-specific, conceptual-stage workflow that promotes greater transparency, consistency, reproducibility, and practical relevance in AI-based cost estimation.

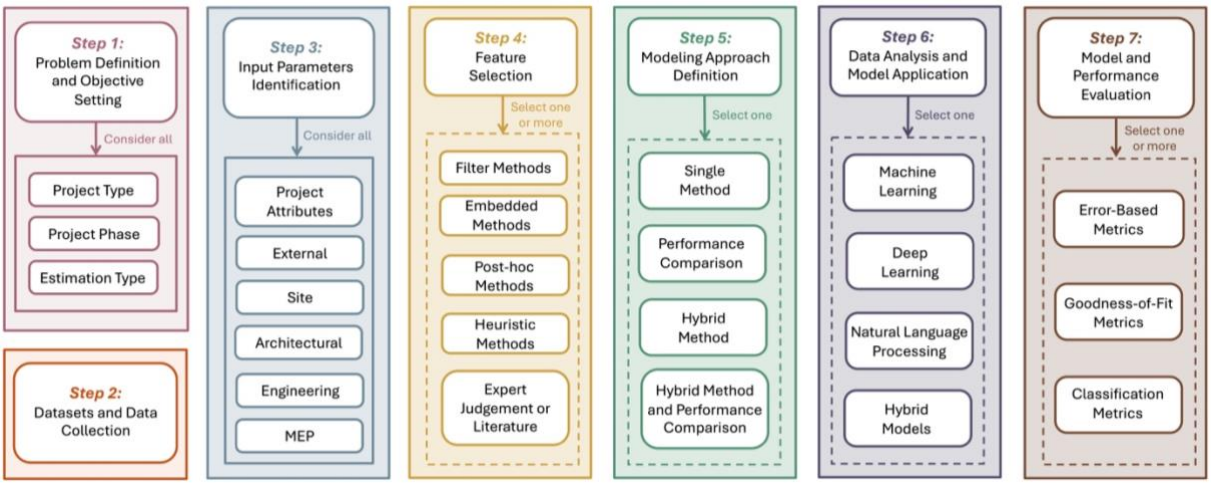


Figure 4: Seven-step framework for AI-based cost estimation.

5. DISCUSSION

5.1 Framework implementation and practical implications

The proposed seven-step framework suggests that AI-based conceptual cost estimation should be implemented as a structured and context-sensitive workflow rather than a purely algorithm-selection task. Early implementation stages should establish clear project boundaries, project type definitions, project phases, and estimation objectives

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because these decisions directly influence dataset composition, parameter relevance, modeling strategies, and evaluation criteria. Since conceptual cost estimation is performed under limited and uncertain information conditions, selecting appropriate input parameters according to project type becomes particularly important for improving prediction reliability and contextual consistency. Compared with conventional conceptual estimating procedures, the proposed framework provides a more structured and systematic approach to the use of historical project information. Conventional procedures generally require estimators to identify comparable historical projects, assess their applicability, and adjust historical costs for differences in time, location, and project-specific characteristics. These procedures therefore depend considerably on the availability of relevant historical information and the estimator's experience and professional judgment. In contrast, the proposed framework organizes historical project data and relevant project characteristics within a systematic data-driven workflow, where AI models can identify relationships between project characteristics and cost across historical projects and apply these relationships to new projects. For instance, adjustments for time and location, which are traditionally applied manually by estimators, can be incorporated directly into the model through inputs such as construction cost indices and location indices (Abuzaid, Bashir, Al-Shihabi, et al., 2026; Jo et al., 2026; Vincy & Kanaga, 2026). This comparison is based on the procedures discussed in the cost estimation literature and the practices reported in the reviewed studies. However, further research is needed to evaluate whether the proposed framework improves estimation accuracy, consistency, and efficiency compared to conventional procedures through its application to real construction projects.

This distinction provides several potential practical advantages. Systematic consideration of relevant project characteristics can improve estimation accuracy and consistency and reduce reliance on subjective judgment and individual estimator experience. Once the historical dataset and estimation model are established, the framework can also reduce the time required to develop subsequent conceptual cost estimates by limiting the need to manually identify, normalize, and adjust historical project data for each new project. Automated machine learning tools may further reduce the effort required for model selection by comparing multiple algorithms within a single workflow (Jo et al., 2026). However, the framework is intended to support rather than replace professional judgment, since practitioners remain responsible for evaluating data quality, interpreting model outputs, and considering project-specific conditions that may not be represented in historical data. For example, expert input can be integrated into the selection of input parameters, as demonstrated through a Delphi process in a recent study (Abuzaid, Bashir, Al-Shihabi, et al., 2026). The framework can therefore support owners, developers, cost estimators, and preconstruction professionals in establishing preliminary budgets, evaluating project feasibility, comparing early project alternatives, and supporting early project decisions. The findings further indicate that reliable conceptual cost estimation depends heavily on dataset quality, parameter relevance, and preprocessing practices rather than model complexity alone. Accordingly, implementation processes should prioritize systematic dataset development, transparent parameter reporting, and appropriate feature-selection procedures capable of reducing redundancy while maintaining interpretability and contextual relevance. The reviewed studies also demonstrate that different project categories involve distinct engineering characteristics, uncertainty profiles, and cost drivers, requiring AI implementation strategies to account for these differences rather than rely on universal modeling approaches.

The framework additionally highlights important practical considerations regarding modeling and evaluation practices. Although hybrid and optimization-enhanced models frequently demonstrated strong predictive performance, their implementation may require greater computational resources and technical expertise and may reduce model interpretability compared with single-algorithm approaches. Therefore, model selection should consider not only prediction accuracy but also interpretability, transferability, computational feasibility, and practical deployment requirements. In addition, future implementations should incorporate stronger validation practices, including external validation, standardized benchmarking, uncertainty quantification, and explainable AI techniques, to improve model transparency, reproducibility, and industry adoption in early-stage construction decision-making environments. A recent study illustrated this practice by validating its model on new projects from a subsequent year (Jo et al., 2026). Overall, the framework provides structured guidance for researchers and practitioners regarding the systematic implementation, validation, and application of AI-based conceptual cost estimation models across different construction project contexts.

5.2 Future research directions

Current AI-based conceptual cost estimation research demonstrates promising predictive capabilities; however, several important methodological and implementation-related limitations remain evident across the reviewed

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studies. Most studies relied on localized datasets derived from specific regions, organizations, or project categories (Abu-Mahfouz et al., 2025; Aquino et al., 2024; Bansal et al., 2025; Guo & Li, 2021; D. Park & Yun, 2023), while relatively limited attention was given to external validation, cross-region testing, cross-organization applicability, and temporal generalization under changing market and cost escalation conditions. Only one study validated its model on projects from a subsequent year to assess temporal generalization (Jo et al., 2026). Consequently, the practical transferability, scalability, and robustness of many proposed AI models remain uncertain across broader construction environments. These limitations point to a need for future research to adopt more comprehensive validation strategies capable of evaluating model performance under varying project scopes, economic conditions, and geographic contexts. Future systematic reviews should consider expanding the search strategy to include broader terminology for conceptual and early-stage cost estimation, together with technique-specific AI and machine-learning terms. This broader search approach may help identify relevant studies that use specific methodological or estimation terminology without explicitly referring to broader AI or conceptual cost estimation terms.

The reviewed studies also revealed relatively limited attention to uncertainty quantification, transparency, and interpretable AI implementation practices. Although several studies reported strong predictive accuracy (Ali et al., 2022; Helaly et al., 2025; U. Park et al., 2022; R. Wang et al., 2025), relatively limited discussion was observed regarding prediction uncertainty, confidence intervals, feature interpretability, or risk-aware estimation outputs. Recent studies have begun to address these aspects through SHAP-based interpretation (Jiang et al., 2026) and probabilistic modeling approaches such as Bayesian networks (Abuzaid, Bashir, Al-Shihabi, et al., 2026), but these practices have not yet been widely adopted. Because conceptual cost estimation involves incomplete and uncertain project information, limited transparency may reduce practitioners' ability to interpret model outputs and use them in decision-making. Future AI-based estimation systems would therefore benefit from explainable AI techniques, uncertainty-aware modeling approaches, and interpretable prediction mechanisms capable of supporting transparent and trustworthy decision-making processes during early project stages. In addition, clearer reporting of preprocessing procedures, including missing data handling, outlier treatment, normalization, and scaling practices, may further improve methodological transparency and reproducibility across future studies.

Another important gap concerns the limited integration of emerging AI advancements within conceptual cost estimation research. Most reviewed studies focused primarily on traditional machine learning, deep learning, and hybrid optimization approaches, including ANN, DNN, RF, SVM, XGBoost, and hybrid BPNN-based models (Abd et al., 2024; Karaca et al., 2020; R. Wang et al., 2025; Zhang, 2024), with limited attention to graph neural networks, multimodal fusion models, transfer learning, zero-shot learning, few-shot learning, and agentic AI frameworks. Although a recent study applied automated machine learning to compare multiple algorithms (Jo et al., 2026), the emerging approaches listed above have not yet been applied to conceptual cost estimation in the reviewed literature. This gap may indicate a need to explore emerging AI approaches that can address challenges associated with heterogeneous data, contextual learning, adaptability, model generalization, and data integration under limited-information conditions. Future research should therefore investigate how these advanced AI paradigms can support more scalable, adaptive, and implementation-oriented conceptual cost estimation systems within construction practice.

6. CONCLUSION

This study examined how artificial intelligence has been applied to conceptual cost estimation at the project level, focusing on the datasets and input requirements, modeling techniques and evaluation practices, and the methodological workflow that can be synthesized from the existing evidence. The PRISMA-guided review, supported by ASReview, identified only 28 eligible peer-reviewed studies, a result that provides an indication of the limited evidence available in this specific research area; although AI applications in construction cost estimation are extensively published, studies specifically addressing project-level estimation at the conceptual stage remain scarce. This scarcity provides evidence of the phase-specific gap that motivated the study and reflects the eligible evidence base identified through the review process. Drawing on these studies, analyzed through quantitative descriptive and qualitative template analyses, the study developed an AI-driven conceptual cost estimation framework grounded in the synthesized evidence.

Beyond their limited number, the reviewed studies reveal a fragmented evidence base where phase-specific conceptual estimation models are scarce, AI techniques are unevenly represented, external validity is constrained

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by localized datasets, and evaluation and reporting practices are inconsistent across studies. Conceptual estimates play an important role in early project decision-making, by establishing budgets, feasibility judgments, and go/no-go decisions, yet are prepared under limited project information, and the absence of a phase-specific evidence base limits the structured guidance available to researchers and practitioners for developing and evaluating AI-based estimation models under these conditions (Elmousalami et al., 2024; Emmanuel & Ali, 2022). These conditions limit cumulative comparison of model performance and present challenges for methodological standardization in the field (Choi et al., 2016; Mohutsiwa & Musingwini, 2015).

In response to these gaps, this study proposed a seven-step conceptual framework comprising the following interrelated steps that provide a structured methodological workflow for AI-enabled decision support systems in conceptual cost estimation: (i) problem definition and objective setting, which clarifies the project type, estimation purpose, and conceptual-phase information boundaries; (ii) datasets and data collection, which identifies sources and assembles structured data necessary for model development; (iii) input parameter identification, which delineates project characteristics, site conditions, external factors, and specifications; (iv) feature selection, which refines these parameters through one or more techniques to identify relevant cost drivers; (v) modeling approach definition, which determines whether the estimation strategy relies on single models, hybrid models, performance comparison, or integrated hybrid-comparison methods; (vi) data analysis techniques, which applies machine learning and advanced analytical techniques to generate cost predictions; and (vii) model and performance evaluation, which assesses predictive accuracy, generalizability, and robustness through one or more appropriate error-based, goodness-of-fit, and classification metrics. Because each step is informed by the limited-information conditions and decision-making requirements of the conceptual phase, the framework is intended to provide a decision-support structure rather than a restatement of the generic model development pipeline.

The synthesized evidence further indicates the potential of AI-based conceptual cost estimation to improve prediction accuracy, reduce dependence on subjective judgment, enhance estimation efficiency, and support more informed decision-making during the early stages of project development. In particular, AI models may provide advantages in capturing nonlinear relationships, hidden patterns, and complex interactions among project cost drivers that traditional estimation approaches may overlook under limited-information conditions (Sanusi et al., 2020; Shamim et al., 2025). These capabilities may support more scalable, repeatable, and data-driven conceptual forecasting processes across different construction project contexts. However, the reviewed studies also revealed important methodological and practical challenges related to dataset generalizability (Guo & Li, 2021; Karaca et al., 2020; U. Park et al., 2022; Zhang, 2024), inconsistent reporting practices (Ali et al., 2022; M.-Y. Cheng & Khasani, 2024; Tong et al., 2021; R. Wang et al., 2025), limited standardization of evaluation procedures (Aquino et al., 2024; M.-Y. Cheng & Khasani, 2024; Guo & Li, 2021; U. Park et al., 2022; Tong et al., 2021), and interpretability limitations (Bansal et al., 2025; R. Wang et al., 2025; Yi & Luo, 2024) associated with several black-box AI techniques. Together, these limitations may constrain the transparency, transferability, and broader industry adoption of AI-based conceptual cost estimation systems (Paul et al., 2025; Sanusi et al., 2020).

Despite its contributions, this study has several limitations. The framework is bounded by the scope of the available literature because AI methods and practices used in industry but not documented in peer-reviewed research were not captured. The study focused exclusively on project-level conceptual cost estimation and excluded component-level studies, although these studies may contain parameters relevant to project-level models. The final dataset comprised 28 studies, which limits the breadth of comparative analysis. A further limitation relates to the quality of the evidence on which the framework is based. Most of the included studies validated their models only on internal data, several relied on small datasets, and few made their data or code available. The quality assessment was based on the information reported in each study and involved researcher judgment. Therefore, the findings and the proposed framework should be interpreted in light of differences in the methodological quality of the included studies. In addition, eight potentially relevant studies could not be fully retrieved during the screening process because full-text access was unavailable. The inclusion and exclusion criteria may also have excluded related studies involving component-level estimation, non-English publications, and grey literature sources. The search strategy also relied on “pre-construction,” “schematic design,” “design stage,” and “early design” as stage terms and “artificial intelligence,” “machine learning,” “deep learning,” and “natural language processing” as AI terms rather than an extensive set of technique-specific and alternative terms. Although these terms covered a range of expressions, relevant studies that described early project stages or AI techniques with other terminology may not have been identified. Moreover, the search was restricted to Scopus and Web of Science because their multidisciplinary coverage aligns with the scope of this review. Although ASReview supported the efficiency and

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systematic management of the screening process, study selection and eligibility decisions still involved researcher judgment. Accordingly, the proposed framework should be interpreted as a literature-derived conceptual framework based on the evidence synthesized in this review rather than a validated or comprehensive guideline applicable to all construction contexts.

The findings of this study identify several directions for future research. As a first step, the completeness and practical applicability of the proposed framework should be assessed through expert evaluation, for example through structured interviews or a Delphi study with cost estimators and preconstruction professionals. The framework should then be applied to real construction projects and compared with established conceptual estimating procedures to examine whether the proposed steps, input parameters, and modeling procedures improve estimation accuracy, consistency, and efficiency across different construction contexts. The findings from these evaluations could also inform potential modifications to the framework based on project-specific requirements and practical implementation challenges. Future research could also examine component-level cost estimation studies, particularly to identify additional input parameters that may be relevant to project-level conceptual cost estimation and could inform further development of the framework. Moreover, expanding data sources through open-data initiatives, cross-country datasets, and partnerships with public agencies and industry organizations may improve model robustness and generalizability. In addition, broader and more systematic adoption of explainable AI (XAI), as well as further investigation of multimodal data fusion, large language models (LLMs), and transfer learning, could be considered. Future studies should also prioritize greater standardization in variable selection, model reporting, and evaluation metrics to improve cross-study comparability. Further research should examine the integration of AI-driven conceptual cost estimation with broader digital construction ecosystems such as BIM, digital twins, and life cycle cost analysis frameworks to support more adaptive and data-informed project planning. By addressing these opportunities, future research may advance the implementation of AI-based conceptual cost estimation and support more accurate, transparent, and data-informed decision-making in construction.

Overall, this study contributes to the advancement of construction cost estimation research and practice by addressing the phase-specific gap identified at the outset. For research, this study provides a structured reference base derived from the reviewed literature. The synthesis consolidates analytical procedures, data requirements, modeling strategies, and evaluation practices from the existing literature. Future studies can draw on this base to support greater consistency in variables, validation procedures, and reporting practices. It also provides a basis for comparative evaluation and methodological refinement as the evidence base grows. For practice, the seven-step framework presents estimators and preconstruction teams with structured guidance for early project planning. It organizes input parameters reported in the reviewed studies that may be considered at the conceptual stage. It summarizes modeling strategies applied to small and heterogeneous early-stage datasets and also synthesizes evaluation criteria used to assess model performance across the reviewed studies. This guidance may support more systematic consideration of available evidence in decisions that establish project budgets and feasibility. As organizations embed estimation within digital project delivery environments, the framework may provide a structured foundation for integration with BIM workflows, digital twins, and life-cycle decision-support systems.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no conflicts of interest relevant to this study.

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DATA AVAILABILITY STATEMENT

Data are contained within the article.

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APPENDIX A: ABBREVIATIONS

The list of abbreviations used in this study is presented below.

Table A1: List of abbreviations.

Abbreviation	Full Form
AA	Accuracy Percentage
AB	Adaptive Boosting
AdaBoost	Adaptive Boosting
AI-CCECA	AI-Driven Construction Cost Estimation and Control Analysis
AIE	Agency In-House Estimate
ANN	Artificial Neural Network
AutoML	Automated Machine Learning
BDT	Bagging Decision Tree
BN	Bayesian Network
BPNN	Backpropagation Neural Network
BR	Bayesian Ridge
BVT	Bias-Variance Trade-Off
CatBoost	Categorical Boosting
CCBSN-BO	Construction Cost Bi-Stacked Network with Bayesian Optimization
DBO	Dung Beetle Optimizer
DistilBERT	Distilled Bidirectional Encoder Representations from Transformers
DNN	Deep Neural Network
DT	Decision Tree
ENR	Elastic Net Regression
ETR	Extra Trees Regressor
F-AHP	Fuzzy-Analytic Hierarchy Process
FLA	Fuzzy Logic Algorithm
GA	Genetic Algorithm
GB	Gradient Boosting
GBR	Gradient Boosting Regressor
GPR	Gaussian Process Regression
GRA	Grey Relational Analysis
KNN	K-Nearest Neighbors
LASSO	Least Absolute Shrinkage and Selection Operator
LGBoost	Light Gradient Boosting
LightGBM	Light Gradient Boosting Machine
LLAR	Lasso Least Angle Regression
LLM	Large Language Model
LR	Linear Regression
LSMBM	Least Square Moment Balanced Machine
LSSVM	Least Squares Support Vector Machine
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
Med AE	Median Absolute Error
MER	Mean Error Rate
MLP	Multilayer Perceptron
MLR	Multiple Linear Regression

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Abbreviation	Full Form
MPE	Mean Percentage Error
MSE	Mean Squared Error
MSRE	Mean Squared Relative Error
Nash	Nash-Sutcliffe Efficiency Coefficient
NGBoost	Natural Gradient Boosting
NLP	Natural Language Processing
NRMSE	Normalized Root Mean Squared Error
OLS	Ordinary Least Squares
OMP	Orthogonal Matching Pursuit
PCA	Principal Component Analysis
PCC	Pearson Correlation Coefficient
PSO	Particle Swarm Optimization
R	Correlation Coefficient
R^2	Coefficient of Determination
RER	Relative Error Rate
RF	Random Forest
RI	Reference Index
RMSE	Root Mean Squared Error
RR	Ridge Regression
SA	Sensitivity Analysis
SHAP	Shapley Additive Explanations
SVM	Support Vector Machine
SVR	Support Vector Regression
TAP	Total Accuracy Percentage
WI	Willmott Index
XGBoost	Extreme Gradient Boosting

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