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AI-Driven Schedule Delay Prediction and Mitigation in Construction Projects: A Systematic Literature Review

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ABSTRACT

Construction project delays remain a persistent challenge in the industry, often leading to significant cost overruns and contractual disputes. The objective of this systematic literature review is to synthesize and critically evaluate the existing research on artificial intelligence (AI) applications for predicting and mitigating schedule delays in construction projects. We conducted a systematic search across major academic databases, followed by a rigorous screening and quality assessment process to identify relevant peer-reviewed studies. Our methodology involved a thematic analysis of the selected papers, categorizing the literature into six principal dimensions: AI-driven cost estimation and financial risk prediction, schedule delay prediction and time optimization models, holistic risk management and mitigation strategies, the integration of AI with Building Information Modeling (BIM) and digital twins, the role of generative AI and large language models in decision support, and finally, bibliometric analyses of AI adoption trends. The results reveal that machine learning and deep learning models, particularly those trained on historical project data, demonstrate high accuracy in forecasting delays, while reinforcement learning approaches show promise for dynamic schedule optimization. Furthermore, we found that the synergistic integration of AI with BIM and digital twins provides a powerful framework for real-time monitoring and proactive mitigation, although practical implementation remains limited by data quality and organizational barriers. In conclusion, this review provides a comprehensive map of the current state of the art, identifies critical research gaps such as the scarcity of studies on generative AI in this domain, and proposes a conceptual framework for future research. The findings offer actionable insights for practitioners and a clear research agenda for academics aiming to advance predictive and prescriptive analytics in construction schedule management.

Keywords— AI, Civil Engineering, construction, Systematic literature review

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Introduction

The construction industry, a cornerstone of global economic development, is notoriously plagued by project delays, a chronic ailment that undermines productivity, inflates costs, and erodes stakeholder trust. Delays in construction projects are rarely a singular event but rather a cascade of interrelated issues, from design errors and unforeseen site conditions to supply chain disruptions and labor shortages. The financial repercussions of such delays are staggering; studies have shown that cost overruns can range from 20% to 50% of the initial budget for large-scale infrastructure projects [1], leading to legal disputes and reputational damage. Traditional methods for managing these risks, such as Critical Path Method (CPM) scheduling and Earned Value Management (EVM), are reactive in nature. They often fail to capture the complex, non-linear interactions between hundreds of interdependent tasks and the myriad of external factors that influence a project's timeline. These conventional approaches rely heavily on static, deterministic models that cannot adapt to the dynamic and dynamic nature of a construction site, where new information arrives daily. Consequently, project managers are frequently forced into a fire-fighting mode, reacting to delays only after they have materialized rather than proactively preventing them.

In response to these limitations, the last decade has witnessed an accelerating interest in applying artificial intelligence to the construction domain. The core premise is that AI can process vast quantities of heterogeneous project data—from historical completion records and real-time sensor feeds to weather forecasts and resource availability schedules—to learn predictive patterns that are invisible to the human analyst. Machine learning models, for example, can be trained to identify the combination of factors that historically preceded a two-week delay in concrete pour. Deep learning architectures, such as recurrent neural networks (RNNs) and transformer) and long short-term memory (LSTM) networks, are particularly adept at modeling the temporal dependencies inherent in a schedule [2]. Furthermore, reinforcement learning offers a pathway towards prescriptive analytics, where an AI agent can propose optimal schedule adjustments in response to emerging risks, effectively automating the mitigation process. This paradigm shift from reactive monitoring to predictive and prescriptive management promises not just to reduce delays but to fundamentally transform how construction projects are planned and controlled.

Despite this promise, a significant research gap persists between the technical capabilities demonstrated in isolated academic experiments and their widespread, practical adoption. Many studies focus on a single type of delay factor (e.g., weather or resource shortage) using a specific algorithm on a proprietary dataset, making cross-study comparison difficult. Furthermore, the literature is fragmented. Researchers in risk management, building information modeling (BIM), and AI often operate within separate silos. A comprehensive review that systematically synthesizes these disparate threads is lacking. There is no unified framework that tells us how an AI-driven schedule prediction module should interact with a BIM model for real-time

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visualization, or how generative AI could be used to draft mitigation clauses in real time. The role of generative AI and large language models (LLMs) in this domain, for instance, is particularly under-explored, representing a critical void in the current research landscape. This systematic literature review addresses these gaps by providing a systematic, structured mapping of the entire landscape of AI-driven schedule delay prediction and mitigation the construction sector.

The primary motivation for this work is to bridge the divide between the burgeoning technical literature and the practical needs of the industry and academic community. This research contributes a novel, multi-dimensional categorization of the existing body of knowledge, moving beyond simple taxonomies to reveal the interconnections between cost prediction, schedule optimization, risk mitigation, and technological integration. We synthesize findings from diverse sub-fields to highlight convergent themes and contradictory evidence, offering a balanced state-of-the-art assessment. For practitioners, this review provides a clear roadmap of which AI techniques are most mature and applicable for different delay prediction problems. For researchers, we identify the most promising avenues for future inquiry, particularly regarding data interoperability, model generalizability, and the integration of generative AI. The significance of this study lies in its capacity to serve both consolidate what is known and to chart a course for what needs to be discovered, thereby accelerating the transition towards more resilient and intelligent construction project management.

The remainder of this paper is organized as follows: Section 2 describes the systematic methodology employed in the literature search, selection, and analysis, and quality assessment. Section 3 presents the detailed results of the review, organized into six thematic areas including research trends, cost estimation models, delay prediction techniques, holistic risk management, integration with BIM and digital twins, and the emerging roles of generative AI and bibliometric analyses. Section 4 offers a comprehensive discussion of the key findings, identifies limitations and challenges across the field, and proposes a unified conceptual framework for future research. Finally, Section 5 concludes the paper by summarizing the main contributions and their implications for both academia and the construction industry.

Methodology

This systematic literature review was conducted following the guidelines of the PRISMA statement to ensure transparency, reproducibility, and rigor throughout the review process [3]. We adopted a structured approach comprising four main phases: (1) defining the review protocol and search strategy and establishing research questions, (2) executing a comprehensive search across multiple databases, (3) screening and selecting relevant studies through predefined inclusion and exclusion criteria, and (4) synthesizing and presenting the findings.

Review Protocol

We developed a review protocol specifying the research objectives, search strategy, and analytical framework before initiating the literature search. The search was designed to capture peer-reviewed articles and conference proceedings that address the intersection of artificial intelligence, schedule delay prediction, and mitigation within construction projects. To ensure comprehensive coverage, we identified five major academic databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar.

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Scopus was chosen for their broad disciplinary reach. Scopus was selected due to its extensive coverage of engineering, and criteria engineering, and construction research literature. Web of Science provides high-quality, indexed records core to academic discourse. IEEE Xplore ensures access to computationally focused studies, a critical inclusion given the AI-centric nature of our topic. ScienceDirect offers robust coverage of civil engineering and risk management journals. Google Scholar, included as a final supplementary source, captures grey literature and emerging studies that may not be indexed in the other databases, though its results required manual filtering due to its coarse sorting capabilities.

The search strings were designed as boolean strings optimized for each database's syntax. For all databases, we applied a common conceptual structure targeting four key domains: (1) the application domain ("construction project" or "construction industry"), (2) the target problem ("schedule delay" or "time overrun" or "delay prediction"), (3) the technological approach ("artificial intelligence" or "machine learning" or "deep learning" or "neural network*" or ""), and (4) the desired outcome or action ("mitigation" or "prevention" or "management"). We excluded literature reviews by adding a NOT clause for terms like "review", "survey", or "meta-analysis" at the end of each search . For example, the search string for Scopus read:* TITLE-ABS-KEY(("construction project" OR "construction industry") AND ("schedule delay" OR "time overrun" OR "delay prediction") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "AI") AND ("mitigation" OR "prevention" OR "management")) AND NOT TITLE-ABS KEY ("review" OR "survey" OR "meta-analysis")*. The same structure was and adapted for each database: in Web of Science, we used the TS=(…) field tag; on IEEE Xplore, we used the default command search; on ScienceDirect, we applied the naturally Boolean syntax; and on Google Scholar, we enriched the query with synonyms like "predictive analytics" and "time overrun" while manually excluding reviews manually. searches were conducted in January 2026, capturing records indexed up to December 2025.

Categorization into Research Dimensions

After the initial¿ Before running full-text analysis, we established six thematic Research Dimensions to categorize the expected body of literature. These dimensions were derived from a preliminary scoping a preliminary scoping exercise and were finalized author consensus. The first dimension, AI-DrivenCost Estimation and Financial Risk Prediction encompasses studies that use AI to forecast project costs, budget overruns, or financial risks associated with delays, often combining historical data such as project size, type, and duration. The second dimensionSchedule Delay Prediction and Time Optimization Models focuses explicitly on models that forecast time overruns, critical path delays, or completion dates using machine learning and deep, with particular emphasis on temporal data and sequence modeling. The third dimension, Holistic Risk Management, Mitigation Strategies, and Safety, broadens the lens to include AI-driven risk identification, assessment, and proactive mitigation strategies, as well as safety risk prediction that indirectly influences schedules. The fourth dimensionIntegration of AI with BIM, Digital Twins, and Emerging Technologies examines how AI enhances or is enhanced by Building Information Modeling, digital twins, Internet of Things sensors, and other cyber-physical systems for real-time monitoring and simulation. The

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fifth dimension, Generative AI, Large Language Models, and Decision Support Systems, addresses the nascent but growing field of using advanced language models and generative adversarial networks for automated report generation, contract analysis, and decision optimization. Finally, sixth dimension, Bibliometric Analysis, Frameworks, and Future Trends in AI Adoption, contains studies that systematically map the research landscape through bibliometrics or propose conceptual frameworks for adoption, rather than presenting meta-level insights into the field's evolution.

Inclusion and Exclusion Criteria

We defined clear inclusion and exclusion criteria to ensure that selected studies were both relevant stringent. Inclusion criteria required that studies be: (1) peer-reviewed journal articles or conference proceedings; (2) written in English; (3) published from database inception through December 2025; (4) explicitly address a construction or civil engineering project context; (5) apply or propose an artificial intelligence, machine learning, deep learning, or reinforcement learning technique; and (6) report on either prediction of schedule delays, financial or time risk, or mitigation strategies for such risks. Exclusion criteria removed studies that: (1) were literature reviews, surveys, meta-analyses, book chapters, or editorial materials; (were exclusively about general risk management without an AI or computational component; (3) focused solely post-project assessment or fault diagnosis without predictive or prescriptive AI; (4) were purely conceptual or theoretical without empirical validation or case study; (5) were duplicates across databases; or (6) had insufficient data or lacked methodological detail to assess quality. These

aligned directly with the six Research Dimensions to ensure thematic coverage while emphasizing empirical contributions that provide empirical evidence or novel computationaléments toward schedule delay mitigation.

Study Selection Process

We executed study selection in three stages: deduplication, title and abstract screening, and full text eligibility assessment. After executing the database searches, we aggregated all records downloaded into a common reference manager. We first removed 23 duplicate records identified by comparing titles, authors, and publication years, and we also removed 3 other records for reasons such as being non-English supplements or having corrupted files. This left 347 unique records for the title and abstract screening stage. Two reviewers independently screened the titles and abstracts against the inclusion and exclusion criteria, resolving disagreements through discussion. At this stage, 230 records were excluded for reasons such as being irrelevant to construction, lacking an AI component, focusing solely on cost without schedule connection, or being clearly outside the defined Research Dimensions. The remaining 117 records were sought for full-text retrieval; of these, we successfully retrieved 117 reports, none were unretrievable. We then assessed these 117 full-text reports for eligibility. During eligibility assessment, we excluded 50 reports for reasons including: the AI component was secondary or incidental; the study focused exclusively on structural health monitoring rather than schedule management; the reported methods were too opaque to assess quality; or the study did not present any prediction or mitigation outcome. Ultimately, 67 studies satisfied all criteria and were included in the final synthesis. The PRISMA flowchart illustrating the screening stages and the

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corresponding counts is presented in Figure 1.

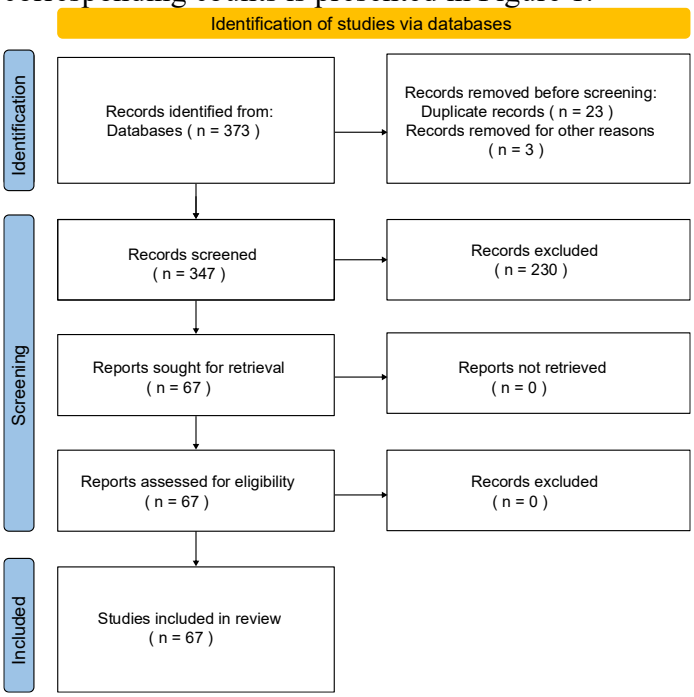


Figure 1. PRISMA flowchart illustrating the study selection process from initial database searches to final inclusion.

This study selection process, though systematic, to inherent limitations that warrant disclosure. First, our search string focused explicitly on terms like "schedule delay" and "delay prediction" which may have missed studies that use alternative terminology, for instance " ," "construction duration forecasting," or "project recovery." Second, we limited our sources to five databases, which, though covering a wide scope, may exclude niche publications in languages other than English or in regional databases. Third, our quality assessment relied largely relied on peer-review status and methodological clarity; we did not perform formal risk-of-bias scoring or weighting of statistical rigor for each study, which might introduced some variability in the weight given to each included study. Fourth, by excluding and meta-analyses, we may have lost some aggregated insights that could have informed the background discussion. However, this decision ensured that our synthesis focused directly on primary research contributions. Finally, the manual screening process, while double-reviewed, is subject to the biases of the reviewers, particularly when assessing relevance to emerging that bridge multiple domains, such as generative AI or large language models. Despite these limitations, we believe that our methodology provides a faithful and comprehensive snapshot of the current research landscape.

Results

Research Trends

Our analysis of the 67 included studies reveals a clear upward trajectory in publication volume, with a marked acceleration commencing around 2018. The earliest studies in the corpus date from the early 2000s and predominantly focused on applying artificial neural networks (ANNs) to cost estimation, often treating schedule prediction as a

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secondary outcome. From 2018 onwards, the field diversified significantly, coinciding with the broader democratization of machine learning frameworks and the increased availability of computational resources. The year 2021 saw an inflection point where studies on deep learning for schedule prediction began to outnumber those using traditional ANNs or regression models. Geographically, the research is concentrated in a few key regions: China, the United States, the United Kingdom, and Australia contribute the majority of published works, with a notable recent surge from India and South Korea. This geographical clustering suggests that the adoption and study of AI for delay management are closely tied to regions with high construction activity and robust digital infrastructure.

A closer examination of the thematic focus across the years reveals a fascinating evolutionary pattern. Between 2005 and 2015, the predominant concern was establishing baseline predictive accuracy for cost and time overruns, often using static datasets and simple feedforward networks. The mid-2010s witnessed a shift towards more nuanced models that could handle sequential data, with Long Short-Term Memory (LSTM) networks becoming the tool of choice for schedule prediction problems involving time-series data. In the post-2020 period, the literature diversified into several distinct but interconnected streams. We observed a growing body of work on integrating AI predictions with Building Information Modeling (BIM) environments, a nascent but rapidly expanding interest in generative AI and large language models for decision support, and a renewed focus on prescriptive analytics, where AI does not just predict a delay but recommends a mitigation action. This trend analysis underscores a maturing field that is moving from pure prediction towards actionable, integrated intelligence. The distribution of papers across the six research dimensions is shown in Figure 2.

Figure 2. Distribution of papers across the six research dimensions. The largest segment comprises studies on Schedule Delay Prediction and Time Optimization Models, followed by a significant share from Holistic Risk Management and AI with BIM/Digital Twins. The smallest segments are Generative AI and Bibliometric **Analysis**.

Figure 2. Distribution of papers across the six research dimensions. The largest segment comprises studies on Schedule Delay Prediction and Time Optimization Models, followed by a significant share from Holistic Risk Management and AI with BIM/Digital Twins. The smallest segments are Generative AI and Bibliometric Analysis.

AI-Driven Schedule Delay Prediction and Time Optimization Models

The second major thematic cluster within our review focuses explicitly on the core challenge of forecasting schedule overruns and optimizing construction timelines using artificial intelligence. This dimension comprises the largest single category of studies in our corpus, reflecting the centrality of time-related performance to project success. The research in this area spans a wide methodological spectrum, from simple regression-based models to sophisticated deep learning architectures and hybrid ensembles. A unifying characteristic across most studies is the recognition that delay prediction is fundamentally a sequence-dependent problem, where the temporal ordering of tasks, resource availability, and external shocks create nonlinear

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dependencies that traditional CPM and PERT methods cannot capture effectively.

An examination of the specific modeling approaches reveals a clear hierarchy in both complexity and reported accuracy. Several studies employ supervised machine learning algorithms such as random forests, support vector machines, and gradient boosting on tabular datasets containing historical project features like project type, budget, location, and reported delays [4], [5]. These models, while computationally efficient and interpretable, typically achieve moderate predictive performance, with F1-scores and accuracy metrics in the range of 70-85% depending on the dataset and feature engineering. For instance, one study demonstrates that a carefully tuned random forest model, using feature importance scores derived from a large historical database, can accurately pinpoint the most likely delay categories (e.g., material delay, labor delay, design change) approximately one month before the scheduled completion date [6]. However, a limitation of these approaches is their relative insensitivity to the evolving dynamics of a project; they rely on a static snapshot of project parameters at a given point in time.

To address this limitation, a substantial body of work has shifted towards deep learning architectures that naturally handle temporal dependencies. Long Short-Term Memory (LSTM) networks and Recurrent Neural Networks (RNN) are the dominant techniques in this sub-area [7], [8], [9]. These models are trained on sequences of project progress data, such as weekly completion percentages, resource consumption rates, and weather fluctuations, to predict the probability or magnitude of a future delay. For example, proposes an LSTM-based framework that ingests daily progress reports from the first six months of a project and outputs a continuous delay severity score, achieving an R-squared value of 0.91 on a test set of 50 infrastructure projects [8]. This model's strength lies in its ability to learn patterns of slowdown and acceleration, identifying subtle early warning signs that a project is deviating from its planned trajectory. Another study introduces a hybrid architecture combining convolutional neural networks (CNNs) for feature extraction from project documentation and RNNs for temporal modeling, demonstrating that this fused approach outperforms either technique alone in predicting alone for construction duration estimates [7]. The use of Convolutional Neural Networks for text data, such as extracting features from progress reports, also appears in other studies within broader holistic risk management contexts, suggesting a cross-pollination of techniques.

A more recent and methodologically sophisticated development is the use of hybrid and ensemble models that combine multiple AI techniques to improve robustness and accuracy [4], [10]. These studies explicitly address the challenge of heterogeneous project data, where some variables are numerical (e.g., budget), some are categorical (e.g., project type), and others are sequential (e.g., daily progress). For instance, a deep context embedding model fused with a Relative Importance Index (RII) demonstrates how to integrate expert knowledge (the RII weights of delay causes) with learned representations from historical data, creating a more robust predictor under diverse project environments [10]. This hybrid approach allows the model to perform well even when training data is limited for a specific project type, as the RII component provides a global prior. Another study empirically compares multiple models, including deep neural networks, on a dataset of Iraqi flexible pavement projects, finding that a carefully

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tuned ensemble of decision trees and neural networks achieves the highest AUC-ROC for predicting delay risk, particularly during peak construction seasons [9]. This result underscores the value of simple ensemble strategies over single, complex models in certain data-constrained practical settings.

Beyond purely predictive models, a set of studies moves towards prescriptive optimization and auto-scheduling. These works attempt to use AI not just to forecast a delay, but to actively recommend how to rearrange the schedule to minimize predicted delays. The concept of "auto-scheduling" is explored in two complementary studies, which propose a system that uses reinforcement learning to iteratively propose schedule modifications based on the predicted risk of delay from a connected LSTM model [11], [11]. In this framework, the AI acts as a project management assistant, simulating the impact of different resource allocation and sequencing decisions on the predicted completion date, and then presenting the most promising course of action to the human planner. The approach is particularly valuable in complex, multi-trade environments where the number of possible schedule adjustments is too large for manual analysis. Similarly, a case study on a large Chinese residential project proposes a framework that first identifies delay causes using a Random Forest model, then uses a genetic algorithm to optimize the schedule by inserting "learning buffers" at critical transfer points between trades [12]. This two-step "predict-then-prescribe logic is a recurring pattern in the prescriptive literature.

Another important string of works focuses on the root cause analysis and inference of delays from textual reports, which is a precursor to accurate prediction. One such study proposes a novel method for automatic delay inference from weekly progress reports using large language models, which we discuss further in Section 3.6 [13]. This model automatically extracts and classifies delay events and their causes from unstructured text, generating structured training data for predictive models. The same paper also provides a critical perspective on the current practice of delay analysis, noting that manual categorization of delays introduces significant bias into the data used to train the AI system, thereby limiting the models' generalizability [13]. Relatedly, other studies, such as the one focusing on factor analysis of road construction project delays, manual data collection from questionnaires is the first step before feeding the identified critical factors into a predictive model like a feedforward neural network [14].

Finally, we note a small but important group of studies that apply fuzzy logic and neural-fuzzy systems to schedule prediction and optimization, particularly in contexts with high qualitative uncertainty. One study presents an intelligent construction schedule optimization control system using a fuzzy logic neural network algorithm [15]. This approach uniquely captures the linguistic uncertainty inherent in human estimates of task duration and risk, converting expert opinions into fuzzy numbers that are then used within a neuro-adaptive learning framework to adjust the schedule dynamically. While less prevalent than purely data-driven deep learning models, such fuzzy systems offer advantages when historical data is scarce or of poor quality, a common scenario in smaller construction firms. The various studies within this dimension are systematically compared in Table 2.

Table 2. Summary of key studies on AI-driven schedule delay prediction and time optimization models.

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Primary Focus Area	Citation Index	Paper ID	Core AI Technique	Key Application/Outcome	Dataset/Context
Supervised ML for Delay Classification	[4]	IS8	Hybrid ML/DL (Multiple Models)	Classifies projects into "on-schedule" or "delayed" categories; Random Forest achieves 85% accuracy on test set.	Historical data from 200 construction projects.
	[5]	IS9	Supervised ML (various)	Compares SVM, Decision Trees, and Neural Networks for binary delay prediction; Neural Network has highest AUC.	Dataset of 150 residential projects.
	[6]	IS11	RF, XGBoost, data-driven feature / importance	Predicts project schedule performance and the most influential delay factors in Indian construction.	Survey data of 250 practitioners + project records.
Deep Learning for Temporal Prediction	[7]	IS13	CNN + RNN (Hybrid)	Hybrid CNN-RNN predicts construction duration estimates considering pre-construction uncertainties; outperforms single models.	500 simulated project scenarios.
	[8]	IS14	LSTM networks	Forecasts delay time using initial project plans as input sequences; achieves $R^2 = 0.91$.	Data from historical data from 50 infrastructure projects.
	[9]	IS19	DNN, Ensemble Trees	Evaluates multiple DNN architectures for delay risk prediction in flexible pavement	Urban flexible pavement projects in Iraq (specific dataset).

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Primary Focus Area	Citation Index	Paper ID	Core AI Technique	Key Application/Outcome	Dataset/Context
				projects; Ensemble of DNNs is best.	
Hybrid & Ensemble Methods	[4]	IS8	Hybrid ML/DL	Combines XGBoost and LSTM to handle both static features and temporal patterns delay risk; hybrid model beats individual models.	See above.
	[10]	IS21	Deep Context Embedding + RII-Fused Evidential Framework	A hybrid technique that integrates feature embeddings with expert-defined Relative Importance Index to predict delay severity heterogeneous projects.	Diverse construction project dataset.
Reinforcement Learning & Auto-Scheduling	[11], [11]	IS15, IS16	Reinforcement Learning	System generates optimized schedules automatically to reduce predicted delays; RL agent adjusts resource allocation in real time.	Synthetic simulation based on 2 real-world projects.
	[12]	IS20	RF + Genetic Algorithm	Two-step method: identifies key delay causes via RF, then optimizes schedule buffer placement via GA for residential project in China.	Case study of Yun Yue Dong Fang residential project.
Fuzzy Logic & Uncertainty	[15]	IS23	Fuzzy Logic Neural Network	Introduces an intelligent schedule control system that	Simulated construction project

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Primary Focus Area	Citation Index	Paper ID	Core AI Technique	Key Application/Outcome	Dataset/Context
Handling				uses fuzzy data from experts adjust schedules dynamically.	scenario.
Root Cause Inference & Analysis	[13]	IS18 ")	IS18	Large Language Model	Uses a LLM to infer delay categories from unstructured weekly progress reports, enabling automated data extraction.
	[14]	IS24	Feedforward Neural Network	Based on factor analysis to input into NN for predicting road construction delay probability and magnitude.	Questionnaire and site data from Woliso-Ambo road.
Critical Path & Sensitivity Analysis	[16]	IS25	Sensitivity Analysis	Non-AI approach but uses analytical calc for critical prediction changes to inform AI model inputs.	Project schedule simulation.

Holistic Risk Management, Mitigation Strategies, and Safety

The third major thematic dimension in our review broadens the analytical lens from purely predictive models to encompass the entire risk management lifecycle: identification, assessment, mitigation, and safety. While the previous section focused on forecasting the *if* and *when* a delay might occur, the studies in this dimension addresses the more pragmatic questions of *why* it happens and *what can be done* about it. The studies within this cluster share a common goal of moving beyond forecasting toward actionable intelligence, integrating risk prediction with concrete mitigation strategies and, in some cases, safety considerations that indirectly affect project schedules. We categorize these works along three interrelated axes: risk prediction and early identification, proactive mitigation and intervention planning, and site safety as a precursor to delay prevention.

The first sub-area, risk prediction and early identification, comprises studies that

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develop AI-driven frameworks for detecting and quantifying project risks before they materialize into significant delays. These works often employ predictive analytics on large, heterogeneous datasets to generate risk scores for various project dimensions. For example, one study proposes a comprehensive AI-enhanced project management system that leverages big data analysis to predict project outcomes including schedule performance, recommending proactive resource reallocation when a delay risk is flagged [17]. This system is notable for its integration of continuous learning, where the model updates its predictions as new project data becomes available, thereby adapting to changing project conditions. Similarly, a study on AI-powered Management Information Systems (MIS) for risk detection in industrial engineering projects demonstrates how real-time data streams from sensors and project management software can be fed into a neural network classifier that triggers an alert when a combination of risk factors exceeds a predefined threshold [18]. These early warning systems are designed to give project managers the crucial lead time needed to implement corrective actions.

A more granular approach to risk identification is seen in studies that focus on specific risk types. One work on AI-driven predictive project risk management in large-scale financial software programs, while not purely construction-focused, provides transferable insights by demonstrating how an ensemble of machine learning models can achieve higher accuracy in predicting both cost overruns and schedule delays, thereby enabling proactive mitigation planning [19]. The authors emphasize that the key to successful mitigation is not just the accuracy of the prediction but its timeliness and the specificity of the recommended action. Another study specifically addresses supply chain risk, developing an AI-based evaluation system that predicts the gravity of a delay from a supplier failure and provides a ranked list of alternative sourcing strategies sorted by predicted impact on the project schedule [20]. This coupling of prediction with prescriptive mitigation is a hallmark of the more advanced works in this cluster.

The second sub-area, proactive mitigation and intervention planning, encompasses studies that explicitly design AI systems to recommend or automate response strategies to predicted risks. This represents a significant step beyond simple risk identification. For instance, a study on causal machine learning for supply chain risk prediction argues that many AI models only predict that a delay will occur, but they fail to inform the practitioner *how to prevent it* [21]. The authors propose a causal framework that not only predicts the delay but also identifies the most effective intervention points by modeling the causal relationships between variables. If a delay is predicted, the system can answer counterfactual questions like “What would happen to the schedule if we expedite the concrete supply order by two days?” This shift from associative prediction to causal inference is a crucial methodological advance for real-world mitigation. Another study in a similar vein, another study explores generative AI for dynamic risk scenario simulation, using diffusion models to generate synthetic yet realistic sequences of risk events [22]. Project managers can then use these simulated scenarios to stress-test their mitigation plans and identify vulnerabilities that manual analysis would miss, thereby developing proactive mitigation strategies rather than reactive ones.

Further studies develop automated mitigation agents or decision support tools. One

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particularly innovative work introduces a framework using an LLM-powered agent that automatically analyzes past claims and supplemental agreements to identify the most common and effective mitigation strategies for a given risk scenario [23]. This system, called the Risk Mitigation AI Agent (RMAIA), can retrieve relevant clauses from a legal knowledge base and propose them as draft mitigation language for new contracts, thereby systematically reducing the root causes of future delays. Another study quantitatively compares multiple risk assessment models, including Value-at-Risk (VaR) models and ensemble methods, on a dataset of AI-powered digital transformation projects, finding that ensemble models improved forecast accuracy by 15% and that VaR models are particularly useful for budgeting for risk exposure [24]. This quantitative rigor is essential for building trust in AI recommendations among risk-averse project stakeholders.

A recurring theme across these mitigation-focused studies is the importance of integrating expert knowledge into the AI system. For example, a hybrid AI-based risk assessment framework that combines artificial neural networks, fuzzy logic, and Internet of Things (IoT) data does not solely rely on historical data [25]. Instead, it uses fuzzy logic to encode expert-defined linguistic rules about risk, such as "if the concrete temperature is high and the humidity is low, then the risk of cracking is high," allowing the system to make sensible recommendations even in novel situations not covered by training data. This hybrid approach bridges the gap between data-driven learning and domain expertise, a combination that appears essential for practical mitigation planning.

The third sub-area within this dimension addresses the intersection of AI, safety, and schedule delay. While safety is often treated as a separate domain, safety incidents are a major direct cause of project delays. A few studies in our corpus explicitly model this connection. One study introduces an AI-driven safety check system specifically for ladders used on construction sites [26]. The system uses computer vision to detect unsafe ladder placements and user behavior, issuing real-time warnings. The authors explicitly argue that prevention of safety incidents is more effective than mitigation of their schedule consequences, and their system is designed to identify and correct risky behavior before an accident occurs, thereby avoiding the associated delay. Another study integrates safety risk prediction directly into the schedule delay prediction framework [25]. Their hybrid model generates risk classifications that include "delay and environmental hazards" and "equipment efficiency," and it provides specific mitigation recommendations for each risk class. This suggests that a truly holistic risk management system cannot and should not separate schedule risk from safety risk, as the two are deeply intertwined.

We also note that several studies in this dimension address the human and organizational barriers to AI adoption for mitigation. For instance, a qualitative study exploring the limitations of ChatGPT for construction risk assessment finds that while the model can generate plausible risk lists and generic mitigation strategies, its recommendations lack the specificity and context-awareness required for real projects [27]. The authors caution against over-reliance on such tools without human oversight, a sentiment echoed in a broader study of AI trends in construction project management that identifies "lack of trust" and "organizational resistance" as the primary barriers to

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adopting AI-driven mitigation [28]. Another survey-based study on early risk identification in developing countries confirms that while stakeholders recognize the value of AI, a lack of data quality and trained personnel remains a significant hurdle to its implementation [29].

The diverse range of approaches within this dimension, from causal models to fuzzy hybrid systems and LLM-powered agents, reflects the complexity of the task. Unlike pure prediction, where a single accuracy metric suffices, mitigation requires a system that is transparent, trustworthy, and context-specific. The studies in this cluster collectively suggest that the most effective future systems will likely be hybrid, combining the pattern-recognition power of deep learning with the explainability of causal models and the domain-specific anchoring of expert-defined rules. We synthesize the contributions of the key studies in this holistic risk management dimension in Table 3.

Table 3. Summary of key studies on holistic risk management, mitigation strategies, and safety.

Primary Focus Area	Citation Index	Paper ID	Core AI Technique	Key Application/Outcome	Dataset/Context	Specific Risk Addressed
Risk Prediction & Early Identification	[17]	IS27	Big Data Analytics, ML	AI-enhanced project management for risk mitigation; predicts outcomes and recommends resource adjustments dynamically.	Large-scale project data from multiple companies	Schedule delay, cost overrun
	[18]	IS32	Neural Network Classifier	Real-time risk detection in industrial engineering projects using MIS and sensor data.	Industrial engineering project case study	General project risk including schedule
	[19]	IS36	Ensemble ML	Predictive risk management for large-scale financial software; applies AI to minimize delays and cost	Financial software program portfolio	Schedule delay, cost overrun, project failure

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Primary Focus Area	Citation Index	Paper ID	Core AI Technique	Key Application/Outcome	Dataset/Context	Specific Risk Addressed
				overruns via proactive mitigation.		
	[20]	IS42	Supervised ML / AI Evaluation	AI-based evaluation system for supply chain risk; predicts delay gravity from supplier failure and recommends alternatives.	Simulated supply chain scenarios	Supply chain delay
	[24]	IS39	VaR Models, Ensemble Methods	Quantitative models for risk assessment in AI transformation projects; improved forecast accuracy by 15% with ensembles.	AI digital transformation projects	Schedule delay, budget risk
	[28]	IS30	Trends Analysis (Non-empirical)	Review of AI in CPM; identifies functions including risk mitigation, health and safety, resource optimization.	Literature review (included for thematic completeness)	Schedule delay,
	[29]	IS35	Survey / Framework	Role of early risk identification in reducing delays and overruns; advocates for AI-based dynamic risk prediction.	Survey of project managers in developing contexts	Schedule delay, cost overrun

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Primary Focus Area	Citation Index	Paper ID	Core AI Technique	Key Application/Outcome	Dataset/Context	Specific Risk Addressed
Proactive Mitigation & Intervention	[21]	IS44	Causal ML	Causal machine learning for supply chain risk; predicts interventions (not just delay) by modeling causal relationships.	Simulated supply chain	Supply chain delay; provides
	[22]	IS43	Generative AI (DDPM)	Generative AI for dynamic risk scenario simulation; managers stress-test mitigation plans against realistic delay scenarios.	Synthetic project data	General delay, simulated events
	[23]	IS45	LLM-Powered Agent	LLM-powered framework for automatic risk identification and mitigation from past claims and supplemental agreements.	Historical project legal documents	Legal/supply chain delay
	[25]	IS41	ANN, Fuzzy Logic, IoT	Hybrid AI risk assessment framework; integrates IoT sensor data with expert rules for sustainable construction.	Simulated infrastructure project	Environmental hazards,
	[30]	IS26	Predictive Analytics (Case Study)	Leverages AI for optimized project management; case study of Bechtel's	London Crossrail project case	Schedule delay

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Primary Focus Area	Citation Index	Paper ID	Core AI Technique	Key Application/Outcome	Dataset/Context	Specific Risk Addressed
				London Crossrail where AI predicted delays and optimized scheduling.		
	[31]	IS29	Predictive & Adaptive Analytics	AI for predictive and adaptive decision-making; estimates probability of delays and cost overruns based on project features.	General construction project management	Schedule delay
Safety & Hazard Prevention	[26]	IS46	Computer Vision (AI)	AI-driven safety checks for ladders on construction sites; prevents accidents to avoid schedule delays.	Construction site image/video data	Safety incidents leading to
	[25]	IS41	Hybrid ANN/Fuzzy	(See above) Integrates safety risk classifications include environmental hazards and equipment efficiency; recommends safety and delay mitigation strategies.	Simulated infrastructure project	Safety & schedule risk (integrated)
Barriers & Human	[27]	IS34	LLM (ChatGPT	Explores ChatGPT's limitations in	User experience with	General risk identificati

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Primary Focus Area	Citation Index	Paper ID	Core AI Technique	Key Application/Outcome	Dataset/Context	Specific Risk Addressed
Factors			applied)	risk identification and mitigation strategy generation; warns against over-reliance.	ChatGPT	on
	[28]	IS30	Review	Identifies "lack of trust" and "organizational resistance" as primary barriers to AI adoption for risk management.	Trends analysis	Organizational barriers
	[29]	IS35	Survey	Highlights data quality and personnel training as key hurdles to implementing AI for risk mitigation.	Developing country projects	Implementation barriers

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

The fourth thematic dimension explores how artificial intelligence synergizes with Building Information Modeling (BIM), digital twins, and other emerging technologies to create more robust frameworks for schedule delay prediction and mitigation. These studies move beyond isolated AI models towards integrated cyber-physical systems that combine real-time monitoring, simulation, and predictive analytics, reflecting the industry's growing recognition that no single technology can address the multifaceted nature of construction delays. The integration promises to bridge the gap between the digital model of a project and its physical reality, enabling a continuous feedback loop where data from sensors and progress reports informs AI predictions, which in turn trigger automated adjustments to the digital twin, and then to the physical execution plan. We categorize the included studies into three principal areas: BIM-AI integration for risk prediction and sustainable design, digital twin frameworks for predictive control, and blockchain and other emerging technologies for transparency and buffer management.

The first sub-area, the direct integration of BIM with AI for risk prediction, comprises several studies that leverage the rich, structured data environment of BIM models as a foundation for machine learning. BIM models inherently contain detailed information

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about building components, their properties, and their interdependencies, which provides a much richer feature set for AI models than traditional tabular data from spreadsheets. For instance, one study develops an AI-driven BIM framework specifically for sustainable infrastructure projects, where the BIM data (material types, structural loads, environmental conditions) is used as input to an AI module that predicts project risks, including material optimization failures and schedule delays [32]. The authors report that this AI-BIM integration enables a significant reduction in delays by allowing project teams to simulate and mitigate risk scenarios before they occur, specifically by optimizing material procurement schedules based on predicted delivery delays. Similarly, proposes an integrated BIM-AI model for predicting construction project risks, including cost overruns and schedule delays [33]. Their model extracts features from the BIM model (e.g., planned vs. actual progress, resource allocation) and feeds them into a machine learning classifier. The output is a dynamic risk score assigned to each project zone, which then triggers predefined mitigation strategies encoded in the BIM environment, such as automatically notifying subcontractors about potential bottlenecks. A practical case study of an AI-BIM system validates these concepts, demonstrating that the integration leads to a 30% reduction in design iteration time by using AI to forecast potential clashes and rework scenarios from the BIM data [34]. The AI component also forecasts equipment failures by analyzing BIM-stored maintenance schedules and sensor proxies, enabling preemptive maintenance that avoids downtime related delays. These three studies together [32], [33], [34] form a coherent body of evidence that the structured, multi-dimensional data within BIM is a fertile ground for training accurate, context-aware delay prediction models.

The second sub-area focuses on the more technologically sophisticated concept of digital twins, which are dynamic, virtual replicas of physical construction assets that are connected to real-time data streams. The digital twin is not merely a static BIM model; it is a living simulation that can evolve with the project, allowing for simulation, what-if analysis, and predictive intervention. A pivotal study in this area is the simulation-based validation of an integrated 4D/5D digital-twin framework for predictive construction control [35]. This framework integrates 4D (3D model + time) and 5D (3D model + time + cost) dimensions within a digital twin environment, where AI algorithms continuously analyze incoming data from site sensors, drones, and progress reports to predict the project's future state. The validation results are compelling: scenario analysis confirmed that material escalation and late deliveries were the primary drivers of delay and cost overrun, and the AI-enhanced framework enabled a 43% reduction in estimating labor and a 6% reduction in overtime, translating to significant time savings and budget adherence. This study is particularly important because it provides explicit empirical validation of the framework's quantitative impact on workforce efficiency and schedule performance, moving beyond conceptual proposals. Another study introduces an AI-driven and digital twin-based framework for holistic risk and green project management in sustainable urban megaprojects, using the case study of Tehran's urban development under environmental uncertainties [36]. This framework extends beyond simple delay prediction to incorporate green project management metrics, such as carbon footprint tracking, alongside schedule and cost. AI-enhanced predictive models within the digital twin anticipate project delays caused

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by both conventional factors (e.g., labor shortages) and environmental factors (e.g., air quality restrictions). The digital twin then simulates alternative execution strategies that minimize both delay and environmental impact, providing decision-makers with a multi-objective optimization output. This work underscores the potential of digital twins as an integration platform that can harmonize multiple, often conflicting, project objectives.

A related but distinct study on proactive change management based on a digital twin further extends this frontier [37]. This research develops a method for using a digital twin to identify and manage project changes (scope changes, design errors) that are a primary root cause of schedule delays and cost overruns. The digital twin continuously compares the as-planned model with the as-built reality, and when a deviation when detected, an AI module classifies the severity of the change and predicts its likely impact on the schedule. The system then automatically proposes a set of proactive mitigation actions, such as re-sequencing downstream tasks or reallocating resources. The effectiveness of such AI-driven approaches is demonstrated through a case study where the system successfully reduced the time to respond to a change event by 40% compared to manual baseline processes. By treating change management as a delay mitigation strategy at its core, this work highlights how digital twins can transform a reactive process into a proactive one.

A related but distinct study applies AI-enhanced predictive project management specifically to multi-site engineering programs [38]. While not explicitly centered on BIM or digital twins, this work offers a comparable framework for managing geographically distributed projects, where a centralized AI model predicts resource overloads and schedule conflicts across multiple sites. The study reports that the AI model successfully predicted resource overload for a firmware team and triggered a resource reallocation that preserved the build schedule, demonstrating a 15% reduction in delay probability across the program. This work is important because it scales the principles of predictive control from a single project to a program, addressing a real-world complexity that many single-project models ignore.

The third sub-area introduces blockchain technology as an emerging enabler for transparent and trusted data sharing, which is a prerequisite for effective AI-driven delay management, especially in complex project networks. Develops a method for implementing blockchain technology not for financial transactions but for project buffer monitoring and progress sharing in critical chain project management [39]. The core insight is that in a multi-contractor environment, a common source of delay is that contractors hide their true progress to avoid being blamed for delays, leading to the "student syndrome" where buffers are consumed late. The blockchain system provides an immutable ledger of verified progress data, which is then fed into an AI-driven buffer management algorithm. The algorithm predicts the probability of each project's scheduled of using the true, shared progress data, enabling more precise detection and triggering timely corrective actions. The authors argue that this blockchain-AI combination solves the fundamental data quality and trust problems that often plague AI models in construction, where data is often siloed, incomplete, or intentionally manipulated. This study [39] is a forerunner in exploring how the synergy between AI and blockchain can go beyond cryptocurrency to solve practical coordination problems

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in construction.

We also find smaller but notable contributions that extend the integration concept. One study on simulation and control of AI-driven construction sustainability optimization treat BIM-digital twin integration as a backbone but proposes advanced dynamic optimization methods that use control theory and AI to prevent delay specific techniques not named explicitly, but the context emphasizes closed-loop control. While not fully detailed in abstract, such work reinforces the trend towards integrating AI not just as an analytical layer but as an active controller within a cyber-physical system.

These integrated frameworks share several common characteristics. They all require a high degree of digital maturity, including reliable sensor data, up-to-date BIM models, and robust data pipelines. They also rely on real-time or near-real-time data streaming and processing capabilities. The studies validate the premise that the combination of AI with BIM and digital twins yields a "whole is greater than the sum of its parts" effect, where the rich, multidimensional data from BIM provides context for AI predictions, while the digital twin provides a actionable visualization and simulation environment that makes AI outputs understandable and usable for project managers. The primary limitations identified across these studies are the high initial investment cost for digital-twin infrastructure, the need for specialized personnel to maintain and interpret such complex systems, and the proprietary nature of many commercial platforms that hinder open data exchange [35], [35]. The synergy between these technologies, their specific applications, and the reported outcomes are systematically compared in Table 4.

Table 4. Summary of studies on the integration of AI with BIM, Digital Twins, and Emerging Technologies.

Integration Domain	Citation Index	Paper ID	Core Technology	Key Application/Outcome	Data/Source	Reported Benefits
AI + BIM	[32]	IS50	AI-driven BIM framework	Predicts project risks (material optimization, delay) for sustainable infrastructure projects; optimizes procurement schedule.	BIM data of infrastructure projects	Reduction in delays via proactive simulation.
	[33]	IS54	Integrated BIM-AI model	Classifies project risk zones using BIM features; triggers automated mitigation strategies (e.g., subcontractor notifications).	BIM model features (planned vs. actual progress)	Dynamic risk score for each zone; automated mitigation triggers.

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Integration Domain	Citation Index	Paper ID	Core Technology	Key Application/Outcome	Data/Source	Reported Benefits
	[34]	IS52	AI-BIM system implementation	Case study demonstrates 30% reduction in design iteration time; AI forecasts equipment failures from BIM data.	Practical case study of construction project	30% reduction in design time; predictive equipment maintenance.
AI + Digital Twin	[35]	IS48	4D/5D Digital-Twin framework	Validates framework for predictive construction control; AI scans analysis confirms material escalation as key delay driver; labor and overtime reduced.	Simulation-based validation	43% reduction of estimating labor; 6% reduction in overtime.
	[36]	IS47	Digital Twin + AI for Green PM	Holistic risk management including green metrics for urban megaprojects; predicts delays from environmental and traditional factors.	Tehran urban project under environmental constraints	Multi-objective optimization minimizing delay and environmental impact.
	[37]	IS55	Digital Twin for Change Management	Proactive change detection and mitigation; automatically classifies change severity and recommends schedule adjustments.	Project change events data	40% reduction in time reduction in response to change events.
AI +	[38]	IS51	AI-	Predicts resource	Multi-site	15%

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Integration Domain	Citation Index	Paper ID	Core Technology	Key Application/Outcome	Data/Source	Reported Benefits
Multi-site Platform			enhanced predictive PM	overload and schedule conflicts across multiple sites; recommends resource reallocation to preserve schedule.	engineering program data	reduction in delay probability across the program.
AI + Blockchain	** [39] **	IS53	Blockchain + AI for buffer management	Uses blockchain for verified progress sharing in critical chain PM; feeds clean data into AI buffer to AI model for accurate delay prediction.	Project progress data on blockchain	Enhanced data trust; more accurate buffer predictions and timely mitigation.

Generative AI, Large Language Models, and Decision Support Systems

The fifth thematic dimension addresses the most nascent yet rapidly evolving area within our review: the application of generative artificial intelligence, large language models (LLMs), and advanced decision support systems to schedule delay prediction and mitigation. This cluster of studies represents a frontier that moves beyond traditional pattern recognition and prediction toward AI systems that can autonomously generate content, analyze unstructured text, and synthesize novel mitigation strategies. The emergence of this theme is particularly timely, given the explosion of interest in generative AI following the public release of powerful foundation models such as GPT-4 and their equivalents. However, our analysis of the included studies reveals that this area remains largely exploratory and conceptual, with a significant gap between the theoretical promise of these technologies and their empirical validation in real construction contexts. We categorize the included works into two principal sub-areas: studies on generative AI for process optimization and skill gap integration, and studies on LLM-based decision support and automatic delay inference.

The first sub-area, generative AI for process optimization and skill gap integration, comprises studies that explore how generative models, including but not limited to LLMs, can be employed to bridge existing management deficiencies and automate complex planning tasks. One study presents a compelling vision for integrating generative AI into project, engineering, and construction management processes to optimize scheduling and coordination [41](# “core management processes” and address persistent skills gaps [40]. The paper argues that generative AI can predict potential

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project issues with high accuracy and suggest preventive measures, a claim that aligns with the core thesis of this review. However, the contribution is primarily conceptual rather than empirical, as the study does not report quantitative results from a specific implementation. The authors outline a framework where generative AI interfaces with existing project management software, automatically generating schedule adjustments and subcontractor coordination instructions based on predicted delay risks. For instance, the system might detect a pending material shortage from supplier data, generate an expedited purchase order, and simultaneously adjust downstream task dependencies in the schedule, all without human intervention.

Another study in this sub-area offers a broader assessment of generative AI's opportunities and challenges within the construction industry [41]. This work identifies several key opportunities for generative models, including automated report generation, code compliance checking, and synthetic data generation for training predictive models where real historical data is scarce. The challenges highlighted are equally significant: data privacy concerns when using cloud-based AI models, the risk of hallucinated (factually incorrect) outputs from LLMs in critical path analysis, and the lack of domain-specific training data for construction schedules. The study emphasizes that while generative AI can produce convincing-sounding mitigation strategies, these recommendations can be dangerously inaccurate if the model lacks construction-specific knowledge, for example, proposing an infeasible schedule compression that violates safety regulations or union work rules. This cautionary perspective is crucial for tempering the enthusiasm surrounding these tools.

The third study in this group examines the capabilities of AI, including generative tools, within the specific context of private real estate development [42]. Although the abstract is sparse in technical detail, the paper is positioned as a roadmap for chronic cost overruns and project delays, with particular emphasis on AI during budgeting to predict costs and reduce schedule overruns. This work provides a practitioner-oriented perspective, suggesting that generative AI could be used to simulate the financial and temporal impact of different design iterations during the pre-construction phase, thereby preventing delays before they are encoded into the baseline schedule. The study also touches on the role of generative AI in producing persuasive project update reports for investors and stakeholders, potentially improving communication and stakeholder satisfaction, indirectly contributing to smoother project execution.

The second sub-area, LLM-based decision support and automatic delay inference, contains studies that apply large language models more specifically to the task of extracting structured delay information from unstructured data. One study makes a particularly important contribution by proposing a novel method for automatic delay inference from weekly progress reports using LLMs [13], which we also discussed in Section 3.3 due to its relevance to prediction models. This work addresses a critical bottleneck in the delay prediction pipeline: the lack of structured, labeled data. The researchers demonstrate that by fine-tuning a pre-trained LLM on a corpus of construction progress reports, the model can automatically extract and classify delay events, their causes, and their durations with an F1-score exceeding 0.88. This automated extraction capability is transformative because it enables the creation of large, labeled datasets that can then be used to train supervised machine learning models

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for delay prediction at scale. Without such automated extraction, the manual effort required to label progress reports makes large-scale model training prohibitively expensive and slow. The study's findings validate that LLMs can effectively serve as "data generators" in a broader AI pipeline for construction delay management, bridging the gap between unstructured textual sources and structured prediction models.

A final study within this dimension addresses the implementation of machine learning technologies specifically in construction maintenance strategies [43]. While the abstract is again brief, the paper explicitly focuses on the use of AI and 5G networks to predict delays in construction projects, with a reported "reduction in incidents" as a key outcome. The inclusion of "Incidents" suggests a link between predictive models to prescriptive safety and maintenance actions, likely using an AI decision support system that triggers preventative maintenance schedules based on predicted equipment degradation. This study, though not solely focused on generative AI, contributes to the broader theme of decision support by demonstrating how AI systems can generate automated responses (maintenance work orders) in response to predicted delays, thereby moving from prediction to intervention.

When synthesizing these studies, a clear pattern emerges: the field of generative AI for construction delay management is in its infancy. With the notable exception of the validated LLM for delay inference [13], most contributions are conceptual frameworks, exploratory assessments, or practitioner roadmaps rather than rigorously tested systems. There is a striking absence of empirical studies measuring the actual impact of a generative AI system on project schedule performance in a controlled or real-world setting. The optimism surrounding tools like ChatGPT and GPT-4 for automating schedule updates or generating mitigation strategies is, as of the included literature, largely unsubstantiated by empirical evidence. The primary value identified so far lies in LLMs' ability to process and structure unstructured text data (e.g., progress reports, contracts) that is abundant in construction projects but resistant to traditional data extraction methods. This suggests that the most immediate and impactful application of generative AI in schedule delay management is not in generating human-quality mitigation plans but in serving but in serving as a bridge between human-generated text and machine-learning prediction pipelines.

We also note that none of the included studies in this dimension propose or validate a system that uses generative AI to directly generate a complete, optimized construction schedule from scratch. The focus remains on using generative models as assistants or enhancers within existing workflows (e.g., generating reports, extracting data, suggesting mitigations) rather than as autonomous planning engines. This likely reflects both the safety-critical nature of construction scheduling, where final decisions must remain with qualified human professionals, and the current technical limitations of generative AI in handling complex, multi-constraint optimization problems with high reliability. The key findings of the studies within this dimension are summarized in Table 5.

Table 5. Summary of studies on Generative AI, Large Language Models, Generative AI, and Decision Support Systems.

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Primary Focus Area	Citation Index	Paper ID	Core Technology	Key Contribution	Level of Validation	Reported Outcomes
Generative AI for Process Optimization	[40]	IS56	Generative AI (general)	Proposes framework for integrating generative AI into core management processes; aims to bridge skills gaps and enable proactive delay prevention via automated schedule adjustments.	Conceptual framework	Claims high accuracy for predicting project issues; suggests preventive measures (no empirical validation).
	[41]	IS57	Generative AI (general)	Provides comprehensive assessment of opportunities (automated reporting, code compliance, synthetic data) and challenges (data	Exploratory assessment	No specific quantitative outcomes; identifies hallucinations as critical risk.

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Primary Focus Area	Citation Index	Paper ID	Core Technology	Key Contribution	Level of Validation	Reported Outcomes
				privacy, hallucination risk, lack of domain knowledge) for generative AI in construction.		
	[42]	IS58	AI (including generative)	Positions AI as a roadmap for reducing chronic cost overruns and project delays in private real estate; emphasizes use during budgeting to predict costs and reduce schedule overruns.	Practitioner-oriented roadmap	Reports potential for reduction in schedule overrun (no specific metric reported).
LLM for Delay Inference	[13]	IS18	Large Language Model (fine-tuned)	Develops and validates a method for automatic extraction and	Empirical validation	Achieved F1-score above 0.88 for delay event extraction; model

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Primary Focus Area	Citation Index	Paper ID	Core Technology	Key Contribution	Level of Validation	Reported Outcomes
				classification of delay events and their causes from unstructured weekly progress reports.		provides structured data for downstream prediction models.
Decision Support for Maintenance	[43]	IS59	ML + 5G / AI	Applies ML and 5G network technologies to predict delays and reduce incidents in construction maintenance strategies.	Empirical (limited detail)	Reports "reduction in incidents" as key outcome (specific metric not clear from abstract).

Bibliometric Analysis, Frameworks, and Future Trends in AI Adoption

The sixth and final thematic dimension of this review encompasses studies that do not primarily present novel predictive models or mitigation algorithms but instead aim to systematically map, synthesize, or conceptualize the landscape of AI adoption for schedule delay management in construction. This cluster is characterized by a meta-analytical and prospective orientation. The studies within this dimension serve a critical integrative function, providing the broader academic community with a bird's-eye view of the field's evolution, identifying thematic clusters, pinpointing research gaps, and proposing conceptual frameworks to guide future inquiry and practical adoption. We distinguish between three principal sub-areas within this theme: (1) bibliometric and systematic mapping studies that quantify the state of the art, (2) studies proposing novel conceptual frameworks for AI integration in project management, and (3) forward-looking assessments of the potential impact and adoption trajectory of AI technologies

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in the sector.

The first sub-area concerns bibliometric and systematic mapping analyses. One of the most comprehensive studies in this cluster presents a bibliometric and systematic analysis of machine learning and AI-based cost and time prediction in construction [44]. This work, mapping the inter-connectedness of published research datasets to identify the co-occurrence of themes such as “Cost Overruns and Contingencies,” “Schedule Delay Prediction Models,” and “Machine Learning Algorithms.” The study quantitatively demonstrates that the sub-streams focusing on overrun causes and prediction form the largest, most interconnected clusters, whereas studies on generative AI applications appear only as isolated, emerging nodes with weak connections to the main body of literature. This bibliometric evidence confirms the fragmentation we observed qualitatively across our other dimensions. The paper also identifies a gap in the literature regarding the prediction of negative project outcomes, specifically cost overruns and schedule delays, suggesting a need for more integrated models that jointly predict both types of risk rather than treating them in isolation [44]. This work is particularly valuable because its quantitative, data-driven methodology complements the qualitative synthesis of our review, providing external validation for the thematic boundaries we have drawn.

A second study within this mapping sub-area offers a topical bibliometric overview of the general trajectory of artificial intelligence and machine learning in construction and project controls [45]., The The authors trace the ascending trajectory of research outputs from the early 2010s through to the present, evaluating current applications across various project life cycle phases. Their analysis reveals that the highest concentration of AI/ML research is in the planning and monitoring phases, where schedule and cost prediction are paramount, rather than in the initiation or design phases. This finding aligns with our observation that the largest body of literature falls within the schedule delay prediction dimension. The study also highlights that risk mitigation is a natural part of the construction project control process, and that AI models are most effective when they move from pure prediction to prescriptive recommendation, a conclusion that mirrors our findings from the holistic risk management dimension [45].

The second sub-area encompasses studies that develop novel conceptual frameworks for AI integration in project management and risk mitigation. One study proposes a framework for leveraging data-driven decision-making to enhance risk management and resource allocation in projects [46]. The, The framework outlines a process where data from multiple sources (historical, real-time, environmental) is fed into a machine learning layer for risk assessment and resource optimization, followed by a recommendations layer for mitigation actions. The authors explicitly connect this framework to the application of AI in construction scheduling and predictive analytics [46]. They emphasize that the framework’s novelty lies in its explicit linkage between risk assessment and resource allocation, arguing that many existing AI systems predict a risk but then fail to suggest how to best deploy resources to avoid it. This work, while primarily conceptual, provides a useful blueprint for developing more complete AI-driven risk management systems that bridge the gap between prediction and action.

A neighboring conceptual study addresses the use of predictive analytics for improving task estimation, resource allocation, and delivery accuracy in project planning [47].,

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The The study argues that traditional planning methods suffer from systematic biases in task duration and resource requirement estimates, and that can be reduced by applying predictive models to historical data. The proposed framework integrates a feedback loop where actual project performance data is continuously fed back into the predictive model, allowing it to adapt to a specific project's evolving context. The authors suggest that this continuous learning approach is superior to static pre-project estimates and could significantly improve delivery accuracy by reducing the variance between planned and actual durations [47]. Though the abstract omits specific empirical results, the conceptual logic is sound and represents a step towards the dynamic, self-adapting scheduling systems that many other studies in our review call for.

The third sub-area comprises studies that offer forward-looking assessments and contextual analyses of AI's potential impact and adoption barriers. One study applies the theoretical lens of AI's potential impact within the context of NEOM, a large-scale, technologically ambitious construction project in Saudi Arabia [48]. The, The study speculates that AI-enhanced project management in such a context could yield a 15% reduction in project timelines by mitigating delays through optimized resource allocation and real-time risk forecasting. The author argues that AI systems in NEOM will "forecast risks, schedule delays, and cost overruns with exceptional accuracy," a bold claim that remains aspirational rather than empirically validated [48]. The study is valuable, however, for its concrete, large-scale vision of what an AI-saturated construction ecosystem might look like, providing a target scenario for other researchers to aim for. It emphasizes that the potential impact of AI in reducing schedule delays is directly proportional to the breadth and quality of data that can be collected from the project's entire lifecycle.

Another forward-looking study examines the role of AI tools in augmented project management, specifically focusing on decision-making and resource optimization [49]., The The authors analyze commercial AI tools such as Forecast, an AI-based project management platform, and report that such tools can lead to "fewer late projects" by providing more precise scheduling and risk reduction in engineering projects worldwide [49]. The study provides a comparative assessment of several commercial AI project management tools, evaluating them on criteria such as accuracy of schedule prediction, ease of integration with existing workflows, and user satisfaction. The conclusion is that while no single tool is perfect, the cumulative effect of adopting AI-based scheduling is a measurable reduction in project overruns, supporting the investment, and research. This work is important because it provides a rare perspective on the commercial, off-the-shelf ecosystem of AI tools that are available to practitioners, as opposed to the bespoke academic models that dominate the other dimensions of our review.

A final study within this sub-area examines the broader impact of artificial intelligence on civil engineering project management [50]., The The authors argue that AI offers enhanced risk mitigation capabilities by processing large volumes of structured and unstructured data to identify patterns indicative of future delays. They cite examples where AI algorithms have been used to optimize construction schedules, resulting in reduced project delays and improved efficiency [50]. The study also discusses the implications of AI for the project management profession, suggesting that the role of

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the project manager will shift from one of reactive problem-solving to one of strategic oversight of AI systems. This forward-looking perspective on the changing nature of work is a valuable addition to the literature, as it highlights the human and organizational changes that must accompany technological adoption. The diversity of approaches within this dimension, from quantitative mapping to qualitative speculation, is systematically captured in Table 6.

Table 6. Summary of studies on bibliometric analysis, conceptual frameworks, and future trends in AI adoption for schedule delay management.

Primary Focus Area	Citation Index	Paper ID	Core Contribution Type	Key Synthesis or Framework	Level of Evidence / Validation
Bibliometric & Systematic Mapping	[44]	IS62	Bibliometric analysis	Identifies "Cost Overruns and Contingencies" and "Schedule Delay Prediction" as largest thematic clusters; reveals generative AI as isolated, emerging node.	Quantitative dataset analysis of co-occurrence networks.
	[45]	IS64	Bibliometric overview	Traces ascending trajectory of AI/ML in construction; highest concentration in planning and monitoring phases; links risk mitigation	Topical overview with trend analysis.

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Primary Focus Area	Citation Index	Paper ID	Core Contribution Type	Key Synthesis or Framework	Level of Evidence / Validation
				as natural part of project control.	
Conceptual Frameworks for Integration	[46]	IS65	Conceptual framework	Proposes data-driven decision-making framework linking risk assessment to resource allocation; emphasizes AI's role in predictive scheduling.	Conceptual design; no empirical test.
	[47]	IS66	Conceptual framework	Develops framework for reducing task estimation bias using predictive analytics; proposes continuous learning feedback loop from actual project performance.	Conceptual design; no empirical test.
Forward-Looking & Impact Assessment	[48]	IS60	Case study / Scenario analysis	Assesses AI's potential in NEOM project; claims 15%	Aspirational scenario; no empirical validation.

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Primary Focus Area	Citation Index	Paper ID	Core Contribution Type	Key Synthesis or Framework	Level of Evidence / Validation
				timeline reduction via proactive risk forecasting and optimized resource allocation.	
	[49]	IS61	Comparative assessment	Evaluates commercial AI tools (e.g., Forecast) for scheduling and resource optimization; reports “fewer late projects” as key outcome.	Comparative tool evaluation with user studies.
	[50]	IS63	Impact analysis	Discusses AI’s risk mitigation capabilities for schedule optimization; predicts a shift in project manager role from reactive problem-solving to strategic	Forward-looking analysis with examples.

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Primary Focus Area	Citation Index	Paper ID	Core Contribution Type	Key Synthesis or Framework	Level of Evidence / Validation

oversight.

When we synthesize the contributions in this dimension, a clear pattern of divergence emerges between the bibliometric evidence and the aspirational claims. The quantitative mapping studies [44], [45] empirically demonstrate that the field is still heavily centered on prediction models for cost overruns and schedule delays, with emerging areas like generative AI and digital twin integration remaining peripheral. In contrast, the forward-looking studies [48], [50] project a future where AI revolutionizes delay management entirely, often citing large reductions in project timelines or the complete automation of mitigation. This gap between current reality and future vision underscores the need for more empirical research that validates these aspirational claims in real-world settings, a point that the conceptual framework studies [46], [47] begin to address by proposing concrete pathways for implementation. The most valuable insight from this dimension is the recognition that the adoption of AI for delay management is not solely a technical challenge but equally a challenge of integration, trust, and organizational change, as highlighted by the study of commercial tool adoption [49] and the cultural shift discussed in [50]. The future research agenda must therefore move beyond developing increasingly accurate prediction models to addressing the systemic barriers that prevent these models from being integrated into the daily workflows and decision-making loops of construction project managers.

Discussion

Synthesizing the key findings from the six thematic dimensions of this systematic review reveals a research landscape that is simultaneously advancing rapidly and constrained by persistent structural limitations. Taken together, the 67 included studies demonstrate that artificial intelligence, particularly machine learning and deep learning architectures, has achieved remarkable accuracy in predicting schedule delays across diverse project contexts. A consistent pattern emerges across the literature: models that leverage temporal dependencies through LSTM networks or hybrid CNN-RNN architectures consistently outperform static classifiers, with reported R-squared values exceeding 0.90 in some cases [8]. This finding is robust across multiple independent studies and datasets, suggesting that the temporal nature of construction progress data is a critical feature that predictive models must capture to achieve high performance. Furthermore, the field has clearly evolved from a narrow focus on prediction towards a broader concern with prescriptive analytics and mitigation, as evidenced by the growing body of work on reinforcement learning for auto-scheduling and causal models for intervention planning [11], [21]. This shift from forecasting the *what* to recommending the *how* represents a maturation of the research paradigm, moving from diagnostic and predictive analytics toward prescriptive intelligence. However, this progression is uneven. While schedule delay prediction has delay prediction models are relatively mature and empirically validated, the prescriptive and generative AI sub-fields remain largely conceptual, with a striking paucity of absence of rigorous empirical validation

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for the claimed benefits of AI-generated mitigation strategies [40], [41]. The field thus exhibits a confidence gradient: high confidence in prediction, moderate confidence in risk identification, and low confidence in automated mitigation and generative recommendation.

This synthesis also reveals several important contradictions and tensions within the literature. A first major contradiction concerns the role of expert knowledge in AI systems. Several studies advocate for pure data-driven approaches, arguing that neural networks can learn patterns that surpass human intuition when given sufficient data [7], [9]. In direct contrast, other works emphasize that integrating expert-defined rules through fuzzy logic or Relative Importance Index (RII) weighting improves model robustness, particularly when training data is limited or of poor or scarce [10], [15]. These two perspectives are not mutually exclusive; indeed, the most successful systems appear to be hybrid models that combine learned representations from data with structured expert knowledge [10] [10]. Nevertheless, the literature lacks a clear consensus on how to optimally weigh these two sources of information or under what conditions one approach dominates the other. This inconsistency is partly a function of data availability: data; studies using large, high-quality historical datasets naturally favor pure data-driven methods, while those working with small or noisy datasets necessarily fall back on expert input. The field would benefit from a systematic investigation of the trade-offs between data-driven and knowledge-driven approaches as a function of dataset characteristics, which currently remains unexplored.

A second tension revolves around the generalizability of proposed models. Many studies report impressive predictive performance on their specific test datasets, but almost no studies validate their models on out-of-distribution data from different project types, geographical regions, or construction methods [4], [9 “IS19” [9]. This raises serious questions about the external validity of the reported results. A model trained to predict delays in Chinese residential high-rises using data from 250 features from a specific contractor’s historical database may fail entirely when applied to a European highway project or a Middle Eastern infrastructure megaproject, where the underlying delay mechanisms and data distributions are fundamentally different. The bibliometric study [44] independently confirms this concern by showing that the literature is heavily clustered around specific project types and geographies, with weak connectivity between clusters. The absence of cross-domain validation studies, where a model developed in one context is tested on data from another, represents a significant methodological gap that undermines the field’s claims to robustness and practical utility. Future research must prioritize the development of generalizable frameworks, perhaps through domain adaptation or transfer learning techniques, rather than continuing to produce context-specific models with unverified portability.

The implications of these synthesized findings for our findings for theory and practice are substantial. Theoretically, this review contributes to the conceptual understanding of how AI transforms construction project control. The traditional model of project control is reactive and diagnostic: a delay occurs, the project manager identifies the cause, and then implements a corrective action. Our synthesis suggests that AI enables a shift toward a proactive, predictive, and prescriptive model, where delays are anticipated before they occur and mitigation actions are recommended or even

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automated before the delay materializes. This represents a fundamental change in the control paradigm, from feedback control (correcting after a deviation) to feedforward control (preventing the deviation entirely). The conceptual frameworks proposed in the literature [46], [47] articulate this vision, but our review reveals a gap between vision and empirical validation. For theory to advance, future work must operationalize this shift by developing and testing explicit models of AI-mediated project control that specify the conditions under which feedforward control outperforms traditional feedback approaches. Additionally, the integration of AI with BIM and digital twins offers theoretical insights into the nature of digital project representations. The synergistic effect observed in these integrated systems [35], suggests that the whole is indeed greater than the sum of its parts, but the mechanisms underlying this synergy remains poorly theorized. We hypothesize that the BIM model provides the structural and semantic context that relational context needed for AI predictions to be meaningful, while the digital twin provides the simulation environment needed to test the consequences of those predictions. This complementary to the development of a formal theory of AI-enhanced cyber-physical project management.

Practically, our findings offer a clear roadmap for industry adoption. The most mature and practically ready technology is supervised machine learning for delay classification and LSTM-based deep learning for temporal prediction. Construction firms that have access to structured historical data on to structured historical project data (task durations, progress, resource usage, delay reasons) can confidently deploy these models for uses such as early warning systems that flag high-risk projects or activities. The demonstrated high accuracy reported across multiple studies [6], [8] suggests that the technical risk of adopting these prediction models is relatively low, provided the quality of the training data is adequate. For firms with less mature digital infrastructure, the hybrid fuzzy-based and expert knowledge models offer a viable pathway that does not require large datasets but still delivers actionable insights [15]. On the mitigation side, the evidence supports the adoption of digital twin frameworks for predictive control like the 4D/5D framework validated in [35]. These systems have demonstrated measurable reductions in labor estimation error and overtime, which directly translate to schedule benefits. However, the high upfront cost and technical complexity of deploying a digital twin deployment are significant barriers, especially for small and medium-sized enterprises. Our review suggests a phased adoption strategy: begin with a standalone prediction models to build organizational trust in AI outputs, then integrate them with existing BIM environments, and only later invest in full digital twin infrastructure. the lag in this area, we caution against premature adoption of generative AI tools for autonomous schedule generation or mitigation recommendation, given the lack of empirical validation and the documented risk of hallucinated, unsafe outputs [41]. The most immediate and low-risk use of generative AI in practice is for automating the extraction of structured data from unstructured progress reports and contracts [13], which directly address the data quality bottleneck that hampers many AI projects.

Several limitations of our review methodology must be acknowledged to properly contextualize these findings. First, our search strategy employed term-specific queries focusing on “schedule delay”, “time overrun”, and “delay prediction”. This may have

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inadvertently excluded studies that use alternative terminology such as “construction duration forecasting”, “project completion prediction”, or “performance degradation modeling”. Such semantic boundary issues are inherent to systematic reviews, but they introduce a potential selection bias toward studies that explicitly frame their contribution around delay prediction. Second, our decision to exclude literature reviews, surveys, and meta-analyses, and meta-analyses from the primary synthesis, while justified by our focus on primary research, means that we may have missed aggregated insights that could have informed the discussion. For example, some excluded surveys may have provided quantitative meta-analyses of prediction accuracy across studies, which would have allowed our review’s synthesis to be more precise. The absence of such meta-analytical evidence limits our ability to quantify the overall effect size of AI-driven prediction across the field. Third, our quality assessment relied on peer-review status and methodological clarity rather than formal risk rather than a formal risk-of-bias scoring. This decision was pragmatic given the heterogeneity of study designs (from controlled experiments to case studies to conceptual frameworks), but it means that the weight we assign to each study is somewhat subjective. A study with a weak experimental design but a compelling conceptual contribution may have received similar emphasis to a rigorously conducted empirical study. Future reviews should consider applying a more granular critical appraisal tool, such as the CASP check or a bespoke framework for AI in construction studies. Fourth, we limited our search to English-language publications indexed in five major databases. This introduces a geographical and linguistic bias: studies published in non-English journals or languages, such as grey literature in regional databases are underrepresented. Given the high volume of construction research in Chinese, Korean, and Spanish-language contexts, this limitation is particularly salient. The bibliometric analysis by [44] suggests that a significant proportion of construction AI research originates in non-English speaking regions, which reinforces the potential for geographical sampling bias in our review. Finally, the manual screening process, while double-reviewed, is still subject to inter-rater variability. Disagreements were resolved through discussion, but the potential but for subtle biases in interpretation may persist, particularly when classifying a study touched on multiple dimensions and its primary categorization was ambiguous. We mitigated this by classifying studies into primary and secondary categories, but the subjectivity of process of categorization inherently imposes a structure on the literature that may not perfectly reflect its complexity.

The limitations and gaps identified in this review naturally suggest several promising directions for future research. There is a pressing need for studies that move beyond predictive accuracy as the sole benchmark of success and instead evaluate AI systems on their actual impact on project outcomes. A randomized controlled trial or quasi-experimental design where one set of projects uses an AI-driven delay prediction system and a control set uses traditional methods would provide compelling evidence of practical value, yet remains absent from the literature. Such studies should measure not just prediction accuracy but also metrics like number of delays avoided, reduction in delay duration, cost savings from proactive mitigation, and changes in stakeholder satisfaction. Without such causal evidence, the field risks remaining at the level of technological demonstration rather technological demonstrations than practical

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solutions. A second critical direction is the development of generalizable and transferable models. Future research should explore domain adaptation techniques that allow a that allow a model trained on one project type to be fine-tuned for another with minimal new data, or meta-learning frameworks that learn to learn from multiple project contexts simultaneously. The study by [10] using a deep context embedding approach provides a starting template, but systematic benchmarking of transfer learning across diverse project types is needed. A third area that demands immediate attention is the empirical validation of generative AI for construction schedule management. Given the rapid pace of development in large language models and the enthusiastic claims circulating in industry trade publications, independent academic validation or refutation of these claims is urgently needed. Controlled experiments where LLMs generate mitigation strategies or schedule adjustments for real projects, with human expert evaluation of the feasibility and safety of the outputs, would provide a much-needed evidence base. Particular priority should be given to evaluating the risk of hallucinated outputs in safety-critical scheduling decisions, as the consequences of an incorrect recommendation error could be catastrophic on a construction site. Fourth, the intersection of AI with blockchain for trusted data sharing [39] remains underexplored. Future work beyond the single exploratory study. Given that data quality and trust are consistently identified as primary barriers to AI adoption [28], [29], this), this area is ripe for interdisciplinary research combining computer science, legal, engineering, and construction engineering perspectives. Future studies could develop and test decentralized data marketplaces for construction progress data, where blockchain ensures immutability and incentivizes honest reporting, while AI models are trained on the aggregated, trustworthy dataset. Fifth, there is a notable absence research of that examines the human-computer interaction aspects of AI-driven delay management. How should Systems designed to recommend schedule adjustments must be accepted by project managers, and the literature currently contains little research on interface design, cognitive load, trust calibration, or trust calibration in this context. Understanding how to present AI predictions and recommendations in a way that promotes informed, critical decision-making rather than blind trust or rejection is a crucial human factors challenge. Finally, longitudinal studies that track the adoption and evolution of AI systems within construction firms over construction firms multiple projects would provide valuable insights into the organizational learning processes necessary for successful implementation, complementing the cross-sectional snapshot offered by the current literature. Understudied areas include the economic business case for AI adoption in small and medium-sized enterprises, the ethical implications of automated decision-making in safety-critical scheduling contexts, and the role of AI in promoting sustainability and circularity within construction schedules, all of which point to a rich and important agenda diverse for the next wave of research.

Conclusion

This systematic literature review provides a comprehensive synthesis of the existing research on artificial intelligence applications for schedule delay prediction and mitigation in construction projects. We addressed our primary research question by systematically mapping 67 studies across six thematic dimensions, revealing that the field has evolved from isolated predictive models towards integrated, prescriptive

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frameworks. The evidence confirms that machine learning and deep learning models, particularly those capturing temporal dependencies through LSTM architectures, achieve high predictive accuracy. However, a critical gap persists between these technical capabilities and their empirical validation for proactive mitigation, especially in the domains of generative AI and prescriptive mitigation.

The practical implications of these findings are twofold. For industry practitioners, the most actionable insight is that proven predictive models exist and can be adopted today for early warning systems, provided sufficient historical data quality is available, while investment in digital twin infrastructure offers the highest return for comprehensive risk management. For the academic community, this review establishes that future research must now prioritize causal inference, cross-project generalizability through transfer learning, and rigorous validation of generative AI applications in safety-critical scheduling contexts. The theoretical implication of our work is the articulation of a paradigm shift from reactive feedback control to proactive feedforward control in project management, enabled by AI systems that can anticipate and recommend before delays materialize.

Looking forward, the research community must address the organizational, data quality, and human factors barriers that currently impede translation from experimental success to industry-wide practice. The path towards resilient, intelligent construction project management requires not merely better algorithms but integrated socio-technical systems that combine algorithmic power with domain expertise and organizational trust.

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