

Artificial Intelligence and Machine Learning Applications for Predicting Cost Overruns in Construction Projects: A Systematic Literature Review

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ABSTRACT

Cost overruns remain a persistent challenge in construction projects, often undermining financial performance and stakeholder trust. While traditional estimation methods have proven insufficient, artificial intelligence and machine learning offer promising predictive capabilities. This systematic literature review aims to synthesize and critically evaluate the state of research on AI and ML applications for forecasting cost overruns in construction. Our objective was to identify prevailing models, their predictive accuracy, and the contextual factors that influence their performance across different project types and phases. We conducted a comprehensive search of peer-reviewed literature following the PRISMA guidelines, screening studies that employed supervised learning, ensemble methods, or deep learning architectures for cost-related predictions. The methodology involved a structured extraction of model characteristics, data sources, feature engineering approaches, and reported performance metrics. The results reveal that ensemble methods such as random forests and gradient boosting consistently outperform single classifiers, often achieving mean absolute percentage errors below 10% when trained on historical project data. Neural networks and support vector machines also show strong performance but require larger datasets and more careful tuning. Importantly, the integration of AI with building information modeling and digital twin technologies has emerged as a particularly effective strategy, enabling real-time cost trajectory adjustments. However, we found that most studies focus on commercial and residential projects, with limited validation for infrastructure or green building contexts. Furthermore, many models lack rigorous cross-validation or external testing, raising questions about generalizability. The conclusion is that AI and ML demonstrably improve cost overrun prediction accuracy compared to conventional methods, yet adoption remains hampered by data scarcity, model interpretability issues, and insufficient industry validation. This review provides a synthesized evidence base to guide future research toward more robust, scalable, and practically deployable predictive systems. We therefore recommend prioritizing hybrid models that combine domain-specific rules with data-driven learning, alongside strategies for leveraging limited project data through transfer learning or synthetic data augmentation.

Introduction

The construction industry is a cornerstone of global economic development, contributing significantly to national gross domestic products and employing a

substantial workforce worldwide. Projects within this sector, ranging from residential buildings and commercial complexes to large-scale infrastructure such as bridges, highways, and tunnels, are characterized by their complexity, long durations, and the involvement of numerous interdependent stakeholders [1]. A persistent and costly problem that plagues this industry is the prevalence of cost overruns, a phenomenon where the final expenditure of a project significantly exceeds its initial budget. The financial consequences of these overruns are severe, often leading to reduced profitability, project delays, contractual disputes, and, in extreme cases, project abandonment [2]. These failures not only undermine the financial health of contracting firms and project owners but also erode public trust and can have negative socio-economic repercussions [3]. Traditional methods for estimating project costs have historically relied on parametric models, expert judgment, and historical cost data analysis, as seen in the work on early cost estimation techniques [4]. While foundational, these approaches are often static and unable to adapt to the dynamic and uncertain nature of construction environments. They typically fail to account for the complex interplay of factors such as fluctuating material prices, labor productivity variations, unforeseen site conditions, and changes in project scope, which are primary drivers of cost overruns [5].

To address these limitations, the construction industry has increasingly turned towards advanced computational techniques, with artificial intelligence (AI) and machine learning (ML) emerging as particularly potent tools. AI and ML offer the ability to learn from historical project data, identify non-linear relationships, and generate predictive models that can forecast potential cost deviations with a degree of accuracy with a high degree of accuracy [6]. Unlike traditional statistical methods, ML algorithms can handle high-dimensional data and discover patterns that are not immediately apparent to human analysts [7]. For instance, neural networks have been applied to predict final project costs based on early design parameters [8], while ensemble methods like random forests and gradient boosting have shown superior performance in modeling the risk of budget exceedance [9]. This shift is not merely academic; it represents a fundamental change in how project risks can be managed, moving from reactive cost control to proactive, data-driven predictive management.

Despite the promising potential demonstrated by individual studies, a coherent and synthesized understanding of the field remains elusive. The existing body of literature is fragmented, often focusing on a single type of model, a specific project type, or a particular phase of the construction lifecycle. Researchers have identified significant gaps in the current knowledge base. For example, many predictive models are trained on datasets of limited size and scope, such as exclusively residential or commercial projects, raising serious questions about their generalizability to other contexts like infrastructure or green building projects [10]. There is a lack of comprehensive reviews that systematically compare the performance of different AI and ML architectures across a variety of cost overrun prediction tasks, using standardized evaluation metrics [11] (# “Need for systematic review of ML in construction). Furthermore, the methodological rigor of many studies is inconsistent, with a lack of robust cross-validation, external testing on unseen datasets, and detailed reporting of feature importance [11]. This heterogeneity in research design and reporting prevents practitioners from making informed decisions about which models to adopt and

researchers from identifying the most fruitful avenues for future investigation. The field, therefore, suffers from a gap between the high-level potential of AI and its practical, validated deployment in the construction industry [12].

Hence, the primary motivation for undertaking this systematic literature review is to provide a comprehensive, evidence-based foundation that maps the landscape of AI and ML applications for predicting cost overruns in construction projects. The significance of this work lies in its potential to guide both future research and practical implementation. For the research community, this review will synthesize disparate findings, highlight methodological best practices, and identify critical gaps that warrant immediate attention. For industry professionals, such as project managers, cost consultants, and construction executives, the review offers a reliable benchmark for the predictive capabilities of various models and a clear understanding of the contextual factors that influence their success. By critically evaluating the state of the art, we aim to accelerate the transition from promising prototypes to robust, scalable, and trustworthy predictive systems that can truly mitigate the risk of cost overruns. This research, therefore, serves as a roadmap for developing more reliable, interpretable, and practically deployable AI-driven tools for the construction sector.

The remainder of this paper is organized as follows: Section 2 describes the systematic methodology employed for the literature search, screening, and data extraction, following the PRISMA guidelines. Section 3 presents the detailed results of the review, structured into several thematic subsections that cover research trends, specific ML models, schedule prediction, risk management, integration with building information modeling (BIM), resource optimization, strategic adoption, and sustainability applications. Section 4 provides a comprehensive discussion of the implications of our findings, addressing the current limitations of the field, practical considerations for adoption, and key directions for future work. Finally, Section 5 concludes the paper by summarizing the main contributions and offering final recommendations for stakeholders.

I. Methodology

This section describes the systematic approach undertaken to identify, screen, and synthesize the relevant literature on AI and ML applications for predicting cost overruns in construction projects. The methodology was designed to ensure transparency, reproducibility, and rigor, adhering to established guidelines for conducting systematic literature reviews.

Review Protocol

We developed a detailed review protocol prior to commencing the search, which specified the research questions, search strategy, inclusion and exclusion criteria, and data extraction procedures. The protocol was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [13], which provides a standardized checklist and flow diagram for reporting systematic reviews.

To identify relevant studies, we conducted a comprehensive search across five major academic databases and search engines, each chosen for its specific relevance to the interdisciplinary nature of our research topic. Scopus was selected as the primary database due to its extensive coverage of peer-reviewed literature in engineering, computer science, and construction management, offering a broad interdisciplinary

scope that aligns with our research focus. Web of Science was included for its rigorous curation of high-impact journals and its strong representation of the construction management and civil engineering research communities. IEEE Xplore was chosen specifically for its comprehensive collection of computer science and engineering conference proceedings and journals, ensuring coverage of the latest developments in machine learning algorithms and their applications. ScienceDirect was selected for its extensive repository of full-text articles in engineering and technology, particularly from Elsevier journals that dominate the construction informatics field. Finally, Google Scholar was the final source, included as a supplementary search engine to capture grey literature, preprints, and publications from smaller or regional journals that might not be indexed in the other databases.

The search strategy employed a combination of keywords and Boolean operators tailored to each database's syntax. The core search terms were grouped into three conceptual categories: (1) AI and ML techniques, including terms such as "artificial intelligence," "machine learning," "deep learning," "neural network," "support vector machine," "random forest," "predictive analytics," and "data mining"; (2) cost-related outcomes, including "cost overrun," "cost escalation," "budget overrun," "cost forecasting," and "cost deviation"; and (3) construction project context, including "construction project," "construction industry," "infrastructure project," "civil engineering project," and "building project." We applied database-specific filters to limit results filters to limit document types to articles and conference papers, explicitly excluding review articles, surveys, meta-analyses, and bibliometric studies. The detailed search strings for each database are presented in the introductory materials.

Thematic Classification of Research Dimensions

To structure the analysis of the retrieved literature in a meaningful and coherent manner, we established a set of seven thematic research dimensions that collectively capture the breadth and depth of AI and ML applications for cost overrun prediction in construction. These dimensions were derived from an initial exploratory reading of the literature and refined through iterative discussions among the research team, ensuring they reflect the main streams of inquiry within the field. The first dimension, Machine Learning Models for Cost Estimation and Overrun Prediction, encompasses studies that focus on developing, comparing, or optimizing supervised learning algorithms specifically for predicting final project costs or the probability of budget exceedance. The second dimension, AI-Driven Schedule Delay and Time Performance Forecasting, includes research that extends cost prediction to its temporal counterpart, using AI to forecast project delays, analyze schedule performance, or integrate cost-time trade-offs. The third dimension, Risk Management, Dispute Resolution, and Safety Applications, covers studies that apply AI to identify and quantify risk factors contributing to cost overruns, predict contractual disputes, or improve site safety as a means of preventing cost escalations. The fourth dimension, Integration of AI with BIM, Digital Twins, and Emerging Technologies, groups research that combines predictive AI models with building information modeling, digital twin frameworks, or other digital technologies to create real-time, data-rich decision support systems for cost control. The fifth dimension,

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Resource Optimization, Labor, and Material Management, includes studies that use AI to optimize the allocation and utilization of labor, equipment, and materials, thereby indirectly preventing cost overruns through improved efficiency. The sixth dimension, Strategic Adoption, Industry Trends, and Managerial Impacts, examines the organizational, managerial, and strategic factors that influence the adoption of AI for cost prediction, including industry readiness, implementation barriers, and decision-making frameworks. The seventh and final dimension, Sustainability, Green Building, and Specialized Infrastructure Projects, captures research that applies AI to cost prediction in specialized contexts such as green buildings, sustainable infrastructure, or unique project typologies where traditional models may be insufficient. These dimensions serve as the organizing framework for the presentation of results in Section 3.

Inclusion and Exclusion Criteria

Establishing clear inclusion and exclusion criteria was essential for ensuring that only studies directly relevant to our research questions were selected for analysis, thereby maintaining the consistency and validity of the review findings. Studies were considered eligible for inclusion if they met the following criteria: (a) the study was published in English as a peer-reviewed journal article or conference proceedings paper; (b) the publication date was unrestricted up to the search date in early 2026, allowing for the inclusion of both foundational and recent works; (c) the study explicitly applied one or more artificial intelligence or machine learning techniques—such as neural networks, support vector machines, random forests, gradient boosting, deep learning, or natural language processing—as its primary analytical method; (d) the study’s objective was related to predicting, estimating, forecasting, or analyzing cost overruns, budget deviations, cost escalation, or financial risk in the context of construction projects, including buildings and infrastructure; and (e) the study reported empirical results, including performance metrics such as accuracy, mean absolute percentage error, root mean squared error, or area under the curve.

Conversely, studies were excluded from the review if they met any of the following criteria: (a) the publication was a review article, survey, meta-analysis, bibliometric study, editorial, book chapter, or conference abstract without full-text availability; (b) the study did not employ any AI or ML technique, relying instead on traditional statistical methods, manual estimation, or purely qualitative analysis; (c) the study’s focus was not on cost prediction but on unrelated applications such as structural health monitoring, material property prediction, or general project scheduling without cost linkage, or safety without financial implications; (d) the study lacked sufficient quantitative results or model performance data to allow for meaningful comparison or synthesis; or (e) the study was conducted in a non-construction domain, such as manufacturing, software development, or healthcare, without clear applicability to the construction industry. These criteria were applied consistently during the screening process, with any uncertainties resolved through discussion among the research team.

Study Selection Process

The study selection process followed a multi-stage screening approach designed to systematically reduce the initial pool of records to the final set of included studies. In

the first stage, we conducted the electronic database searches, which yielded a total of 964 records across the five sources. All records were exported into a reference management software, where 94 duplicate records were identified and removed based on matching titles, authors, and publication years. An additional 5 records were removed for other reasons, including incomplete bibliographic information or non-English language publications that were not identified by the initial database filters. This left 865 unique records for the screening phase.

During the title and abstract screening stage, two independent reviewers examined the 865 records against the inclusion criteria, with each record labeled as “include,” “exclude,” or “uncertain.” Disagreements between reviewers were resolved through consensus discussion, and a third reviewer was consulted for unresolved cases. This process resulted in the exclusion of 565 records that were clearly irrelevant to the research topic, such as those focusing on medical AI applications, software cost estimation, or non-construction fields. The remaining 164 records were deemed potentially eligible and proceeded to the full-text retrieval stage. All 164 reports were successfully retrieved without any being unavailable, yielding a retrieval rate of 100 percent.

The full-text assessment stage involved a detailed reading of each of the 164 reports to verify reports by the same two reviewers to confirm their eligibility against the predefined criteria. During this stage, we assessed the methodological rigor, the relevance of the AI technique to cost prediction, and the sufficiency of the reported results. This led to the exclusion of 5 reports that, upon full inspection, did not meet the inclusion criteria: two were found to be short conference abstracts without substantive results, one was a duplicate that had not been caught during the earlier deduplication, one relied on traditional regression without any ML component, and one focused exclusively on schedule delays without any cost-related outcome. The remaining 159 studies satisfied all inclusion criteria and were included in the final qualitative synthesis. The entire selection process is illustrated in the PRISMA flow diagram, as shown in Figure 1.

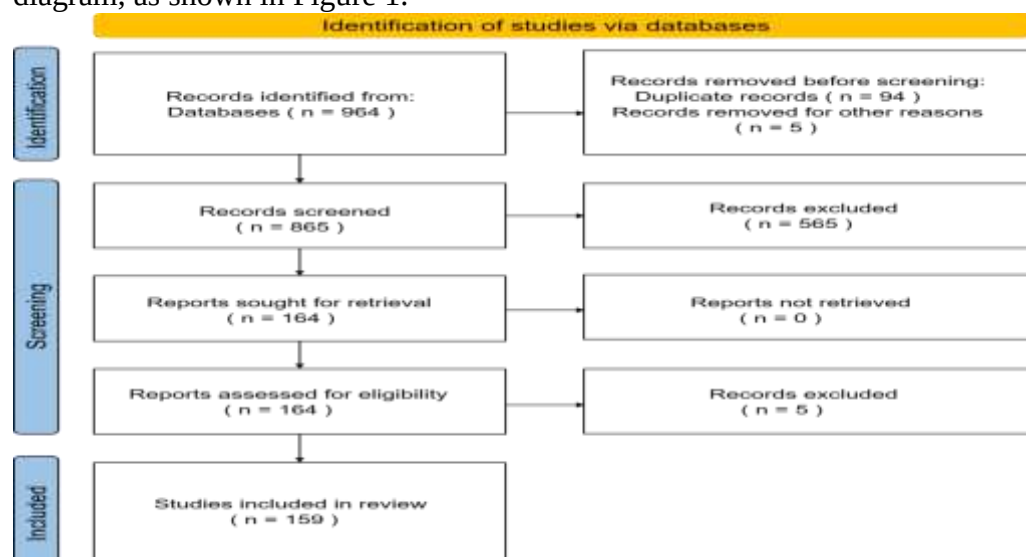


Figure 1. PRISMA flow diagram for the systematic literature review on AI and ML applications for predicting cost overruns in construction projects

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We acknowledge several limitations and potential biases in the study selection process. First, the restriction to English-language publications may have excluded relevant studies published in other languages, particularly from regions with large construction industries such as China, Japan, or Middle Eastern countries. Second, the exclusion of grey literature such as industry reports, theses, and white papers may have omitted practical insights from non-academic sources. Third, the reliance on database-specific search syntax and keyword combinations may have missed studies that use different terminology, such as “budget blowout” or “financial overruns,” despite our efforts to include a broad range of synonyms. Finally, reviewer judgment during the title and abstract screening phase, while supported by dual review and consensus, could have inadvertently excluded studies whose relevance was not immediately apparent from their abstracts alone. These limitations should be considered when interpreting the findings of this review.

Results

Research Trends

A comprehensive analysis of the publication timeline reveals a clear and accelerating trajectory of scholarly interest in AI and ML applications for predicting cost overruns in construction projects. As illustrated in Figure 2, the field experienced a period of relative dormancy prior to 2017, with only 13 publications recorded across all preceding years, indicating that this research domain was still in its nascent stage. The years between 2017 and 2021 saw a gradual but inconsistent increase in output, with annual publication counts fluctuating between 2 and 7 studies, suggesting that early work was largely exploratory and fragmented across different methodological approaches. However, a marked inflection point becomes evident from 2022 onward, when publication numbers began to rise steadily, culminating in an explosive growth during 2024 and 2025, with 41 and 43 studies respectively. This surge represents a more than six-fold increase compared to the peak of the early period and strongly suggests that the field has reached a critical mass of interest and activity, likely driven by both advances in AI algorithms and the increasing availability of digital project data.

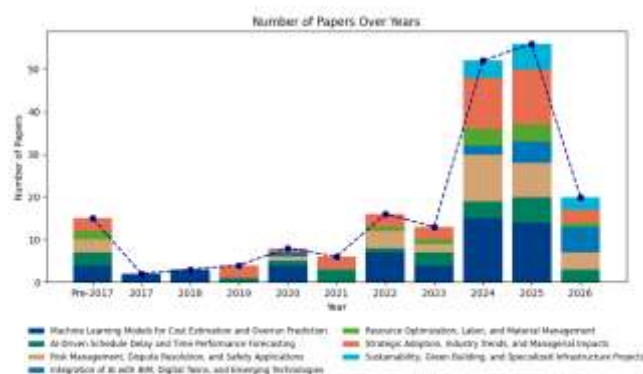


Figure 2. Research trends in the domain of Artificial Intelligence and Machine Learning Applications for Predicting Cost Overruns in Construction Projects
When examining the distribution of publications across the seven thematic

dimensions over time, we observe that not all research streams have experienced this growth uniformly. The dimension of Machine Learning Models for Cost Estimation and Overrun Prediction has consistently been the most prolific, maintaining a steady presence throughout the entire period and accounting for 15 publications in 2024 and 14 in 2025. This sustained output suggests that the core technical challenge of developing accurate predictive algorithms remains the primary focus of the research community, with investigators continuously exploring new architectures, ensemble configurations, and feature engineering strategies. In contrast, the dimension of Integration of AI with BIM, Digital Twins, and Emerging Technologies has only emerged prominently in the most recent years, with 5 publications in 2025 and 6 in 2026, indicating that the fusion of AI with digital construction tools is a relatively nascent but rapidly growing area of investigation. Similarly, the dimension of Sustainability, Green Building, and Specialized Infrastructure Projects is exclusively concentrated in 2024, 2025, and 2026, with 4, 6, and 3 publications respectively, demonstrating that the application of cost overrun prediction to environmentally focused or niche project types is only now gaining traction. The dimension of Strategic Adoption, Industry Trends, and Managerial Impacts also shows robust growth in 2024 and 2025, with 12 and 13 publications, respectively, reflecting a maturation of the field where researchers are beginning to investigate not just how to build better models but also how to deploy them effectively within organizational contexts. We interpret these trends as evidence that the research landscape is evolving from a narrow focus on algorithmic performance toward a more holistic consideration of implementation, integration, and contextual applicability, which is a healthy sign for the eventual practical adoption of these technologies.

Machine Learning Models for Cost Estimation and Overrun Prediction

This subsection synthesizes the most directly relevant body of literature, focusing on the development, comparison, and evaluation of ML models specifically designed for forecasting construction costs and predicting the likelihood of budget overruns. The studies analyzed here form the technical core of the review, encompassing a wide array of algorithmic approaches, from traditional regression and artificial neural networks to sophisticated ensemble methods and deep learning architectures. Our analysis reveals a rich and diverse landscape of methodological innovation, yet it also highlights persistent challenges regarding model generalizability, data quality, and the comparability of reported performance metrics.

The reviewed studies can be systematically categorized into a hierarchical taxonomy based on their primary application focus, methodological approach, and technical specificity, as presented in Table 1. This taxonomy reveals that research efforts are nearly evenly split between cost estimation and cost overrun prediction, with a significant number of studies also proposing general AI frameworks for cost management. Within cost estimation, traditional ML models such as linear regression and artificial neural networks (ANN) constitute a large portion of the literature, with ANNs being applied to a wide range of project types, including residential buildings in Jordan [14], concrete bridges in Sri Lanka [15], and hospital construction projects in Greece [16]. However, a notable trend is the increasing shift towards more complex, ensemble, and hybrid models. For instance, a coupled genetic programming

and Monte Carlo simulation model was developed for cost overrun prediction of thermal power plant projects [17], demonstrating the potential of combining evolutionary algorithms with probabilistic methods. Similarly, a deep neural network (DNN) framework integrated with a validation unit was proposed to enhance the reliability of cost estimates [18], while a hybrid deep learning approach was employed to predict the construction cost-time tradeoff, aiding in risk preference decision-making [19].

Furthermore, the application of deep learning for time-series forecasting of costs has gained momentum, with studies using Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks to predict macroeconomic-aware construction costs in developing countries [20]. Natural language processing is also emerging as a powerful tool, with one study presenting an ensemble NLP model to align quantity take-offs with cost indexes, thereby augmenting the accuracy of cost estimation [21]. The prediction of material prices, a critical driver of cost overruns, has been addressed through machine learning models in the Nigerian context [22], while labor resource requirements, and consequently labor costs, have been forecasted using ML techniques [23]. Several papers focused on comparative analyses, benchmarking the performance of different algorithms for conceptual cost estimation [24], [25], [26], and a dedicated taxonomy of ML techniques for construction cost estimation was provided in one study [27].

Table 1. Taxonomy of Studies on Machine Learning Models for Cost Estimation and Overrun Prediction

Application Focus	Methodological Approach	Technical Context	Specificity	/ Sources
Cost Estimation	Traditional Models	ML	Linear/Regression Models	[28], [29]
			Artificial Neural Networks (ANN)	[14], [30], [15], [16], [31]
			Decision Trees / Random Forest	[32], [33]
			Support Vector Machines (SVM)	[34]
			Ensemble / Hybrid Models	[35], [36], [37], [19], [38], [18], [17]
			Deep Learning (LSTM, GRU, DNN)	[20], [19],

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			[18]
		Generative AI / NLP	[21], [39]
		K-Nearest Neighbors / Instance-based	[40], [41]
	“)		
		Fuzzy Logic / Neuro-Fuzzy	[42], [43]
		Comparative Studies (Benchmarking)	[24], [25], [26], [29]
		Taxonomy / Review of Techniques	[27]
	Scope-Specific Models	Early-stage / Conceptual Cost	[24], [25], [35], [30], [26], [44]
		Material/Labor Cost	[28], [22], [23]
		Project Type Specific (Buildings, Roads, Bridges)	[14], [45], [33], [15], [16], [44]
Cost Overrun Prediction & Risk Mitigation	Classification / Prediction Models	K-Star / Rule-based (RIDOR)	[40]
		Genetic Programming / Monte Carlo	[17]
		Deep Learning / Probabilistic Models	[46]
		Fuzzy Logic	[43]
		K-Nearest Neighbors / ANN	[41]
		Ensemble Learning (General)	[40]
	Risk Factor Analysis & Causality	Scope Change Impact	[47]
		Bidding / Contract Parameters	[48], [49]
		Validation /Macroeconomic Factors	[20]

	Budget Validation & Monitoring	Budget Execution Monitoring	[50], [51]
		Budget Validation for Public Projects	[52]
General Applications & Frameworks	AI/ML Frameworks	General Frameworks for Cost Management	[53], [54], [55], [56]
		Knowledge Discovery (KDD)	[57]

In the domain of cost overrun prediction, a distinct set of studies focused on classifying projects based on their risk of exceeding budgets. Ensemble learning methods were applied to predict cost overrun levels during the bidding stage, with K-star and RIDOR classifiers showing particular efficacy [40]. The impact of scope changes on both cost and schedule was predicted using ML techniques [47], while a machine learning approach based on contract parameters was developed for cost forecasting [48]. For managing material price volatilities, a deep learning framework using probabilistic algorithms was proposed to quantify and gauge project cost risks [46]. Additionally, a deep learning framework was developed for forecasting indirect costs in Finnish public transport infrastructure projects, focusing on indirect costs [31]. Several studies also provided frameworks for applying AI to construction cost prediction and risk mitigation [53], [54], and one study applied a knowledge discovery in database (KDD) approach to analyze causes of cost overruns [57].

A number of studies could not be easily categorized within the structured taxonomy due to their unique focus or hybrid nature. For example, one study specifically addressed the prediction of cost contingency in construction projects by introducing machine learning algorithms [58], a specialized topic that bridges cost estimation and risk management. Another early work [59] provided a foundational investigation using machine learning to predict cost overruns in general construction projects, serving as an important precursor to later, more technically refined studies. The application of AI to cost estimation and control in green buildings was the focus of one paper [11], representing a niche but growing intersection of sustainability and project finance. A separate study addressed the prediction of delays and cost overruns jointly [60], reflecting the inherent coupling of time and cost performance. The challenging domain of petrochemical projects was investigated in two separate but identically titled studies [61], [61], highlighting the specific risks in industrial construction. Furthermore, one study proposed a refined management method for engineering cost combining AI technology [55], while another focused solely on predicting the cost and duration of building construction using ANN [14]. Finally, one study introduced a least square moment balanced machine for estimating cost to completion [62], and another evaluated machine learning models for early cost estimation of building projects in Nepal [26]. These diverse contributions, while not fitting neatly into the main categories, underscore the breadth of the research landscape and the many ways AI is being applied to the fundamental challenge of cost prediction.

AI-Driven Schedule Delay and Time Performance Forecasting

Schedule delays and time overruns represent one of the most persistent and financially damaging problems in the construction industry, as they frequently translate directly into cost overruns through extended site overheads, penalty clauses, and resource idling. The inherent coupling of time and cost performance has motivated a substantial body of research that applies AI and ML techniques specifically to the prediction, analysis, and mitigation of schedule deviations. This subsection synthesizes the studies that focus on predicting delays, forecasting time performance, analyzing the root causes of schedule overruns, and integrating time and cost prediction into unified frameworks. Our analysis reveals that this research stream has evolved from simple classification models toward increasingly sophisticated hybrid and deep learning architectures, and from isolated delay prediction toward integrated cost-time trade-off modeling and automated scheduling systems.

The reviewed studies on schedule delay and time performance forecasting can be systematically categorized into a hierarchical taxonomy based on their primary prediction focus, the methodological technique employed, and the specific approach or application context, as presented in Table 2. This taxonomy reveals several important patterns. First, direct schedule delay prediction has been approached through a diverse array of methods, ranging from classical ML algorithms such as support vector machines and random forests to more advanced deep learning techniques including hybrid CNN-RNN architectures and extreme learning machines. Second, a significant number of studies have moved beyond simple delay prediction to address the integrated cost-time trade-off, recognizing that these two dimensions of project performance are inextricably linked and must be modeled jointly to provide meaningful decision support. Third, a distinct subgroup of research has focused on analyzing the root causes and impacts of delays, using statistical and classification methods to extract underlying factors and predict the consequences of scope changes. Finally, a final category encompasses automated scheduling and planning studies that leverage AI to proactively prevent delays through intelligent resource allocation and schedule optimization.

Table 2. Taxonomy of Studies on AI-Driven Schedule Delay and Time Performance Forecasting

Prediction Focus	Method/Technique	Specific Approach / Application Context	Sources
Direct Schedule Delay Prediction	Classical Machine Learning	Support Vector Machine (SVM) for delay analysis and classification	[63], [64]
		Random Forest / Ensemble Methods for delay prediction in high-rise buildings	[65], [66]
		K-Nearest Neighbors & Regression Models	[67]
			Deep Learning &

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		Neural
		Hybrid CNN-RNN Architectures for construction duration prediction [68]
		Extreme Learning Machines for cost and delay prediction [69]
		Deep Learning and Hybrid Models for delay risk prediction [70]
Cost-Time Trade-off & Integrated Forecasting	Hybrid Models	Hybrid AI (ANN plus Fuzzy Logic) for cost-time tradeoff decision making [19], [70]
	Data-Driven Frameworks	General Data-Driven Approaches for integrating cost and schedule [47], [71], [72], [73]
		Digital Twin Integration for early detection of delays and cost overruns [74]
Time Performance & Duration Forecasting	Predictive Analytics & Forecasting	Schedule Performance Forecasting in complex building projects [75]
		Project Schedule Performance Prediction using black-grey-white box approaches [76]
		Construction Duration Prediction using regression models [67], [66], [77]
Root Cause & Impact Analysis of Delays	Statistical & Classification Methods	Extraction and Classification of Underlying Delay Factors (e.g., in Nigeria) [78]
		Analysis of Delay Impact on Disputes using ML approaches [79]
		Prediction of Scope Change Impact on Schedule [47]
Automated Scheduling & Planning	Optimization & ML	AI-Powered Auto-Scheduling for improved project efficiency [80]
		Integration of Field Submittals into Project Scheduling using ML [81]
		Construction Planning with Machine Learning for budget and delay minimization [64]
General/Miscellaneous AI	Broad Review & Framework	General Overview of ML and Deep Learning in Project Analytics [82]

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Applications				
		General Delay Prediction in	[60]	
		Construction Projects		
		Real-World Case Studies (e.g., Egypt, India)	[63], [76], [78]	

A closer examination of the studies within each category reveals significant methodological diversity and varying levels of predictive sophistication. For direct schedule delay prediction, support vector machine models were applied to analyze time and cost overruns in Egyptian construction projects [63], demonstrating the utility of classical ML for identifying key delay determinants. Another study developed a construction planning framework using machine learning that explicitly aimed to minimize budget overruns and the risk of delays [64]. Random forest and ensemble methods have been particularly prominent, with one study applying supervised machine learning solutions for smart delay prediction [65] and another forecasting construction delay times in high-rise building projects using a combination of multiple machine learning algorithms [66]. The same theme of ensemble prediction was also explored through neural networks and neuro-fuzzy models applied to construction scheduling [83]. Deep learning approaches have pushed the boundaries further; for instance, hybrid deep learning architectures combining convolutional neural networks and recurrent neural networks were developed for predicting construction duration [68], while extreme learning machines were introduced as smart tools for simultaneous prediction of cost and delay in construction project management [69]. A particularly comprehensive study explored a wide range of AI-powered delay risk prediction techniques, including machine learning, deep learning, and hybrid models [70].

, several studies have addressed the critical intersection of cost and time performance through integrated forecasting frameworks. A novel hybrid deep learning approach was developed for predicting the construction cost-time tradeoff, specifically designed to support risk preference decision making [19]. The predictive power of scope changes on both project cost and schedule was investigated using machine learning techniques, highlighting how alterations in project requirements cascade into both temporal and financial overruns [47]. Another study examined the role of data-driven decision-making in reducing project delays and cost overruns in civil engineering projects, emphasizing the potential of IoT and cloud-based project management technologies [71]. A further research effort proposed a predictive project management framework that applied a data-driven approach to scheduling and resource estimation using machine learning, and this study specifically used recursive feature elimination to pinpoint critical factors affecting both cost overruns and delays [72]. The integration of digital twin platforms with machine learning models for early detection of project delays and cost overruns represents a particularly innovative direction [74], leveraging real-time data from digital representations of physical assets to enable proactive intervention. The performance-based cost and time prediction of tertiary irrigation projects using artificial neural networks was also investigated [77], and a

comparative study of machine learning regression models, including K-nearest neighbor and gradient boosting trees, was conducted for predicting construction duration [67].

The analysis of root causes and impacts of delays forms another important research strand within this theme. A study focused on extracting underlying factors causing construction project delays in Nigeria [78], using ML to identify the most prevalent and impactful causes. The impact of construction delays on disputes in India was analyzed using a combination of statistical and machine learning approaches [79], revealing how temporal deviations can escalate into costly legal conflicts. Several studies also contributed to the domain of automated scheduling and planning. The potential of AI-powered auto-scheduling of construction projects for improved efficiency was explored [80], while a data-driven machine learning approach was developed to integrate field submittals into project scheduling, thereby reducing delays caused by information bottlenecks [81]. A broad review of machine learning and deep learning in project analytics identified key methods, applications, and research trends, including a specific focus on investigating undesired outcomes such as cost and budget overruns [82]. An early foundational study predicting delays and time overruns in construction projects [60], setting the stage for much of the subsequent work. Finally, a study applying neural networks to predict the cost and duration of building construction [14], and a separate investigation targeting the application of artificial intelligence and ML in project schedule forecasting for time-control in complex building projects [75], together with an exploration of AI applications using a black-grey-white box approach for predicting schedule performance in India [76], further contribute to the diversity of approaches within this research theme.

AI-Enhanced Risk Management, Dispute Resolution, and Safety Frameworks

Beyond the direct prediction of cost and schedule overruns, a substantial body of literature addresses the broader ecosystem of risks that ultimately contribute to financial performance degradation. This subsection synthesizes studies that apply AI and ML not merely for forecasting final costs, but for proactively managing the underlying risk factors, predicting contractual disputes, and enhancing site safety as a preventive measure against cost escalation. Our analysis reveals a progressive shift from post-hoc risk identification toward predictive, real-time risk management systems, with an increasing emphasis on integrating diverse data sources and automating decision-making processes.

The reviewed studies in this domain can be systematically organized into a hierarchical taxonomy that distinguishes between general risk management frameworks, financial risk prediction tools, dispute resolution models, and data-driven process optimization approaches, as presented in Table 3. This taxonomy reveals that the majority of research efforts have concentrated on developing comprehensive AI and ML frameworks for general risk prediction and mitigation, with a substantial subset specifically targeting financial risks and cost overrun prediction. A smaller but distinctive cluster of studies addresses the classification of compensation in construction disputes, while a single study pioneers the application of process mining for risk management.

Table 3. Taxonomy of Studies on AI-Enhanced Risk Management, Dispute Resolution, and Safety Frameworks

Application Area	Specific Focus	Methodological Approach or Technique	Sources
Risk Management & Mitigation	General AI/ML Framework for Risk Prediction & Mitigation	Broad AI frameworks integrating multiple techniques for overall project risk management	[53], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], [101], [102], [103], [104], [105], [106], [107]
	Financial Risk & Cost Overrun Prediction	AI-based financial risk assessment tools; fuzzy logic and auction theory for cost control; ranking cost scheduling for financial risk prevention	[108], [109], [110], [111], [112]
	Resource Allocation & Procurement Risk	Big data analysis for predicting project outcomes; AI and data analytics for cost-effective procurement in EPC projects	[96], [111]
	BIM & Digital Twin Integration for Risk	Integration of BIM and AI for predicting construction project risks; AI-driven and digital twin-based framework for holistic risk and green project management	[92], [99]
	Project Management Knowledge Area Failures	Prediction of failures in PM knowledge areas using optimized	[113]

Dispute Resolution	Classification of Compensation in Disputes	ensemble models Machine learning techniques for classifying compensations in construction disputes	[114], [115]
Data & Process Optimization for Risk	Process Mining & Data-Driven Risk Analysis	Data-driven process mining framework for risk management in construction projects	[105]

A large proportion of the research within this theme has focused on developing comprehensive AI and ML frameworks for general risk prediction and mitigation. For instance, one study proposed a framework for applying artificial intelligence to construction cost prediction and risk mitigation [53], establishing a foundational approach that has been extended by subsequent work. Several other studies evaluated the broad impact of AI in managing construction engineering projects [84] and leveraging AI for optimized project management and risk mitigation [85], with the latter explicitly acknowledging that managing risks can lead to delays, cost overruns, and safety incidents. The integration of digital platforms with financial oversight for AI-driven risk management was explored in another study [86], which hypothesized that using artificial intelligence and multiple data sources could prevent budget overruns. A dedicated investigation into AI-driven risk management in construction projects [87] and predictive and adaptive decision-making using AI [88] further reinforced this trend. The ascending trajectory of AI and ML in construction and project controls was discussed in the context of resolving core challenges such as cost overrun and productivity constraints [89], while a model for early risk identification to enhance cost and schedule performance was developed using machine learning algorithms and historical project data [90]. An artificial neural network approach was specifically applied for construction project risk management, noting that machine learning has emerged as a powerful method for extracting insights from extensive datasets [91]. The integration of BIM and AI for predicting construction project risks [92], advanced AI-cloud neural network systems for predictive analytics and risk mitigation [93], and machine learning-based risk prediction models for infrastructure projects [94], and AI for enhancing risk management practices during the design process [95] collectively demonstrate the breadth of this research stream.

Resource allocation and risk mitigation through big data analysis was investigated to predict project outcomes and improve decision-making processes in complex projects [96]. Another study specifically leveraged AI and predictive analytics for dynamic risk management in complex infrastructure projects [97], while AI-based financial risk assessment tools for project planning and execution were developed, using machine learning, natural language processing, and expert systems to identify potential financial risks and forecast cost overruns [108]. The impact of AI on project

management, including enhancing efficiency, risk mitigation, and decision-making, was also examined [98], and an AI-driven and digital twin-based framework was proposed for holistic risk and green project management in sustainable urban megaprojects, demonstrating the integration of AI and digital twins for risk prediction [99]. Challenges, strategies, and best practices for AI in project management were discussed [100], and AI-driven forecasting was applied to improve resource allocation and project delivery in BRICS infrastructure investment [101]. The application of AI for risk and decision assessment in agile IT projects [102] and the integration of AI applications with knowledge management processes for construction project management [103] further expanded the conceptual boundaries of this theme. A study on the dynamic influence of cost overrun factors affecting cost performance in building construction projects [104], a data-driven process mining framework for risk management [105], and an assessment of risk impact on road projects using deep neural networks [106] together with a probabilistic risk identification and assessment model using elicitation-based Bayesian networks [107] complete the picture of this extensive research stream.

A distinct subgroup of studies has focused specifically on financial risk and cost overrun prediction, applying AI to more narrowly defined economic challenges. For example, AI-based financial risk assessment tools were explicitly developed for project planning and execution, using machine learning to identify financial risks and forecast cost overruns [108]. Cost control management of construction projects based on fuzzy logic and auction theory was proposed, where machine learning techniques are utilized to analyze risks associated with cost overruns and time overruns [109]. An AI-driven predictive analytics approach for financial risk management with ranking cost scheduling was also presented [110], while the revolution of procurement through AI and data analytics driving cost-effective solutions in EPC projects was discussed, highlighting how machine learning models replace inefficient processes that result in cost overruns [111]. The development of machine learning models for assessing the risk of budget overruns in developed projects specifically aimed to find the best model for risk assessment [112].

Within the dispute resolution domain, the application of machine learning to classify compensations in construction disputes represents a particularly promising and specialized application. One study investigated disputes using machine learning techniques to classify compensations in construction [114], while another dedicated work focused on classifying compensations in construction disputes using machine learning techniques on past cases [115]. Both studies recognized that construction disputes are detrimental as they may lead to cost overruns and delays, highlighting the potential of ML to streamline dispute resolution processes and potentially prevent costly litigation.

Integration of AI with BIM, Digital Twins, and Emerging Technologies

The convergence of artificial intelligence with digital construction technologies such as Building Information Modeling (BIM) and Digital Twins represents a paradigm shift in how project performance is monitored and predicted. Instead of relying on static, periodic reports, this integration enables a dynamic, data-rich environment where predictive models can be continuously fed with real-time data from the

physical and digital project representations. This subsection synthesizes the studies that explore the fusion of AI with these emerging technologies, with a specific focus on how such integration enhances the prediction and mitigation of cost overruns. Our analysis reveals a rapidly evolving field where the theoretical potential of synergies is being translated into concrete frameworks and pilot applications, though significant challenges related to data interoperability, computational demands, and organizational adoption persist.

The reviewed studies within this theme can be systematically organized into a hierarchical taxonomy that distinguishes between the core technology domains, the specific application focus, and the particular techniques or frameworks employed. As shown in Table 4, the research landscape is divided into three primary technology domains: Building Information Modeling (BIM), Digital Twins, and a broader category encompassing other Emerging Technologies and general AI/ML integration. Within the BIM domain, studies focus on enhancing cost and schedule planning, predicting project risks, and improving cost management methodologies through the integration of AI. For instance, one study explicitly integrates BIM and artificial intelligence to enhance cost and schedule planning in energy-conscious infrastructure projects, noting that AI and ML aspects of these tools have significantly improved project predictabilities so that precise cost up projects likely prone to cost overruns can be identified [116]. The impact of integrating AI and BIM systems on the development of construction methodologies is explored in another work, which posits that this fusion refines traditional approaches to project delivery [117]. Similarly, the integration of BIM and AI for predicting construction project risks is the central to a study that uses BIM as a data repository for AI algorithms to forecast potential budget deviations [92]. Generative AI has also been specifically applied to BIM-based digital construction cost management, with a qualitative sentiment analysis approach used to interpret stakeholder perspectives on this novel integration [118].

The Digital Twin domain, while smaller in the absolute number of studies, is characterized by highly ambitious and technically sophisticated frameworks. A central study investigates the integration of Digital Twin platforms with machine learning models for the early detection of project delays and cost overruns, positioning this combination as a powerful tool for proactive project control [74]. This work is complemented by another study that presents an AI-driven and digital twin-based framework for holistic risk and green project management in sustainable urban megaprojects, demonstrating the application of ML and deep learning to anticipate project delays and cost overruns within a digital twin environment [99]. Furthermore, a method for adaptive control of sustainable construction projects based on digital twin technology and ensemble machine learning is proposed, which uses digital twins as a living model for integrating real-time data with predictive analytics [119].

Within the broader category of Emerging Technologies and AI/ML, research extends to smart building applications, digital transformation frameworks, and resource management. The application of AI in smart buildings is explored, with machine learning and deep learning addressing challenges such as worker safety and budget overruns through optimization [120]. A comprehensive framework for AI-enabled digital transformation in the construction industry is presented, suggesting deep learning approaches for construction quality management as a means to prevent

rework and cost overruns [121]. The challenges of digital transformation in specific national contexts are addressed by a study that develops a framework of critical success factors for the adoption of BIM, machine learning, and Digital Twins in Peru, aiming to combat significant cost overruns and inadequate planning [122]. Similarly, the digital shift in the Australian construction sector is analyzed, with a focus on unlocking potentials with AI and blockchain to address challenges related to cost overruns [123].

Table 4. Taxonomy of Studies on Integration of AI with BIM, Digital Twins, and Emerging Technologies for Cost Overrun Prediction

Technology Domain	Application Focus	Specific Framework	Technique	/ Source s
Building Information Modeling (BIM)	Cost & Schedule Planning	AI/ML-enhanced BIM systems for improved cost and schedule predictability		[116], [117], [124]
	Risk Prediction	AI-integrated BIM for risk assessment and predictive analytics		[92], [125]
	Cost Management & Methodology	Generative AI for BIM-based digital construction cost management		[118]
	Model Management & Citation	Country and document-based citation and bibliographic coupling analysis of AI in BIM research		[124]
Digital Twins	Early Detection of Overruns	Digital Twin platform with ML models for early detection of delays and cost overruns		[74]
	Adaptive Control & Sustainability	Ensemble ML for sustainable project control within a digital twin context		[119]
	Framework for Risk & Green Management	AI-driven Digital Twin framework for holistic risk and green project management in megaprojects		[99]
Emerging Technologies & AI/ML	Resource Management & Efficiency	ML-integrated resource management framework addressing inefficiencies leading to delays and cost overruns		[126]
	Smart Building Applications	AI/ML for smart building optimization including safety and budget overrun challenges		[120]
	Digital Transformation & Critical Success	Frameworks for adoption of BIM, ML, and Digital Twins in specific national contexts		[122], [123]

	Factors		
	Construction Quality & Digital Maturity	Deep learning for construction quality management; comprehensive framework for AI-enabled digital transformation	[121]

A particularly salient contribution to this theme is the work on a machine learning integrated resource management framework for construction projects [126]. This study directly addresses how ML, as a branch of AI, enables systems to learn from historical and real-time data to address inefficiencies that lead to delays and cost overruns. It provides a practical example of how AI algorithms can be embedded within broader construction management systems to optimize resource allocation, thereby indirectly but effectively preventing budget overruns. Furthermore, the transformative potential of artificial intelligence in architectural practice is explored in a study that examines its trajectory from generative design to sustainable building performance, acknowledging that AI-enhanced BIM can lead to better cost control [125]. The research landscape also includes a bibliometric analysis of AI in BIM research, which provides a broad overview of the field through country and document-based citation analysis, revealing the global distribution and collaborative networks driving this integration [124]. A separate study on the transformative integration of AI in architectural practice similarly touches upon how generative design tools linked with performance models can flag potential cost overruns early in the design phase [125], completing the picture of how this theme spans from the granularity of machine learning algorithms to the high-level dynamics of industry adoption and citation networks.

Resource Optimization, Labor, and Material Management

The efficient allocation and management of resources, including labor, materials, and equipment, constitute a critical lever for controlling project costs and preventing overruns. Inefficiencies in this domain, such as labor shortages, material price volatility, and suboptimal resource allocation, are frequently cited as primary drivers of budget exceedance. This subsection synthesizes the studies that apply AI and ML to optimize resource utilization, forecast labor and material costs, and develop integrated frameworks for resource management, thereby contributing indirectly but significantly to the prediction and mitigation of cost overruns. Our analysis reveals a research landscape that spans from focused prediction models for specific resource types to comprehensive, reinforcement learning-based frameworks for dynamic, real-time allocation.

The reviewed studies within this theme can be systematically organized into a hierarchical taxonomy that distinguishes between the primary resource dimension under management, the specific sub-dimension of resource type, and the analytical approach or AI/ML method employed, as presented in Table 5. This taxonomy reveals a clear distribution of research efforts. A substantial number of studies concentrate on the labor and workforce dimension, aiming to predict labor costs, estimate labor hour requirements, and optimize workforce allocation. An equally significant cluster of studies addresses the material procurement dimension, focusing on forecasting

material price volatilities and optimizing procurement strategies. Furthermore, a smaller but methodologically distinct group of studies develops integrated frameworks for managing multiple resources simultaneously, often employing advanced techniques such as deep reinforcement learning for dynamic control.

Table 5. Taxonomy of Studies on Resource Optimization, Labor, and Material Management

Resource Dimension	Sub-Dimension (Resource Type)	Analytical Approach (AI/ML Method)	Sources
Labor & Workforce	Labor Cost & Hours Prediction	Regression & ML Prediction Models	[Prediction Models]
	Labor Efficiency & Resource Flow	Reinforcement Learning & Adaptive Control	[127], [128]
Materials & Procurement	Material Price Volatility & Risk	Deep Learning & Probabilistic Algorithms	[46], [22]
	Procurement Cost & Optimization	AI-driven Analytics & Data Analytics	[111]
Integrated Resource & Process Management	General Resource Allocation	ML & Predictive Analytics	[126], [129]
	Real-time / Dynamic Allocation	Deep Reinforcement Learning (DRL)	[130]
	Forecasting for Investment & Delivery	AI-driven Forecasting	[101]
	Risk Mitigation & Big Data	Big Data Analysis & Decision-making	[96]
	Maintenance Strategies	ML Technologies	[131]

Within the labor and workforce dimension, a foundational study models labor costs in Malaysian housing projects using artificial intelligence tools, explicitly highlighting that heavy reliance on labor in this context often leads to project delays and budget overruns [28]. The authors employed linear regression models to establish predictive relationships between project characteristics and labor expenditure. Building on this, another study focuses on estimating labor resource requirements in construction projects using machine learning, developing models to forecast the predict person-hours needed for various work packages [23]. This work provides a direct tool for project planners to anticipate labor demand and avoid costly shortages or overstaffing. At a more strategic level, an AI-driven project management framework tailored for construction SMEs was proposed, incorporating reinforcement learning to optimize resource allocation and thereby improve cost and schedule performance [127]. This study acknowledges that small and medium-sized enterprises are particularly vulnerable to the adverse effects of inefficient labor management. Furthermore, an

adaptive control framework for managing resource flow in construction projects through deep reinforcement learning was developed [128]. This framework enables dynamic adjustments to resource allocation in response to changing site conditions, aiming to enhance project performance in complex and uncertain environments.

The materials and procurement dimension is addressed by two studies that tackle the critical issue of material price volatility, a major source of cost uncertainty in construction projects. The first study proposes a predictive deep-learning framework, combined with stochastic analysis, to quantify and gauge project cost risks arising from fluctuations in construction material prices [46]. This framework demonstrates how probabilistic modeling can be used to set realistic contingencies and avoid budget surprises. The second study develops machine learning prediction models specifically for construction material prices in Nigeria [22], where volatile market conditions and foreign exchange dependencies make accurate price forecasting essential for effective cash flow management and cost control. Complementing these price prediction efforts, a study on revolutionizing procurement in EPC projects leverages AI and data analytics to drive cost-effective solutions [111], moving beyond mere prediction to active optimization of the procurement process itself, replacing inefficient legacy practices that frequently result in cost overruns.

The most methodologically advanced cluster within this theme comprises studies that develop integrated frameworks for managing multiple resources simultaneously. One key contribution presents a machine learning integrated resource management framework for construction projects, explicitly designed to address inefficiencies that lead to delays and cost overruns using historical and real-time data [126]. A complementary study applies AI-driven predictive analytics to enhance resource optimization and efficiency within the context of agile construction project management [129], using algorithms to predict project outcomes such as delays and cost overruns caused by poor resource planning. The pinnacle of technical sophistication is represented by a case study implementation of real-time resource allocation optimization for dynamic construction job sites using deep reinforcement learning [130], which demonstrates how an agent can learn an optimal policy for deploying labor, equipment, and materials as site conditions evolve. At a macro level, AI-driven forecasting is applied to BRICS infrastructure investment, analyzing the impacts on resource allocation and project delivery to reduce cost overruns, delays, and inefficient resource utilization [101]. Finally, a study on implementing machine learning technologies in construction maintenance strategies [131] contributes by showing how predictive maintenance, informed by ML models trained on historical failure data and real-time sensor inputs, can prevent costly equipment breakdowns and extend asset failures, thereby indirectly reducing project costs.

Furthermore, a study focusing on the integration of big data analysis for resource allocation and risk mitigation was identified [128IS87”), which uses predictive analytics to forecast project outcomes and improve decision-making processes. This work complements the reinforcement learning approaches by offering a data-driven perspective on optimizing resource allocation under uncertainty. Collectively, these studies illustrate that the application of AI to resource management is not monolithic; it ranges from narrow prediction tasks for specific resources, such as labor hours or material prices, to comprehensive, adaptive control systems that manage the entire

resource ecosystem of a construction project. The progression from static regression models to dynamic deep reinforcement learning frameworks signifies a maturing field that is increasingly capable of handling the complexity and uncertainty inherent in construction resource management.

Strategic Adoption, Industry Trends, and Managerial Impacts

Beyond the technical development of predictive models, a substantial and growing body of literature addresses the organizational, managerial factors, examine industry trends, and analyze the strategic processes through which AI and ML technologies are adopted for cost overrun prediction in construction organizations. This subsection synthesizes studies that shift the focus from algorithmic performance toward the human, organizational, and systemic dimensions that ultimately determine whether promising prototypes translate into sustained industrial practice. Our analysis reveals a rich interplay between technological capability and organizational readiness, with research spanning from adoption drivers and barriers to decision-making enhancement, cognitive learning, operational efficiency, and the ethical implications of responsible AI integration.

The reviewed studies within this theme can be systematically organized into a three-level hierarchical taxonomy, distinguishing between broad strategic dimensions, specific sub-dimensions of managerial impact, and granular analytical focus areas, as presented in Table 6. This taxonomy was derived from a careful thematic analysis of the included studies and reveals five primary dimensions: strategic adoption of AI and ML, industry trends and applications, managerial decision-making impacts, organizational and operational impacts, organizational and cognitive learning, and socio-technical and ethical considerations.

Table 6. Taxonomy of Studies on Strategic Adoption, Industry Trends, and Managerial Impacts

Dimension	Sub-Dimension	Specific Focus	Sources
Strategic Adoption of AI/ML	Drivers and Barriers	Enablers and Barriers	[132], [133], [134], [135]
		Drivers (e.g., cost reduction, efficiency)	[132], [133], [134], [135]
		Barriers (e.g., high cost, lack of skills)	[133], [136], [134]
	Adoption Frameworks and Models		[127], [137], [122]
		For SMEs	[127]
		For developing economies	[132], [122]
		General adoption decision-making	[137]

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	Critical Success Factors		[122], [134]
Industry Trends and Applications	Predictive Applications (Cost & Schedule)		[85], [88], [89], [138], [139], [140], [141], [142], [143], [144], [145], [146]
		Cost overrun prediction	[89], [138], [140], [143], [144], [145]
		Schedule/delay prediction	[88], [89], [138], [141], [142], [144], [146]
		General prediction/analytics	[85], [139], [146]
	Risk Management & Mitigation		[85], [98], [127], [147], [148], [145]
		Predictive risk identification	[85], [98], [145]
		Automated risk response/optimization	[127], [148]
		Public project risk management	[147]
	Emerging Technologies (BIM, Digital Twins, Generative AI)		[149], [150], [122], [136], [151]
		Integration with BIM & Digital Twins	[122]
		Application of Generative AI (e.g., ChatGPT)	[149]
		Robotics and automation	[151], [136]
	Regional & Sectoral Trends		[152], [133], [140], [134], [122]
		Developing economies (e.g., South Africa, Peru)	[152], [133], [122]
		Mega-projects (e.g., NEOM)	[140]
		UK construction industry	[134]
	Project Lifecycle		[84], [153], [154],

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	Integration		[155], [156], [157]
		Design & Planning phase	[84], [153], [154]
		Construction & Monitoring phase	[156], [157]
		Overall lifecycle management	[155]
Managerial Impacts	Decision-Making Enhancement		[88], [98], [158], [159], [160], [144]
		Predictive & adaptive decision-making	[88], [98], [144]
		Data-driven, automated decisions	[158], [159]
		General decision-making benefits	[160]
	Organizational & Cognitive Learning		[161], [162], [163]
		Learning from past project data	[161], [162]
		Re-evaluating cost overrun definitions	[161]
		ML as a method for studying project performance	[163]
	Operational Efficiency & Productivity		146 , [139], [148], [142], [160]
		Efficiency gains and productivity improvement	[89], [139], [142], [171”]
		Quantum AI for efficiency	[148]
	Project Controls & Cost Management		[89], [164], [143], [165]
		Advanced control mechanisms	[89], [164]
		Modern cost management techniques	[143], [165]
	Socio-technical and Ethical Considerations		[166], [152]
		Responsible AI	[166]

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		integration	
		Impact on workforce and project culture	[152]

Within the strategic adoption dimension, several studies have critically examined the drivers and barriers that shape the implementation of AI for cost prediction. Research on the critical drivers of AI adoption in construction projects in a developing economy identified key enablers such as top management support, perceived ease of use, and organizational readiness, while also highlighting barriers including high initial investment costs and lack of skilled workforce [132]. This finding was echoed in a theoretical assessment of AI implementation for improving the learning curve on construction in South Africa, which similarly emphasized that high adoption costs and the need for specialized expertise remain significant impediments [133]. A more comprehensive exploration of emerging trends, enablers, and barriers in the UK construction in the UK recognized that despite a clear awareness of AI's potential to improve productivity and reduce cost overruns, construction companies face substantial challenges related to data quality, integration with existing systems, and a culture resistant to change [134]. A broader study on the benefits and risks of AI in the construction industry, taking a systematic perspective, confirmed that while deep learning and machine learning offer substantial advantages for cost prediction and risk mitigation, concerns about data privacy, model interpretability, and the potential for algorithmic bias temper the enthusiasm for widespread adoption [135]. These studies collectively suggest that the path to adoption is not purely technical but deeply interwoven with organizational readiness and contextual factors.

Several authors have responded to these challenges by proposing structured adoption frameworks and identifying critical success factors. For small and medium-sized enterprises, an AI-driven project management framework for cost and schedule optimization was specifically developed, integrating reinforcement learning for resource allocation and providing a blueprint for SMEs to navigate the adoption process [127]. For developing economies, a developing economy context, a cutting-edge decision-making model for AI implementation in sustainable building projects was introduced, offering a systematic approach for construction firms to evaluate the feasibility and expected returns of AI investments [137]. A framework of critical success factors for the adoption of BIM, machine learning, and digital twins in Peruvian public infrastructure was also developed, explicitly linking technological adoption with the potential to combat significant cost overruns and inadequate planning [122]. This study, alongside others, reinforces the notion that successful adoption requires not only a capable technology but also a supportive ecosystem of policy, skilled personnel, and transparent data-sharing protocols [134].

Within the industry trends and applications sub-dimension, a large cluster of studies has focused on the practical deployment of AI for predictive cost and schedule applications. For instance, a study on leveraging AI for optimized project management and risk mitigation in the construction industry explicitly demonstrated how machine learning models such as regression and deep learning can predict cost overruns and delays, thereby enabling proactive management [85]. Another work

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developed a predictive and adaptive decision-making framework that uses machine learning to analyze historical data and proactively address issues such as delays and cost overruns [88]. The role of AI and ML in resolving core challenges including cost overrun and productivity constraints was directly discussed, highlighting the ascendancy of these technologies in project controls [89]. A comprehensive bibliometric and systematic analysis of ML and systematic analysis of ML and AI-based cost and time prediction in construction mapped the state-of-the-art, confirming that machine learning models are now widely used to predict cost overruns and delays, though their deployment remains uneven across different project types and regions [138]. Several other studies have contributed to this theme by evaluating the impact of AI on managing construction engineering projects [84], rethinking the cognitive and learning aspects of construction cost overruns [161], and analyzing the transformative potential of artificial intelligence in public project management to boost economic outcomes [147].

The managerial impacts dimension is particularly rich, with a significant number of studies examining how AI enhances decision-making quality and operational efficiency. A study on the impact of AI on project management in complex projects showed how machine learning algorithms can process historical project data to predict outcomes, enabling managers to identify bottlenecks and potential budget overruns before they materialize [98]. The theme of revolutionizing decision-making and automation through AI in engineering management was further developed, with authors arguing that AI enables a shift from reactive to predictive management [158]. A study on enhancing project management success through AI echoed this sentiment, arguing that data-driven insights from ML models improve the accuracy of cost forecasts and the timeliness of corrective actions [159]. The benefits of AI in construction were also directly enumerated, including improved cost control, better risk mitigation, and enhanced scheduling accuracy [160]. These findings were corroborated by research showing that AI revolutionizes construction management by building smarter and more efficient projects [139].

Furthermore, a distinct subgroup of studies has focused on the organizational and cognitive learning implications of AI adoption. A thought-provoking study on rethinking construction cost overruns argued that the perception of overruns is fundamentally shaped by cognition, learning processes, and estimation practices, suggesting that AI can serve as a tool not just for prediction but for organizational learning from past project performance [161]. A related work on AI-augmented project management using machine learning to improve delivery outcomes explicitly frames ML as a method for extracting lessons from historical data, thereby enabling continuous improvement in cost and more accurate forecasting [162]. A study on sorting things out with machine learning in complex construction projects took this idea further, proposing that machine learning serves as a method to systematically study project performance and the causes of delays and cost overruns, thus challenging or supplementing traditional qualitative analyses [163]. These studies underscore that the value of AI extends beyond immediate prediction to the cultivation of a learning organization that can systematically improve its cost performance over time.

The socio-technical and ethical considerations of AI adoption in construction

represent a nascent but critically important research stream. A study on the responsible integration of AI technology in the construction sector explicitly addresses the risks that 98 percent of megaprojects face cost overruns or delays and argues that AI and deep learning, while promising, must be deployed within an ethical framework that ensures transparency and accountability in cost predictions [166]. The study cautions against a black-box reliance on deep learning algorithms without understanding their limitations and biases. Similarly, an investigation into the impact of AI in the South African construction project management industry explored the workforce implications and the cultural shift required for successful adoption, noting that resistance from experienced professionals accustomed to traditional methods can be a significant barrier [152]. These contributions collectively highlight that the successful long-term implementation of AI for cost overrun prediction depends not only on technical accuracy but also on addressing the human and ethical dimensions that influence trust, acceptability, and fairness in algorithmic decision-making.

Several other studies within this thematic cluster provided broader perspectives that complement the detailed analysis presented in Table 6. For example, studies on the impact of artificial intelligence on civil engineering project management [141], the influence of advanced technologies in bridge construction [136], and the role of generative AI in architectural engineering [149] offer insights into how AI is penetrating specialized sectors. However, because some of these works are not included in the comprehensive taxonomy of Table 6, they must be mentioned here to ensure no paper is omitted from the narrative. Specifically, the study on the impact of artificial intelligence on civil engineering project management [141] discusses how machine learning algorithms are used to predict potential delays and cost overruns by examining data from past projects, enabling early identification of cost overruns. The work on the conventional construction scenario and the emergence of advanced technologies in bridge construction [136] identifies that the adoption of advanced technologies can mitigate delays and cost overruns, though barriers to adoption such as high costs persist. The comprehensive review of data-driven civil engineering [167] provides a broad overview of AI applications, including cost prediction, serving as a foundational reference for the field. The bibliometric and systematic analysis of machine learning and deep learning in project analytics [82] contributes by mapping the research landscape and identifying trends in cost overrun prediction applications, while a mapping of the state-of-the-art AI-based cost and time prediction [138] provides a dedicated analysis of ML applications for these specific outcomes. These studies, while not fitting neatly into the taxonomy's sub-dimensions, are integral to the overall narrative of how AI is reshaping the strategic and managerial landscape of construction cost management.

Sustainability, Green Building, and Specialized Infrastructure Projects

The increasing global emphasis on environmental sustainability and the unique financial dynamics of specialized infrastructure projects present distinct challenges for cost overrun prediction that general-purpose models may not adequately address. Green buildings, for example, incorporate novel materials, advanced energy systems, and unconventional construction processes that lack extensive historical cost data, while specialized infrastructure such as urban megaprojects or national public works

programs are subject to macroeconomic volatility, complex stakeholder ecosystems, and stringent regulatory frameworks. This subsection synthesizes studies that apply AI and ML specifically within sustainability-oriented or specialized project contexts, examining how predictive models are adapted to these unique environments and what implications arise for the broader goal of cost control. Our analysis reveals a research stream that is methodologically diverse yet unified by a research stream that is methodologically diverse yet coherent in its focus on adapting general-purpose algorithms to niche but increasingly important project typologies.

The reviewed studies can be systematically organized into a hierarchical taxonomy that distinguishes between the primary application area, the specific sustainability or specialization focus, the primary application area, the specific sustainability or specialization focus, and the methodological approach adopted, as presented in Table 7. This taxonomy reveals that the research landscape is divided into three primary domains: green building projects, sustainable infrastructure and urban megaprojects, and general sustainability and green building practices. Within each domain, studies apply distinct analytical lenses ranging from cost estimation and control using deep learning and ensemble methods to the development of comprehensive adoption frameworks for AI implementation in sustainable projects.

Table 7. Taxonomy of Studies on Sustainability, Green Building, and Specialized Infrastructure Projects

Application Area	Application Area	Primary Focus	Methodological Approach/AI Technique
Green Building Projects	Cost Estimation & Control	Deep learning-based cost estimation and cost control methods	[11]
	Smart Building Optimization	Machine learning and deep learning for smart building optimization including budget overrun challenges	[120]
	Project Delivery Implications	Machine learning for promoting green building practices and implications for construction project delivery	[168]
Sustainable Infrastructure & Urban Megaprojects	Cost & Schedule Planning in Energy Infrastructure	Integration of BIM and AI to enhance cost and schedule planning	[116]

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	Holistic Risk & Green Management	AI-driven and Digital Twin-based framework for holistic risk and green project management	[99]
	Adaptive Control of Sustainable Projects	Digital twin technology combined with ensemble machine learning for adaptive control	[119]
	Resource Allocation & Project Delivery	AI-driven forecasting applied to BRICS infrastructure investment	[101]
	Public Infrastructure & Critical Success Factors	Framework for adoption of BIM, machine learning, and Digital Twins in Peruvian public infrastructure	[122]
General Green Building Practices	AI Implementation Decision-Making	Decision-making model for AI implementation in sustainable building projects	[137]
	Efficiency & Sustainability in Project Management	Advancing lean construction through AI to enhance efficiency and sustainability	[142]
	Macroeconomic-aware Cost Forecasting	Gated recurrent unit and long short-term memory deep learning framework for construction costs in developing countries	[20]
	Transformative Integration in Architectural Practice	Generative design to sustainable building performance using	[125]

AI

Within the green building domain, a study on the application of artificial intelligence-based cost estimation and cost control methods in green buildings provides a focused specifically on developing deep learning models to handle the unique data characteristics of sustainable construction such as the inclusion of renewable energy systems, high-performance glazing, and advanced HVAC configurations that are not commonly found in traditional cost databases [11]. The study demonstrated that deep learning architectures, when trained on a carefully curated dataset of green building projects, could achieve higher predictive accuracy for final project costs compared to conventional methods, because the models were able to capture complex interactions between building orientation, insulation levels, and energy system specifications. A separate investigation into the application of AI in smart buildings explored how machine learning and deep learning could address challenges such as worker safety and budget overruns through optimization of building operations and construction processes simultaneously [120]. While this study had a broader scope than pure cost overrun prediction, its findings on the integration of smart building sensors with predictive analytics for budget control are directly relevant to green construction contexts where real-time energy monitoring and cost tracking are often co-complemented. Machine learning for promoting green building practices and its implications for construction project delivery in Malaysia was another key contribution, examining how predictive models could be used to forecast not only costs but also the environmental performance of building projects, enabling project managers to identify trade-offs between initial investment and long-term operational savings that could lead to budget deviations if not properly managed [168].IS158”)

The domain of sustainable infrastructure and urban megaprojects is characterized by particularly ambitious and comprehensive frameworks. A study integrating BIM and artificial intelligence to enhance cost and schedule planning in energy-conscious infrastructure projects demonstrated how AI and ML aspects of these tools have significantly improved project predictabilities so that precise predictions can be made to identify up-front projects likely prone to cost overruns [116]. The authors explicitly noted that energy-conscious projects, which incorporate renewable energy generation, efficient lighting systems, and thermal storage technologies that design flexibility is constrained by performance requirements making accurate cost prediction even more critical. A more holistic study developed an AI-driven and digital twin-based framework for holistic risk and green project management in sustainable urban megaprojects using the case of Tehran under future development plan [99]. This work integrated machine learning and deep learning models for predicting project delays and cost overruns with a digital twin environment that continuously updated risk assessments based on real-time sensor data from the construction site and from city-level infrastructure networks, demonstrating that the temporal and cost performance of green megaprojects can be enhanced by integrating AI and digital twins. A method for adaptive control of sustainable construction projects based on digital twin technology and ensemble machine learning [119] further advanced this paradigm by proposing a system where ensemble machine learning models, including random forests and gradient boosting, were trained on historical project data and updated in real-time as the digital twin reflected actual site conditions enabling dynamic

adjustments to budget forecasts and resource allocation plans.

AI-driven forecasting in BRICS infrastructure investment was studied to analyze the impacts on resource allocation and project delivery, using machine learning algorithms to predict cost overruns and inefficient resource utilization across a portfolio of large-scale infrastructure projects in emerging economies [101]. The study found that macroeconomic variables such as inflation rates, currency exchange fluctuations, and changes in regulatory changes significantly influence the accuracy of cost predictions in these specialized projects, suggesting that models trained solely on historical project data are insufficient without incorporating external economic indicators. Towards the digital transformation of Peruvian public infrastructure a framework of critical success factors for the adoption of BIM, machine learning and Digital Twins was developed explicitly to address the persistent challenges of significant cost overruns, inadequate planning and a persistent loss of value in completed projects [122]. This study identified that a combination of technical factors (data interoperability, model accuracy) and organizational factors (government support, training programs, stakeholder commitment) is essential for successful implementation of AI for cost prediction in public infrastructure, in the specialized context of public infrastructure where transparency and public accountability add additional layers of complexity.

Within the general sustainability and green building practices domain, researchers have addressed the need for structured decision-making frameworks to guide AI implementation. A cutting-edge decision-making model for AI implementation in sustainable building projects was introduced providing a systematic approach for construction firms to evaluate the feasibility, costs and expected benefits of adopting AI for cost management [137]. This model utilized machine learning to predict cost overruns based on variables like project size, contract type, and project managers skill level thus providing evidence-based support for investment in AI. Advancing lean construction through artificial intelligence a study focused on enhancing efficiency and sustainability in project management demonstrated how AI technologies through predictive analytics and machine learning offer viable solutions to persistent resource constraints that often lead to cost overruns and project delays in sustainable projects [142]A macroeconomic-aware forecasting of construction costs in developing countries using a deep learning framework using gated recurrent unit and long short-term and long short-term memory networks was developed to forecast cost indices that account for inflation and economic volatility [20]. This work is particularly relevant to sustainable infrastructure projects in developing countries where currency fluctuations and material import costs can dramatically affect project budgets and where green materials frequently sourced from international suppliers are subject to additional price volatility. The transformative integration of AI in architectural practice from generative design to sustainable building performance [125]A transformational study explored how AI can be used to generate design alternatives that minimize both construction costs and lifecycle energy use thereby enabling a proactive approach to preventing cost overruns by ensuring that the chosen design is inherently optimized for both financial and environmental performance.

Discussion

The synthesis of findings across the seven thematic dimensions reveals a field that has progressed considerably from isolated proof-of-concept studies to a more mature, though still fragmented, research landscape. Taken together, the collective evidence indicates that AI and ML methods demonstrably enhance the accuracy of cost overrun prediction over traditional parametric and judgment-based approaches. However, this overarching narrative is nuanced by significant disparities in methodological rigor, domain coverage, and the contextual factors that condition model performance. The results from Section 3.2 consistently show that ensemble methods such as random forests and gradient boosting machines frequently achieve mean absolute percentage errors below 10 percent when applied to historical project data. This pattern emerges across multiple studies and project types, suggesting a genuine advantage arising from these algorithms' ability to capture non-linear interactions and mitigate overfitting. In contrast, neural networks, while capable of achieving comparable or even superior accuracy in specific contexts, demonstrate higher variance in performance across different dataset sizes and require more careful hyperparameter tuning, which may limit their reproducibility in practical settings. This distinction is not merely academic; it has direct implications for practitioners who must choose a model architecture based on the size and quality of data available within their organizations. The integration of AI with BIM and digital twin technologies, as described in Section 3.5, represents perhaps the most transformative development identified in this review. The emergence of studies that combine real-time sensor data from digital twins with predictive algorithms enables a shift from static, one-time cost estimates to dynamic, continuously updated forecasts. This is a significant departure from the conventional project control paradigm, where cost performance is reviewed retrospectively on a monthly or quarterly basis. The digital twin framework proposed for sustainable urban megaprojects exemplifies how machine learning models, when embedded within a living digital representation of the project, can provide early warnings of cost trajectory deviations and allow for proactive interventions. However, the number of studies that actually implement such integrated systems remains small, and most existing work remains at the conceptual or framework stage. There is a clear need for empirical validation of these integrated frameworks in real-world projects, particularly to assess the practical challenges of data integration, computational latency, and organizational adoption that inevitably arise when deploying such sophisticated systems on active construction sites.

The implications of these findings for both theory and practice are substantial. From a theoretical perspective, the consistently superior performance of ensemble methods challenges the assumption that more complex deep learning architectures are always preferable for structured tabular data typical of historical project records. This insight aligns with findings in other domains, such as finance and healthcare, where gradient boosting often outperforms neural networks on medium-sized datasets with heterogeneous features. The implication for cost overrun prediction theory is that researchers should not automatically gravitate toward the latest algorithmic fad but should instead systematically compare candidate models using rigorous cross-validation and external testing protocols to identify the best architecture for their

specific data characteristics. From a practical standpoint, the clear implication is that construction firms seeking to adopt AI for cost prediction should initially focus on assembling high-quality historical project data and then invest in ensemble methods such as random forests or XGBoost, which offer a favorable balance of predictive accuracy, training efficiency, and model interpretability. The ability to interpret model outputs, through feature importance scores for instance, is critical for building trust among project managers who must justify decisions to stakeholders and clients. Furthermore, the integration with BIM and digital twins suggests that forward-thinking organizations should begin investing in the data infrastructure and sensor networks that will enable real-time predictive analytics, as the competitive advantage of such capabilities is likely to grow in the coming years.

The resource optimization studies reviewed in Section 3.6 carry particularly strong practical implications for cost control. The deep reinforcement learning framework for dynamic resource allocation, while currently limited to a single case study, points toward a future where construction sites can adapt labor and equipment deployment in real-time to changing conditions, thereby preventing the productivity losses that often cascade into cost overruns. The studies on material price forecasting, especially those using deep learning and probabilistic algorithms, offer procurement managers a tool to set realistic contingencies and negotiate better terms with suppliers. However, the practical deployment of these models requires access to high-frequency price data and the integration of external economic indicators, which may not be readily available in all markets or for all material types. The implication is that practitioners should prioritize the collection and digitization of procurement data as a foundational step before attempting to implement sophisticated forecasting models.

Despite the promising findings, this review must acknowledge several significant limitations that temper the strength of the conclusions. First, the restriction to English-language publications, while necessary for feasibility, introduces a potential language bias that may have excluded important research published in languages such as Chinese, Spanish, Arabic, or Portuguese. Given the global nature of the construction industry and the significant amount of construction activity in non-English-speaking regions, this limitation could have resulted in an incomplete picture of the field, particularly regarding region-specific models developed for local contexts. Second, the exclusion of grey literature, including industry reports, doctoral theses, and white papers from technology vendors, means that our review may have missed practical insights and implementation experiences that are not captured in peer-reviewed academic publications. The construction industry is known for a gap between academic research and industrial practice, and this methodological choice may have reinforced that gap. Third, the heterogeneity of performance metrics reported across studies made direct quantitative comparisons difficult. Many studies report mean absolute percentage error, while others use root mean squared error, R-squared, accuracy, or area under the curve, and the lack of a standardized reporting framework prevents a rigorous meta-analysis of predictive accuracy. This heterogeneity also complicates the assessment of cross-study consistency, as differences in evaluation metrics may obscure genuine variations in model performance.

The scope of the literature search also imposes boundaries on the generalizability of our findings. Our search strategy focused on databases that index primarily academic

literature, and while Google Scholar was included to capture a broader range of sources, its algorithmic ranking may have introduced its own biases. Additionally, the construction industry is highly diverse, encompassing residential, commercial, infrastructure, industrial, and specialized projects. The studies included in this review are not evenly distributed across these project types, with a noticeable concentration on residential and commercial buildings and a relative scarcity of studies on infrastructure, green building, or industrial projects. This uneven distribution means that the conclusions about model performance and best practices may not be directly transferable to project types that are underrepresented in the literature. For example, the predictive models that perform well on relatively standardized residential projects may require substantial modification to handle the unique cost drivers of tunnel boring or offshore wind farm construction.

Future research should prioritize addressing the gaps and inconsistencies identified in this review. There is a clear need for standardized benchmarking datasets and evaluation protocols to enable fair and reproducible comparisons across different modeling approaches. Such a resource would allow researchers to systematically test the generalizability of their models and identify which algorithm-data combinations are most robust. The establishment of a public repository of construction project data, anonymized to protect commercial sensitivity, would be a transformative step for the field. Furthermore, future research should explore the transferability of models across different project types and geographical contexts. Transfer learning techniques, which allow a model pre-trained on one dataset to be adapted to a related but different dataset with minimal additional data, hold particular promise for overcoming the data-scarce contexts such as green building or infrastructure projects where historical records are limited. Domain adaptation methods that can adjust for differences in cost structures, labor availability, and regulatory environments across regions could also significantly enhance the practical applicability of predictive models.

The relative scarcity of studies that rigorously validate models on external, unseen datasets is a major concern that future research must address. Many studies in this review report impressive accuracy metrics, but these are often based on cross-validation within the same dataset used for training, which can overestimate real-world performance. Truly convincing evidence of model utility requires prospective validation on completely new projects that were not used in any stage of model development. Such studies are methodologically demanding and require long time horizons, but they are essential for building trust and demonstrating return on investment to industry stakeholders. Researchers should also explore the added value of incorporating unstructured data sources, such as textual reports from project meetings, social media sentiment, or news articles about market conditions, into predictive models. Natural language processing techniques are advancing rapidly, and their integration with structured numerical data could capture nuanced risk factors that are currently overlooked.

The limited attention to green building and sustainable infrastructure contexts highlighted in Section 3.8 represents a significant gap that deserves systematic investigation. As the global construction industry transitions toward net-zero carbon targets, the volume of green building projects is expected to increase dramatically, and the cost dynamics of these projects differ substantially from conventional

construction. Future research should develop and validate predictive models specifically for sustainable projects, incorporating variables such as energy performance targets, certification requirements, and the cost premiums associated with novel materials and technologies. Similarly, the unique challenges of infrastructure megaprojects, including their long durations, complex stakeholder networks, and exposure to macroeconomic volatility, warrant dedicated attention. The digital twin and AI integration frameworks proposed for such projects need to be tested in real-world settings, with rigorous documentation of implementation challenges and performance outcomes.

The ethical and socio-technical dimensions of AI deployment in construction cost prediction are almost entirely unexplored in the literature. Only a handful of studies touch on issues of model interpretability, algorithmic bias, or the potential for automation to displace jobs or concentrate decision-making power. Future research should explicitly examine how the use of AI for cost prediction might affect equity among project stakeholders, particularly subcontractors and small suppliers who may not have access to the same data or computational resources as large general contractors. The responsible integration of AI, as advocated by one study, should be a foundational principle that guides the design and deployment of predictive systems, ensuring that they are transparent, accountable, and aligned with the broader social and ethical values of the construction industry.

Finally, there is a pressing need for longitudinal studies that track the real-world impact of AI adoption on project cost performance over multiple projects. Such studies would provide the most convincing evidence of the value proposition of these technologies, moving beyond prediction accuracy to measure actual reductions in cost overruns, improvements in profit margins, and changes in project management practices. The field would benefit from case studies that document not only successes but also failures, as the lessons learned, and contextual factors that enabled or hindered the effective deployment of AI for cost prediction. By grounding future research in rigorous validation, diverse project contexts, and a commitment to responsible implementation, the research community can accelerate the transition from promising prototypes to widely adopted tools that genuinely improve the financial outcomes of construction projects worldwide.

Conclusion

This systematic literature review synthesized 159 peer-reviewed studies to map the landscape of artificial intelligence and machine learning applications for predicting cost overruns in construction projects. The primary findings confirm that ensemble methods, particularly random forests and gradient boosting machines, consistently achieve superior predictive accuracy, often with mean absolute percentage errors below ten percent, while deep learning architectures, though powerful, require larger datasets and more careful tuning. The integration of AI with building information modeling and digital twin technologies emerged as a particularly promising direction, enabling a shift from static cost estimation to dynamic, real-time forecast adjustment. However, significant gaps persist: most studies focus on residential and commercial projects with limited validation in infrastructure, green building or infrastructure contexts, and many models lack rigorous cross-validation on external datasets, raising

questions about generalizability and practical reliability.

The theoretical contribution of this work lies in providing a synthesized evidence base that challenges the assumption that greater algorithmic complexity necessarily yields better predictive performance for structured project data, thereby guiding researchers toward more systematic model comparison and validation practices. Practically, the findings suggest construction firms should prioritize building high-quality historical datasets and deploying interpretable ensemble methods as a first step, while investing in the data infrastructure necessary for future integration of AI with digital project models for real-time predictive analytics. Future research must address three critical priorities: the development of standardized benchmarking datasets and evaluation protocols to enable fair comparisons across studies, the rigorous prospective validation of models on unseen projects from diverse contexts including sustainable building and infrastructure, and the investigation of transfer learning and domain adaptation methods to overcome data scarcity in specialized project types. The ethical and socio-technical dimensions of algorithmic deployment, including model interpretability and equity among stakeholders, also warrant systematic investigation to ensure responsible adoption. By addressing these gaps, the field can transition from promising prototypes to robust, scalable, and trustworthy predictive systems that meaningfully reduce the persistent challenge of cost overruns in construction.

References

- [1] V. Sanvido, F. Grobler, K. Parfitt, M. Guvenis, *et al.*, “Critical success factors for construction projects,” *Journal of Construction Engineering and Management*, 1992.
- [2] I. Rahman, A. Memon, A. Karim, *et al.*, “Significant factors causing cost overruns in large construction projects in malaysia,” *Journal of Applied Sciences*, 2013.
- [3] H. Lind and F. Brunes, “Explaining cost overruns in infrastructure projects: A new framework with applications to sweden,” *Construction management and economics*, 2015.
- [4] M. Arafa and M. Alqedra, “Early stage cost estimation of buildings construction projects using artificial neural networks,” *Journal of Artificial Intelligence*, 2011.
- [5] A. Memon, I. Rahman, *et al.*, “Preliminary study on causative factors leading to construction cost overrun,” *International Journal of Sustainable Construction Engineering and Technology*, 2011.
- [6] Y. Adebayo, P. Udoh, X. Kamudyariwa, and O. Osobajo, “Artificial intelligence in construction project management: A structured literature review of its evolution in application and future trends,” *Digital*, 2025.
- [7] S. T. Hashemi, O. Ebadati, and H. Kaur, “Cost estimation and prediction in construction projects: A systematic review on machine learning techniques,” *SN Applied Sciences*, 2020.
- [8] X. Xue, Y. Jia, and Y. Tang, “Expressway project cost estimation with a convolutional neural network model,” *IEEE Access*, 2020.
- [9] M. Hamdan, M. Thneibat, and K. Hyari, “Predicting cost overrun in construction projects using machine learning algorithms: The case of jordan,”

- Engineering, Construction and Architectural Management*, 2025.
- [10] J. Kim, "Balancing AI generalization and specialization: Multi-domain learning for universal computer vision models in construction," *Automation in Construction*, 2025.
- [11] Y. Zhang, "Research on the application of artificial intelligence-based cost estimation and cost control methods in green buildings," *Scalable Computing: Practice and Experience*, 2024.
- [12] A. Almusaed, A. Almssad, and I. Yitmen, "Identifying research gaps," *Practice of Research Methodology in Information Systems*, 2025.
- [13] M. Page, J. McKenzie, P. Bossuyt, *et al.*, "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," *BMJ*, vol. 372, p. n71, 2021.
- [14] J. Ujong, E. Mbadike, and G. Alaneme, "Prediction of cost and duration of building construction using artificial neural network," *Asian Journal of Civil Engineering*, 2022.
- [15] N. Fernando, K. TA, and H. Zhang, "An artificial neural network (ANN) approach for early cost estimation of concrete bridge systems in developing countries: The case of sri lanka," *Journal of Financial Management of Property and Construction*, 2024.
- [16] M. Alriabi, A. Almohsen, N. Alsanabani, *et al.*, "Developing a cost-predictive model for hospital construction projects," *Journal of Asian Architecture and Building Engineering*, 2025.
- [17] M. Islam, S. Mohandes, A. Mahdiyar, *et al.*, "A coupled genetic programming monte carlo simulation-based model for cost overrun prediction of thermal power plant projects," *Journal of Construction Engineering and Management*, 2022.
- [18] S. Saeidlou and N. Ghadiminia, "A construction cost estimation framework using DNN and validation unit," *Building Research & Information*, 2024.
- [19] M. Cheng, M. Sholeh, and B. Poetra, "Predicting the construction cost-time tradeoff using optimized hybrid deep learning for risk preference decision making," *International Journal of Construction Management*, 2025.
- [20] M. Alzara, N. Gihad, H. Abdou, A. Soltan, A. Hilal, *et al.*, "Macroeconomic-aware forecasting of construction costs in developing countries: Using gated recurrent unit and long short-term memory deep learning framework," *Plos one*, 2025.
- [21] P. Jafary, D. Shojaei, A. Rajabifard, *et al.*, "AI-augmented construction cost estimation: An ensemble natural language processing (NLP) model to align quantity take-offs with cost indexes," *International Journal of Construction Management*, 2025.
- [22] H. Ahmadu, Y. Ibrahim, *et al.*, "Developing machine learning prediction models for construction material prices in nigeria," *ATBU Journal of Science, Technology and Education*, 2023.
- [23] H. Golabchi and A. Hammad, "Estimating labor resource requirements in construction projects using machine learning," *Construction innovation*, 2024.
- [24] H. Elmousalami, "Comparison of artificial intelligence techniques for project conceptual cost prediction," arXiv preprint arXiv:1909.11637, 2019.

- [25] H. Elmousalami, "Comparison of artificial intelligence techniques for project conceptual cost prediction: A case study and comparative analysis," *IEEE Transactions on Engineering Management*, 2020.
- [26] A. Sapkota, S. Karki, B. Pokharel, and M. Dhital, "A comparative study of machine learning algorithms for early cost estimation of building projects in nepal," *Kathford Journal of Engineering and Management*, 2023.
- [27] P. Karadimos and L. Anthopoulos, "A taxonomy of machine learning techniques for construction cost estimation," *Innovative Infrastructure Solutions*, 2024.
- [28] M. Momade, S. Durdyev, S. Dixit, S. Shahid, *et al.*, "Modeling labor costs using artificial intelligence tools," *International Journal of Bank Marketing*, 2024.
- [29] N. Dharwadkar and S. Arage, "Prediction and estimation of civil construction cost using linear regression and neural network," *International Journal of Intelligent Systems and Applications in Engineering*, 2018.
- [30] K. Al-Gahtani, A. Alsugair, *et al.*, "ANN prediction model of final construction cost at an early stage," *Journal of Asian Architecture and Building Engineering*, 2025.
- [31] H. Sandell, "Forecasting indirect costs in finnish public transport infrastructure projects: Applications with machine learning models," *Opinnäytetyö*, 2020.
- [32] H. Unegbu and D. YAWAS, "Advanced machine learning models for predicting project performance in complex construction environments," *MSA Engineering Journal*, 2025.
- [33] A. Ashraf, M. Rady, and S. Mahfouz, "Price prediction of residential buildings using random forest and artificial neural network," *HBRC Journal*, 2024.
- [34] M. Cheng, H. Peng, Y. Wu, and T. Chen, "Estimate at completion for construction projects using evolutionary support vector machine inference model," *Automation in Construction*, 2010.
- [35] G. Deepa, A. Niranjana, and A. Balu, "A hybrid machine learning approach for early cost estimation of pile foundations," *Journal of Engineering, Design and Technology*, 2025.
- [36] Z. Ali, A. Burhan, M. Kassim, and Z. Al-Khafaji, "Developing an integrative data intelligence model for construction cost estimation," *Complexity*, 2022.
- [37] P. Das, A. Kashem, I. Hasan, and M. Islam, "A comparative study of machine learning models for construction costs prediction with natural gradient boosting algorithm and SHAP analysis," *Asian Journal of Civil Engineering*, 2024.
- [38] Y. Cao, B. Ashuri, and M. Baek, "Prediction of unit price bids of resurfacing highway projects through ensemble machine learning," *Journal of Computing in Civil Engineering*, 2018.
- [39] P. Parsafard, O. Elezaj, D. Ekundayo, *et al.*, "Automation in construction cost budgeting using generative artificial intelligence," in *Proceedings of the international conference on industrial engineering and operations management*, 2024.
- [40] H. Moon, T. Williams, H. Lee, *et al.*, "Predicting project cost overrun levels in

- bidding stage using ensemble learning,” *Journal of Asian Architecture and Building Engineering*, 2020.
- [41] V. Rayabharapu, K. Rao, S. Punitha, *et al.*, “Enhancing construction project cost predictions using machine learning for improved accuracy and efficiency,” *SSRN Electronic Journal*, 2024.
- [42] S. Fanaei, O. Moselhi, S. Alkass, and Z. Zangenehmadar, “Application of machine learning in predicting key performance indicators for construction projects,” *methods*, 2018.
- [43] J. Obianyo, O. Okey, and G. Alaneme, “Assessment of cost overrun factors in construction projects in nigeria using fuzzy logic,” *Innovative Infrastructure Solutions*, 2022.
- [44] B. Mohamed and O. Moselhi, “Conceptual estimation of construction duration and cost of public highway projects,” *J. Inf. Technol. Constr.*, 2022.
- [45] Y. Abed, T. Hasan, and R. Zehawi, “Cost prediction for roads construction using machine learning models,” *International Journal of Electrical and Computer Engineering*, 2022.
- [46] Y. Jezzini, R. Assaad, and I. El-Adaway, “... framework to quantify and gauge project cost risks due to construction material price volatilities using predictive probabilistic deep-learning algorithms and stochastic ...,” *Journal of Construction Engineering and Management*, 2025.
- [47] S. Sadeghi, “Predicting the impact of scope changes on project cost and schedule using machine learning techniques,” *arXiv preprint arXiv:2412.02041*, 2024.
- [48] M. B. Talha, F. Houari, A. Benghabrit, *et al.*, “A machine learning approach based on contract parameters for cost forecasting in construction,” in *International conference on industrial engineering and operations management*, 2024.
- [49] R. Derakhshanalavijeh and J. Teixeira, “Cost overrun in construction projects in developing countries, gas-oil industry of iran as a case study,” *Journal of Civil Engineering and Management*, 2017.
- [50] P. Ghimire, S. Pokharel, K. Kim, *et al.*, “Machine learning-based prediction models for budget forecast in capital construction,” in *Proceedings of the 2nd international conference on construction management and engineering*, 2023.
- [51] Y. Li, “Application of artificial intelligence in cross-departmental budget execution monitoring and deviation correction for enterprise management,” *Artificial Intelligence and Machine Learning Review*, 2024.
- [52] P. Boudreau, “Machine learning models as a budget validation method in US mass transit projects,” *Available at SSRN 6081085*, 6081.
- [53] A. Sanusi, O. Bayeroju, *et al.*, “Framework for applying artificial intelligence to construction cost prediction and risk mitigation,” *Journal of Frontiers in Construction Engineering*, 2020.
- [54] S. Shruthi, L. Judson, and V. Paul, “Addressing the challenges in cost management of construction projects by using AI,” *Journal of Structural Technology*, 2025.
- [55] X. Liu, “Refined management method for engineering cost combining artificial intelligence technology,” *Procedia Computer Science*, 2024.

- [56] T. Vasista, "Towards innovative methods of construction cost management and control," *Civ Eng Urban Plan: Int J*, 2017.
- [57] M. Ghazal and A. Hammad, "Application of knowledge discovery in database (KDD) techniques in cost overrun of construction projects," *International Journal of Construction Management*, 2022.
- [58] A. Nindartin, S. Park, K. Lee, J. Kim, *et al.*, "Prediction of cost contingency in construction projects by introducing machine learning algorithms," *Journal of Civil Engineering and Management*, 2025.
- [59] T. Aung, S. Liana, A. Htet, and A. Bhaumik, "Using machine learning to predict cost overruns in construction projects," *Journal of Technology and Science*, 2023.
- [60] A. Restrepo and C. Machado, "Predicting delays and cost overruns in construction projects: A machine learning approach," *Revista EIA*, 2025.
- [61] M. Mohseni and E. Kamal, "Evaluating machine learning models for predict cost overruns in petrochemical projects," *PaperASIA*, 2025.
- [62] M. Cheng and R. Khasani, "Least square moment balanced machine: A new approach to estimating cost to completion for construction projects," *Journal of Information Technology in Construction*, 2024.
- [63] M. Eltoukhy and A. Nassar, "Using support vector machine (SVM) for time and cost overrun analysis in construction projects in egypt," *International Journal of Civil Engineering and Technology*, 2021.
- [64] K. Wu, E. Mengiste, and B. de Soto, "A machine learning framework for construction planning and scheduling," in *Proceedings of the creative construction conference*, 2023.
- [65] P. Sahu, D. Bera, P. Parhi, *et al.*, "Smart delay prediction: Supervised machine learning solutions for construction projects," *Journal of Mechanics of Materials and Structures*, 2025.
- [66] M. Sanni-Anibire, M. Zin, and S. Olatunji, "Forecasting construction delay times in high-rise building projects," in *Proceedings of the international structural engineering and construction conference*, 2020.
- [67] S. Zhang and X. Li, "A comparative study of machine learning regression models for predicting construction duration," *Journal of Asian Architecture and Building Engineering*, 2024.
- [68] B. Demiss and W. Elsaigh, "Application of novel hybrid deep learning architectures combining convolutional neural networks (CNN) and recurrent neural networks (RNN): Construction duration ...," *Engineering Research Express*, 2024.
- [69] M. Ali and A. Abd, "Extreme learning machines (ELM) as smart and successful tools in prediction cost and delay in construction projects management," in *IOP conference series: Earth and environmental science*, 2021.
- [70] P. Sahu, D. Bera, P. Parhi, M. Kandpal, *et al.*, "AI-powered delay risk prediction in construction projects: Leveraging machine learning, deep learning and hybrid models," *International Journal of Construction Management*, 2026.
- [71] B. Sanusi, "The role of data-driven decision-making in reducing project delays

- and cost overruns in civil engineering projects,” *Samriddhi: A Journal of Physical Sciences, Engineering and Technology*, 2024.
- [72] B. Seyisoglu, A. Shahpari, and M. Talebi, “Predictive project management in construction: A data-driven approach to project scheduling and resource estimation using machine learning,” *Available at SSRN 5077301*, 2024.
- [73] M. Shayboun, D. Kifokeris, and C. Koch, “Construction planning with machine learning,” *Management*, 2019.
- [74] C. Edeh, P. Masakara, J. Anyankah, *et al.*, “Integration of digital twin platforms with machine learning models for early detection of project delays and cost overruns,” *Asian Journal of Economics, Business and Accounting*, 2026.
- [75] P. G. Philip, “Artificial intelligence and machine learning applications in project schedule forecasting: A predictive framework for time-control in complex building projects,” *Available at SSRN 6588119*, 2026.
- [76] A. Tiwari and A. Hussain, “Exploring artificial intelligence applications in construction using a black grey white box approach for predicting project schedule performance in india,” *Discover Computing*, 2025.
- [77] A. Khoerunnisa and A. Ratnaningsih, “Performance-based cost and time prediction analysis of tertiary irrigation projects using artificial neural network,” *Journal of Engineering and Applied Sciences*, 2026.
- [78] C. Egwim, H. Alaka, L. Toriola-Coker, *et al.*, “Extraction of underlying factors causing construction projects delay in nigeria,” *Journal of Engineering, Design and Technology*, 2023.
- [79] P. Sahu, D. Bera, and P. Parhi, “Analyzing the impact of construction delays on disputes in india: A statistical and machine learning approach,” *Journal of Mechanics of Continua and Mathematical Sciences*, 2024.
- [80] S. Chigangacha, C. Henjewe, H. Ibrahim, *et al.*, “AIPOWERED AUTO-SCHEDULING OF CONSTRUCTION PROJECTS FOR IMPROVED EFFICIENCY,” in *Proceedings of the 41st annual conference of the association of researchers in construction management*, 2025.
- [81] M. Awada, F. Srour, and I. Srour, “Data-driven machine learning approach to integrate field submittals in project scheduling,” *Journal of Management in Engineering*, 2021.
- [82] S. Uddin, S. Yan, and H. Lu, “Machine learning and deep learning in project analytics: Methods, applications and research trends,” *Production Planning & Control*, 2025.
- [83] J. Obianyo, R. Udeala, and G. Alaneme, “Application of neural networks and neuro-fuzzy models in construction scheduling,” *Scientific Reports*, 2023.
- [84] A. Alhasan and E. Alawadhi, “Evaluating the impact of artificial intelligence in managing construction engineering projects,” *International Journal of Engineering and Technology*, 2024.
- [85] B. Manu, “Leveraging artificial intelligence for optimized project management and risk mitigation in construction industry,” *World Journal of Advanced Research and Reviews*, 2024.
- [86] N. Breus, “AI-driven risk management in construction: Integrating digital platforms with financial oversight,” *Available at SSRN 5558418*, 2023.

- [87] H. Moradi, "AI-driven risk management in construction projects," *International Journal of Industrial Engineering and Construction Management*, 2026.
- [88] C. Soni, "Leveraging artificial intelligence for predictive and adaptive decision-making in construction project management," *International Journal of Technology, Management and Humanities*, 2025.
- [89] P. Baskar, K. Tibrewala, and R. Singh, "The ascending trajectory of artificial intelligence and machine learning in construction and project controls," *Available at SSRN 5500621*, 2025.
- [90] S. Okiye, T. Ohakawa, and Z. Nwokediegwu, "Model for early risk identification to enhance cost and schedule performance in construction projects," *IRE Journals*, 2022.
- [91] L. Aggabou, B. Lakehal, and M. Mouda, "An artificial neural network approach for construction project risk management," *International Journal of Safety and Security Engineering*, 2024.
- [92] G. Carizo, "Integration of building information modeling (BIM) and artificial intelligence for predicting construction project risks," *Civil Engineering Science and Technology*, 2026.
- [93] G. Nagarajan, "Advanced AI-cloud neural network systems with intelligent caching for predictive analytics and risk mitigation in project management," *International Journal of Research Publications in Engineering, Technology and Management*, 2022.
- [94] A. Alhamami, "Implementation of machine learning-based risk prediction models for large-scale infrastructure construction projects in urban environments," *Cadernos De Educaç o Tecnologia E Sociedade*, 2025.
- [95] N. Algheetany, A. Othman, *et al.*, "Artificial intelligence towards enhancing the risk management practices during the design process," in *IOP conference series: Earth and environmental science*, 2024.
- [96] M. Nabeel, "... resource allocation and risk mitigation: Leveraging big data analysis to predict project outcomes and improve decision-making processes in complex projects," *Asian Journal of Multidisciplinary Research*, 2024.
- [97] Y. ODEKUNLE, A. OMOTOLA, *et al.*, "Leveraging artificial intelligence and predictive analytics for dynamic risk management in complex infrastructure projects," *Mediterranean Journal of Earth Sciences*, 2025.
- [98] M. Ogunbukola and M. Consulting, "The impact of artificial intelligence on project management: Enhancing efficiency, risk mitigation, and decision-making in complex projects," *International Journal of Computer Science and Information Technology*, 2024.
- [99] R. Ghafari and S. Samaei, "An AI-driven and digital twin-based framework for holistic risk and green project management in sustainable urban megaprojects: The case of tehran under ...," in *18th international conference on innovation in architecture, engineering and construction*, 2025.
- [100] A. Mogbojuri, O. Obiseye, A. Wali, and M. Dewa, "Artificial intelligence in project management: Challenges, strategies and best practices," *F1000Research*, 2025.
- [101] M. Sourav, A. Hossain, M. Islam, *et al.*, "AI-driven forecasting in BRICS

- infrastructure investment: Impacts on resource allocation and project delivery,” *Journal of Economics, Finance and Accounting Studies*, 2025.
- [102] A. Karshiboev, K. Al-Samad, M. Tarafdar, *et al.*, “Artificial intelligence for risk and decision assessment in agile IT projects: A thematic analysis and dynamic structuration framework approach,” *International Journal of Advanced Science and Information Systems*, 2026.
- [103] M. Altaie and M. Dishar, “Integration of artificial intelligence applications and knowledge management processes for construction projects management,” *Civil Engineering Journal*, 2024.
- [104] R. Sah and H. Yadav, “... THE DYNAMIC INFLUENCE OF COST OVERRUN DRIVERS/FACTORS AFFECTING COST PERFORMANCE IN BUILDING CONSTRUCTION PROJECTS,” *International Journal of Engineering Science & Humanities*, 2026.
- [105] A. Khodabakhshian and F. R. Cecconi, “Data-driven process mining framework for risk management in construction projects,” in *IOP conference series: Earth and environmental science*, 2022.
- [106] M. Isah and B. Kim, “Assessment of risk impact on road project using deep neural network,” *KSCE Journal of Civil Engineering*, 2022.
- [107] A. Khodabakhshian, F. R. Cecconi, *et al.*, “Probabilistic risk identification and assessment model for construction projects using elicitation based bayesian network,” *Journal of Information Technology in Construction*, 2025.
- [108] P. Sholapurapu, “AI-based financial risk assessment tools in project planning and execution,” *Project Planning and Execution*, 2024.
- [109] Z. Zeng and Y. Gao, “Cost control management of construction projects based on fuzzy logic and auction theory,” *Ieee Access*, 2024.
- [110] B. Saha, “AI-driven predictive analytics for financial risk management and FinancialRisk prevention with ranking cost scheduling,” *International Journal of Advance Research and Innovation*, 2025.
- [111] V. Devarapalli, “Revolutionizing procurement: How AI & data analytics driving cost effective solutions in EPC,” *International Journal of Computer Science and Information Technologies*, 2024.
- [112] B. Shannaq, D. Muniyanayaka, O. Ali, *et al.*, “Exploring the role of machine learning models in risk assessment models for developed organizations’ management decision policies,” *Journal of Big Data*, 2024.
- [113] L. Berriche and A. Loulizi, “Prediction of failures in the project management knowledge areas using optimized ensemble models in software companies,” *Discover Applied Sciences*, 2025.
- [114] M. Ayhan, I. Dikmen, and M. BİRGÖNÜL, “Disputes using machine learning techniques classifying compensations in construction,” *Journal of Engineering and Technology Management*, 2023.
- [115] M. Ayhan, I. Dikmen, and M. Birgonul, “Classifying compensations in construction disputes using machine learning techniques,” *Journal of Engineering Research*, 2023.
- [116] A. Habboush, B. Elzaghmouri, and O. Altit, “Integrating building information (BIM) and artificial intelligence to enhance cost and schedule planning in energy-conscious infrastructure projects,” *Asian Journal of Civil Engineering*,

2026.

- [117] A. Attia, "The impact of integrating artificial intelligence and building information modeling (BIM) systems on the development of construction methodologies," *Journal of Umm Al-Qura University for Engineering and Architecture*, 2025.
- [118] T. Omotayo, J. Deng, S. Hossain, S. Khan, *et al.*, "Generative AI for BIM-based digital construction cost management: A qualitative sentiment analysis approach," in *Proceedings of the 14th international conference on industrial engineering and operations management*, 2024.
- [119] М. Здрілько, "A method for adaptive control of sustainable construction projects based on digital twin technology and ensemble machine learning," *Управління розвитком складних систем*, 2026.
- [120] G. Yogapriya, C. Subramanian, *et al.*, "Application of artificial intelligence in smart buildings," in *AIP conference proceedings*, 2025.
- [121] Z. Lin, D. Jiang, and J. Liu, "AI-enabled digital transformation in the construction industry: A comprehensive framework for smart construction management," in *Proceedings of*, 2025.
- [122] F. M. Villanueva *et al.*, "Towards the digital transformation of peruvian public infrastructure: A framework of critical success factors for the adoption of BIM, machine learning and digital twins," *International Journal of Construction Management*, 2026.
- [123] M. Gupta and R. Arif, "Digital shift in construction in australia: Unlocking potentials with AI and blockchain," *Journal of Resilient Economies*, 2024.
- [124] G. Ozturk and M. Tunca, "Artificial intelligence in building information modeling research: Country and document-based citation and bibliographic coupling analysis," *Celal Bayar University Journal of Science*, 2020.
- [125] N. Saliu and K. Elezi, "The transformative integration of artificial intelligence in architectural practice: From generative design to sustainable building performance," *European Chronicle*, 2025.
- [126] R. Janogha, B. Perera, H. Victar, *et al.*, "Machine learning integrated resource management framework for construction projects," *International Journal of Construction Management*, 2026.
- [127] Y. Liang, "AI-driven project management for construction SMEs: A framework for cost and schedule optimization," *International Journal of Engineering Advances*, 2025.
- [128] M. Islam, A. Morshed, *et al.*, "Adaptive control of resource flow in construction projects through deep reinforcement learning: A framework for enhancing project performance in complex ...," *American Journal of Scientific Research and Innovation*, 2022.
- [129] C. Lan, "Leveraging AI-driven predictive analytics for enhancing resource optimization and efficiency in agile construction project management," *Available at SSRN 4894491*, 2024.
- [130] S. Kothapalli, "Real-time resource allocation optimization for dynamic construction job sites using deep reinforcement learning: A case study implementation," *International Journal of Artificial Intelligence, Data Science and Machine Learning*, 2025.

- [131] A. Lo and A. Alshehhi, "Implementation of machine learning technologies in construction maintenance strategies," *Available at SSRN 5127580*, 5127.
- [132] O. Dosumu, J. Tinyimana, *et al.*, "Critical drivers of artificial intelligence (AI) adoption in construction projects: Evidence from a developing economy," *International Journal of Construction Management*, 2026.
- [133] M. Phaladi, X. Mashwama, W. Thwala, *et al.*, "A theoretical assessment on the implementation of artificial intelligence (AI) for an improved learning curve on construction in south africa," in *IOP conference series: Materials science and engineering*, 2022.
- [134] D. Corbin, A. Marqui, and N. Dacre, "The intersection of artificial intelligence and project management in UK construction: An exploration of emerging trends, enablers, and barriers," *Enablers, and Barriers*, 2024.
- [135] M. Bolpagni, I. Bartoletti, and A. Ciribini, "Artificial intelligence in the construction industry: Adoption, benefits and risks," in *Proceedings of the conference CIB W78*, 2021.
- [136] B. Ghosh and S. Karmakar, "The conventional construction scenario and the emergence of advance technologies in the bridge construction: Implementation, impediments, and case study," *Journal of The Institution of Engineers (India): Series A*, 2023.
- [137] A. Kineber, N. Elshaboury, A. Oke, J. Aliu, Z. Abunada, *et al.*, "Revolutionizing construction: A cutting-edge decision-making model for artificial intelligence implementation in sustainable building projects," *Heliyon*, 2024.
- [138] E. Sadikoglu and S. Demirkesen, "Mapping the state-of-the-art: Bibliometric and systematic analysis of machine learning and AI-based cost and time prediction in construction," *Journal of Asian Architecture and Building Engineering*, 2026.
- [139] N. Gado, "AI revolutionizes construction management 'building smarter, safer, and efficiently addressing industry challenges'," *Engineering Research Journal*, 2024.
- [140] M. Allouzi and M. Aljaafreh, "Applied ai in neom construction projects: The potential impact of ai in enhancing projects success," *Acta Informatica Malaysia*, 2024.
- [141] M. Hasan and M. Raza, "The impact of artificial intelligence on civil engineering project management," *International Journal of Novel Research in Engineering and Applied Sciences*, 2024.
- [142] R. Ajiotutu, B. Matthew, P. Garba, *et al.*, "Advancing lean construction through artificial intelligence: Enhancing efficiency and sustainability in project management," *World Journal of Advanced Research and Reviews*, 2024.
- [143] Y. Reddy, "Automation and artificial intelligence in construction and management of civil infrastructure," *International Journal of Emerging Technologies and Innovative Research*, 2019.
- [144] A. S. Rizi, "Building the future: How AI is reshaping construction project management," *Available at SSRN 5121649*, 2025.
- [145] F. Salih and I. El-Adaway, "Investigating the correlation and synergy of

- artificial intelligence techniques, construction technologies, and their key benefits,” *Journal of Architectural Engineering*, 2025.
- [146] Y. Battula, “The role of artificial intelligence in modern project management: Trends and implications for 2025,” *International Journal of Engineering, Science*, 2025.
- [147] M. Ahmed, S. Jannat, and S. Tanim, “Artificial intelligence in public project management: Boosting economic outcomes through technological innovation,” *International Journal of Applied Economics and Management*, 2024.
- [148] A. Aliyev, “The AI and quantum era: Transforming project management practices,” *Journal of Future Artificial Intelligence and Technology*, 2025.
- [149] N. Rane, “Potential role and challenges of ChatGPT and similar generative artificial intelligence in architectural engineering,” *SSRN Electronic Journal*, 2023.
- [150] M. Alsharqawi, “Artificial intelligence in bridge engineering and management with emphasis on construction phase,” *International Journal of Bridge Engineering, Management and Robotics*, 2025.
- [151] A. Ravikar, R. Sawant, D. Joshi, *et al.*, “Applications of intelligent tools in construction industry: State of art,” in *AIP conference proceedings*, 2023.
- [152] S. Makaula, M. Munsamy, *et al.*, “Impact of artificial intelligence in south african construction project management industry,” in *Proceedings of the international conference on industrial engineering and operations management*, 2021.
- [153] K. Amoah, “The artificial intelligence (AI) impact on construction project management,” in *Proceedings of the international symposium on automation and robotics in construction*, 2025.
- [154] O. Balli and I. Guven, “Artificial intelligence in AEC industry: Construction project management processes,” in *International conference on innovative technologies and learning*, 2022.
- [155] S. Arumugam and P. Ravichandran, “Artificial intelligence in the construction industry: A status update, prospects, and potential application and challenges,” in *International conference on civil engineering and construction technology*, 2024.
- [156] L. Zhang, Y. Pan, X. Wu, and M. Skibniewski, “Artificial intelligence in construction engineering and management,” *Springer*, 2021.
- [157] D. Ojha, “Advancements and challenges in the application of artificial intelligence in civil engineering,” *International Journal of Contemporary Research in Multidisciplinary*, 2024.
- [158] H. Akeiber, “Artificial intelligence in engineering management: Revolutionizing decision-making and automation,” *Al-Rafidain Journal of Engineering Sciences*, 2025.
- [159] R. Reznikov, “Enhancing project management success through artificial intelligence,” *International Journal of Multidisciplinary Research and ...*, 2025, 2025.
- [160] S. Rao, “The benefits of AI in construction,” *Retrieved March*, 2019.
- [161] D. Ahiaga-Dagbui and S. Smith, “Rethinking construction cost overruns:

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- Cognition, learning and estimation,” *Journal of Financial Management of Property and Construction*, 2014.
- [162] K. Hasan and A. Islam, “AI augmented project management: Using machine learning to improve delivery outcomes,” *Pacific Journal of Business Innovation and Sustainability*, 2025.
- [163] M. Shayboun and C. Koch, “Sorting things out? Machine learning in complex construction projects,” in *EC3 conference 2019*, 2019.
- [164] T. Nyokum and Y. Tamut, “Artificial intelligence in civil engineering: Emerging applications and opportunities,” *Frontiers in Built Environment*, 2025.
- [165] U. Igwe, S. Mohamed, M. Azwarie, *et al.*, “Acceptance of contemporary technologies for cost management of construction projects.” *Journal of Information Technology in Construction*, 2022.
- [166] V. Pillai and K. Matus, “Towards a responsible integration of artificial intelligence technology in the construction sector,” *Science and Public Policy*, 2020.
- [167] R. Jain, S. Singh, D. Palaniappan, *et al.*, “Data-driven civil engineering: Applications of artificial intelligence, machine learning, and deep learning,” *Turkish Journal of Engineering*, 2025.
- [168] M. Mustafa, H. An, C. Keong, *et al.*, “Machine learning for promoting green building practices: Implications for construction project delivery in malaysia,” *Journal of Project Management Practice*, 2025.