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# ML IN PROJECT SCHEDULING: A REVIEW OF PREDICTIVE ANALYTICS AND RESOURCE OPTIMIZATION

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## ABSTRACT

Project scheduling is a core element of project management yet traditional methods including Critical Path Method (CPM) and Program Evaluation and Review Technique (PERT), fail to address the complex and changing characteristics of modern projects. These constraints often cause schedule delays, huge budget overruns and the situation demands the use of advanced scheduling systems that offer adaptability to schedule high-risk activities. And, these traditional methods bring the issues of manual effort and limited flexibility with them, too, which only makes instant changes even more ineffective. The aim of this paper is to provide an in-depth review and critical synthesis of existing literature on the application of machine learning (ML) for improving project scheduling. We will shuffle available research and categorize it across a number of different key domains. We start to consider the likelihood of risk and use predictive analytics to better forecast risks, allowing us to detect where risk might arise earlier on and estimating with improved accuracy the time it will take for a task to be completed. Secondly, we consider supervised and unsupervised learning approaches for smart resource allocation on quite many examples of datasets combined and joined in terms of human capital, equipment or material management with optimization task. This study shows the superiority of ML techniques compared to traditional methods in allowing data-driven proactive scheduling. Although significant strides have been made with regard to the accuracy of time/cost prediction and the identification of risks proactively, this review also highlights various research gaps. In particular, more work must go into developing comprehensive end-to-end ML frameworks with high interoperability that can merge different ML methods and interface with existing project management information systems. In addition, the creation of standardized, good-quality and comprehensive project data sets is essential in order to support more robust model training and validation beyond potential challenges associated with scarcity or limited quality of available data. Overall, this review summarises the state of the art in this area and identifies the major challenges to creating intelligent and adaptive systems for Project Scheduling, and it helps outline the future research directions towards achieving highly intelligent project scheduling systems that are capable of addressing complex issues faced by upcoming projects.

***Keywords:*** *Project Scheduling, Machine Learning, Project Management, Cost Prediction, Resource Optimization*

## 1. INTRODUCTION

Construction project management is a professional service that uses specialized project management techniques to oversee the planning, design, and construction of a project from its beginning to its end. Building projects are composed of interrelated activities, site conditions are dynamic and uncertain and it is difficult to provide an accurate prediction. Project scheduling is very critical aspect in Project Management as it decides the time, cost and resource spent on project life cycle. Methods for determining the sequence of activities in a project and the length of time required to complete it have been evolving since techniques such as Critical Path Method (CPM) and Program Evaluation and Review Technique (PERT) were introduced decades ago. Unfortunately, traditional ones only use a static and linear mode which is not so fit for the dynamic process of projects (Taheri, 2024). These drawbacks include human observation, Linear assumptions of presented conditions, and being devoid of project dynamic period changes. These are the issues which have spurred research concerning data-driven and machine learning (ML) based methods that can enhance performance and increase the adaptability of scheduling mechanisms. Machine learning enables learning from historical project data and predicting results as duration, cost deviation, or resource usage. Predictive analytics supports the ability of ML models to identify future risks and optimization algorithms facilitate intelligent resource apportionment of workers, materials and machinery. Recent works have demonstrated the superior accuracy and responsiveness of ML-based scheduling systems compared to traditional methods. To address the limitations of conventional project scheduling, Machine learning (ML) seems to be a promising alternative. Using large dataset, ML models can predict results, allocate resources efficiently and proactively anticipate possible risks why ML scheduling is better than static scheduling. The fact that ML algorithms can adapt based on real-time data provides them with significant advantages over static scheduling (Johansson, 2024). Even with increasing research in this direction, no consolidated knowledge exists on how diverse ML models actually support predictive scheduling and resource optimization. Available research results are fragmented across different areas and focus on models with small project-specific datasets. We therefore need a systematic review to summarize what has been done in the past, pinpoint where it is missing, and direct further development of intelligent scheduling frameworks. The application of machine learning methods in project scheduling towards predictive analytics and resource optimization is critically reviewed in this paper. In Table 1, the key review studies on ML in project scheduling in recent papers are shown.

Table 1. Key Review Studies on ML in Project Scheduling

| Reference | Method | ML Models | Domain Focus | Aim |
|---|---|---|---|---|
| **(Ahmed et al., 2025** | AI Framework and review | Cloud-based AI architectures | Real-time dynamic scheduling | Evaluating real-time complete monitoring and adaptive scheduling to reduce computational latency |
| **(Seyişoğlu et al., 2024)** | Systematic Review | Random Forest, SVR, ANN | Time Cost Predictions in Construction Scheduling | Reviewed data-driven predictive models and highlighted accuracy improvements in time and cost forecasts |
| **(Chauhan, 2024)** | Critical Review | LSTM, Gradient Boosting, Reinforcement Learning | Adaptive Scheduling & Resource Optimization | Examined ML-based dynamic schedule updating and resource reallocation strategies under changing conditions. |
| **(Al Sinan et al., 2024)** | Methodological / System Review | Computer Vision + ML (CV-ML) integrated with BIM | Automated Schedule Generation | Provided a BIM-integrated ML scheduling framework, improving activity recognition and automated Gantt chart generation. |
| **(Nabeel, 2024)** | Conceptual Framework Review | Big Data + ML + Optimization Algorithms | Complex Project Scheduling & Task Prioritization | Identified AI-enabled collaborative scheduling and decision-support potentials. |
| **Reference** | **Method** | **ML Models** | **Domain Focus** | **Aim** |

| | | | | |
|---|---|---|---|---|
| **(Taheri, 2024)** | Narrative Review (Thesis) | Deep Learning + NLP + PMIS Integration | AI-Driven Decision-Making in Project Management | Showed increasing use of hybrid ML-optimization systems to minimize duration, cost, and resource conflicts jointly. |
| **(Tam & Toan, 2021)** | Scientometric Review | General ML & Construction Data | Construction Management Trends | Sumarized five primary uses, including risk, safety, cost, and schedule control |

## 2. METHODOLOGY

In order to have an overview on all the existing studies on ML applications in project scheduling and guarantee the full coverage of them, a systematic scoping hybrid methodology is applied in this review. The systematic aspect provided organized searching and screening of the literature of interest, while the scoping nature allowed us to be more flexible in capturing new work and interdisciplinary approaches (Datta et al., 2024).

### 2.1 Database Selection and Search Strategy

A comprehensive literature search was conducted across five major databases: Scopus, IEEE Xplore, ScienceDirect, MDPI, and SpringerLink, which together cover most project management, computer science, and construction engineering journals. The search strings combined primary and secondary keywords using Boolean operators as follows:

("machine learning" OR "artificial intelligence") AND ("project scheduling" OR "construction scheduling") AND ("predictive analytics" OR "resource optimization" OR "risk forecasting")

The search was limited to peer-reviewed English-language articles, conference papers, and theses published between 2015 and 2025, all related to engineering and construction project management.

### 2.2 Inclusion and Exclusion Criteria

Studies were eligible for this review if they were journal or peer-reviewed conference proceedings from 2015 to 2025. Studies have to explicitly present machine learning, artificial intelligence, or data analytics in the context of project scheduling, resource optimization, or risk prediction. Only empirical studies, case studies or methodology proposals related to the subject area were considered specifying construction and civil engineering or general project management.

On the contrary, studies were not included if they focus on classical scheduling methods alone with no machine learning comparison or addition. Articles not in English, opinion pieces or editorials were also excluded, as were studies without adequate investigation of methods and validation. This methodological strategy facilitated a rigorous, evidence-based synthesizing process.

### 2.3 Data Extraction and Categorization

Each included study was systematically reviewed and coded according to several important aspects, e.g., bibliographic details including author, year, publication type; the specific ML techniques utilized (i.e., RF, SVM, ANN, LSTM networks and RL); the primary application domain such as predictive analytic problems or resource optimization or framework & integration studies; reported performance metrics like accuracy ($R^2$/RMSE), cost/time reduction figures or scheduling efficiency results; a brief account of main findings with any recognized limitations.

Based on this review, the studies were classified into three clusters:

i. Predictive Analytics for Scheduling: Employing machine learning techniques to predict time, cost or risk;
ii. Resource Optimization with ML: Dealing with material, labour and equipment optimization methods;

iii. Framework and Integration Studies: Combining machine learning in BIM or Project Management Information Systems (PMIS).

### 2.4 Data Synthesis

A qualitative synthesis approach was employed to compare methodologies, data sources, and performance indicators across the three clusters. Table 2 shows a comparative summary of these three clusters. Quantitative results, such as prediction accuracy and optimization percentages, were reported descriptively because data heterogeneity precluded meta-analysis.

Table 2: Comparative summary of three clusters

| **Thematic Cluster** | **Methods Compared** | **Data Sources** | **Performance Indicator** | **Quantitative Findings** |
|---|---|---|---|---|
| Predictive Analytics | Supervised learning regression | Historical project datasets, case studies | $R^2$, RMSE accuracy, delay forecast | GBM: $R^2 = 0.89$ LSTM $R^2 = 0.92$ ~40-50% accuracy improvement |
| Resource Optimization | ANN-based, Genetic Algorithms, RL | Project records, optimization datasets | Cost/time reduction, utilization, resource allocation | RL: 47% less delay, 58% cost reduction, and 25% improved resource utilization |
| Framework/Integration | ML + BIM, ML + PMIS, dashboards | BIM models, PMIS history logs, and data from IoT sensors | The time spent on planning, the number of detected conflicts, and the rate of deployment | 30% planning time reduction, 73% conflict detection, 76.3% phased deployment success |

This structured approach ensures reproducibility and transparency, consistent with the standards of evidence-based review research *(Page et al., 2021)*.

## 3. LITERATURE REVIEW

### 3.1 Traditional Scheduling and Its Limitations

CPM and PERT have dominated construction scheduling systems for decades, but research demonstrates that the traditional CPM and PERT can only predict actual construction duration with an accuracy of 41.3% (Holovchenko, 2024). These techniques establish a specific order of work and schedule critical activities, with consideration to probabilistic-based deterministic or formulating duration estimation (Kerzner, 2019; Hegazy & Menesi, 2021). In reality, construction job sites are dynamic with varying labor productivity, equipment availability, supply chain interruptions and design changes. Since even CPM and PERT consider only static network logic and deterministic activity relationships, these are not adaptable to changing environment (Taheri, 2024; Chatterjee & Prasad, 2022). In addition, it is difficult to have real-time progress monitoring because changes in the schedule of CPM/PERT-based software (e.g., Microsoft Project, Primavera P6) are usually made manually, resulting in a significant reduction in manual labour. With the expanding project size and complexity, deterministic planning has difficulties in predicting cascading delays or measuring uncertainty propagation (Sweis et al., 2023). These limitations have led to the move towards data-driven, algorithmic scheduling and the learning to plan approach in which systems learn rather than assume static predictions about planning (Jaroudi et al., 2023; Shinde, 2024).

## 3.2 ML for Predictive Scheduling

Learning from historical project data, Machine Learning (ML) can be used to predict how long projects will last and what the cost variance and delay probability are. In contrast to the ordinary regression models, ML is able to model non-linear interaction between factors in construction projects such as the number of labor forces, productivity of resources and cost indices and exogenous risk variables (Seyişoğlu et al., 2024; Li & Wu, 2022).

### 3.2.1 Predictive Time and Cost Forecasting

Several research works demonstrate that supervised learning models are superior to regression methodologies for construction forecasting:

Random Forest (RF) models can generate strong predictions on duration by taking the average from multiple decision tree-based algorithms, and better resist noisy and incomplete records.

Support Vector Regression (SVR) has been used to predict the schedule delay by modelling the nonlinear resource–duration relationship (Nabeel, 2024; Mahamid, 2021).

Artificial Neural Networks (ANN) have been employed to establish the relationship between productivity and cost performance with working conditions, showing success at generalizing in multi-dimensional scheduling environments (Shinde, 2024; El-Sayegh & Bashir, 2022)
More recent ensemble methods have been proven to be able to better predict the software development effort, such as GBM or XGBoost, especially when training datasets include different project sizes (Jain et al., 2022; Pawar & Kothari, 2023).

### 3.2.2 Delay and Risk Prediction

ML for risk prediction focuses on early warning and roles for early interventions:

i. Long Short-Term Memory (LSTM) recurrent neural networks can interpret schedule development as a time sequence problem and derive delay propagations trends (Nabeel, 2024; Kim & Han, 2022).
ii. Naïve Bayes and Bayesian Network models were used for risk classification under uncertainty (Abbas et al., 2021).
iii. BIM with ML based frameworks support visualization and identification of conflicts during their creation as they relate 3D sequences of construction activities to performance metrics (Jaroudi et al., 2023; López et al., 2024).

Together, these studies indicate that ML shifts scheduling from reactive reporting to predictive scenario-based forecasting.

## 3.3 ML for Resource Optimization

In the classical sense, resource allocation has been addressed with heuristics and mixed-integer programming approaches that suffer from non-linear trade-offs between time, cost and workforce levelling (Aboel-Hassan & Hassan, 2019). ML provides the opportunity to dynamically optimize by picking up optimal allocation patterns from previous project data. ANN-optimized machine loading balance and optimization for the workforce planning have been demonstrated (Shinde, 2024; Jha & Iyer, 2022). Genetic Algorithms (GA) are evolved over successive mutation –selection cycles which minimizes the total project duration (Nabeel, 2024; Rezaei et al., 2023). Reinforcement Learning (RL) agents automatically learn scheduling policies via simulation projects engagement and show the capability of multi-constraint schedule (Zhang & Cheng, 2024; Liu et al., 2023). Nonetheless, high computational time and requirement of good quality data are the drawbacks.

### 3.4 Integration & Framework Studies

Work in recent years has focused on the integration of ML with BIM and PMIS for automatic and real-time schedule management.ML enables the automatic generation of a 4D BIM schedule from model elements (Cho & Kang, 2022; Jaroudi et al., 2023). Machine-learning powered predictive alerts on big-data projects dashboards enable dynamic schedule management (Nabeel, 2024).
Collaboration tools with AI assistance to enable virtual teams and decision-making processes (Taheri, 2024). However, the lack of common denominators in SLs lead to challenges toward integration owing to incompatible data structures and proprietary software platforms (Almalki & Alshibani, 2023; Seyişoğlu et al., 2024).

### 3.5 Global Research Trends in ML for Construction Management

The literature on and exploration of machine learning (ML) applications in the construction management domain have seen a strong trend in the mid-10s, with increasing recognition of its tremendous impact on the industry (Tam & Toan, 2021). Based on a scientometric review of 161 papers, the five most important uses can be summarised as: (1) risk analysis and reduction, (2) safety management, (3) cost prediction and forecasting, (4) schedule control and (5) energy demand analysis for buildings. The United States is at the top of publications with 35%, followed by China (30%) and Australia (15%), indicating worldwide participation in this area of study (Tam & Toan, 2021). The number of publications shows an exponential increase after 2014- From 19 studies published between 1999 and 2013 to a total of 141 publications from January 1, 2014 until October,2020 (Tam & Toan, 2021). Leading journals such as Automation in Construction, Journal of Computing in Civil Engineering and Journal of Construction Engineering and Management began to be the main publication outlets. Recent deep learning implementations in the construction management include: progress monitoring, safety warning systems, equipment management and IoT data integration (Elghaish et al., 2021).

### 3.6 Implementation Challenges and Critical Barriers

#### 3.6.1 Data Quality and Availability Issues

Schedule information remains predominantly proprietary, subject to confidentiality. From 560 project files in a systematic research study, only 302 (54%) of these were of sufficient data quality for model training—an attrition rate of 46% (Fitzsimmons et al., 2022). The fragmentation of data further exacerbates availability challenges, with each organization using different project management tools that don't share a common data schema or field definitions. This lack of uniformity in the industry would require a considerable amount of data transformation and cleansing, which apparently consumes 40–60% of the ML implementation effort (Datta et al., 2024). Construction schedules have few task descriptions, which is less text for machine learning and natural language processing technique to model upon, and different definitions of outcomes between organisations have contributed a barrier to validate the cross-project models (Tam & Toan, 2021).

#### 3.6.2 Model Generalization and Transfer Learning

The cross-project transferability is yet an open problem, which refers to ML models built on infrastructure projects performing poorly when they are transferred to commercial or residential construction (Johansson, 2024; Yao et al., 2024). Differences are produced by different risk patterns, regional differences in labor and weather, differences in project size and complexity, and kind of contract. Transfer learning and domain adaptation methods offer more promising solution however are yet to be developed. Firms need to accommodate model accuracy and transparency, as deep learning offers better predictive accuracy at the expense of a comprehensible decision logic (Datta et al., 2024).

#### 3.6.3 Integration with Project Management Systems

Current Project Management Information Systems (PMIS) software lacks standard APIs or data exchange protocols, and focuses on data entry and reporting at the expense of ML integration (Datta et al., 2024; Al-Sinan et al., 2024). The same cannot be said about real-time integration of PMIS data, because many PMIS are inherently batch-processed solutions which do not support on-line updates of ML models. System performance is heavily influenced by architectural choices whereby cloud-based solutions decrease computational latency by 74.3% compared to on-premises deployments (Ahmad et al., 2025). Successful deployment needs phased roll-out plans, organizations that have used gradual approaches have reported 76.3% success of the deployment while 31.5 percent for comprehensive implementation (Ahmad et al., 2025).

#### 3.6.4 Human Factors and Adoption Barriers

User interface design advancements increase user acceptance by 68.9%, however, trust in AI recommendations is only 41.7% of construction practitioners (Ahmad et al., 25). The best human answer is 28% with a utilization override rate of 17.3%, which shows that the crowd still does not fully trust machines for some key decisions. Early pilots tackling a specific scheduling issue have shown an ROI of 3.27:1 in 7.5 months whilst developing capacity to scale their technical capability (Ahmad et al., 2025). If companies are to succeed in applying the technology, they need systems that help them develop AI literacy and better skills.

### 3.7 Recent Advances and Emerging Directions

#### 3.7.1 Natural Language Processing for Scheduling

The context of transformers and attention-based models, implicit dependencies and scheduling relationships are learned through attention mechanisms without having to manually construct constraint matrix (Amer et al., 2021; Al-Sinan et al., 2024). ML transformer language models learn building construction vocabulary vectors based on a few words to extract activities from previous schedules, however, issues are raised concerning domain specific words and shortcuts in construction terminology.

#### 3.7.2 Predictive Analytics and Real-Time Optimization

More advanced architectures now incorporate data acquisition, pre-processing, model training and real-time optimization and feedback systems and use more than one ML paradigms like supervised, unsupervised and reinforcement learning (Ahmad et al., 2025). These systems are designed based on taking many inter-related variables at one time and get the time-to-time self-improvement by learning machinery. IoT censoring of the construction operations have 94.30% coverage, real time complete monitoring and adaptive scheduling (Ahmad et al., 2025). Predictive models optimize work site design, and resource planning by predicting resource needs, examine potential bottlenecks in the process to improve flow of operations and to make the process more efficient (Captech, 2024).

#### 3.7.3 Cost Estimation and Optimization

The optimization for intelligent building construction cost mitigates the difficulty in Modeling of design change, supply chain instability and labor cost differences, making the estimation as accurate as possible (Zhang et al., 2024). Deep learning filter systems assemble detailed and realistic budgets from day one using regional labor and material costs as well as market conditions. Such supplier’s performance analysis will allow construction firms to determine the top-performing suppliers, thus be able to negotiate better terms through procurement optimization (Captech, 2024). Companies that have deployed AI into cost management report dramatic decreases in over-budgeting and improved financial predictability.

## 4. RESULT ANALYSIS AND DISCUSSION

This review synthesized 25 peer-reviewed studies on machine learning applications in project scheduling, organized across three thematic clusters: (1) predictive analytics, (2) resource optimization, and (3) system integration. Key findings demonstrate ML's superiority over traditional methods, with 40-50% improvements in accuracy, 47% reductions in delay, and 58% reductions in costs (Johansson, 2024; Yao et al., 2024).

### 4.1 Performance Analysis of ML Models

#### 4.1.1 Supervised Learning Model Performance

Different ML model works differently in Project Scheduling. GBM ($R^2 = 0.89$, MAE = 3.2 days) and LSTM ($R^2 = 0.92$) achieved superior performance compared to traditional methods (CPM: 41.3% accuracy). Statistical validation through ANOVA ($p = 0.004$) and paired t-tests ($p = 0.002$) confirmed significance (Fitzsimmons et al., 2022; Johansson, 2024). In Table 3, the comparative analysis of different ml techniques.

Table 3: Comparative analysis of different ML techniques

| ML Technique | Accuracy/$R^2$ | Primary Application | Source |
|---|---|---|---|
| Gradient Boosting (GBM) | 0.89 | Duration Forecasting | Johansson, 2024 |
| LSTM Networks | 0.92 | Temporal Delay Propagation | Nabeel, 2024 |
| Random Forest (RF) | 0.86 | Resource Prediction | Seyişoğlu et al., 2024 |
| Support Vector Machine (SVM) | 0.74 | Risk Classification | Johansson, 2024 |

#### 4.1.2 Risk Prediction Results

Hybrid approaches combined Gaussian Mixture Modeling with Empirical Bayesian Networks and SVMs achieved 54.4% improvement over Monte Carlo Simulation, reducing prediction error from 36.6 weeks to 16.6 weeks across 293263 tasks (Fitzsimmons et al., 2022). SVM categorization achieved 74 % accuracy in identifying high risk activities, enabling proactive mitigation (Johansson, 2024).

### 4.2 Resource Optimization Results

Performance drivers: material cost (35%), task duration (25%), weather (15%), schedule quality (12%) and concurrent task impact on the work week's remaining flex pool intensity (13%) were found by Random Forest feature importance analysis, allowing for 25% resource allocation accuracy improvement compared to traditional methods. Reinforcement Learning demonstrated 47% average delay reduction, 58% cost overrun reduction, 92% resource utilization (78% baseline) and convergence within 2,000–4,000 training episodes (Johansson, 2024; Yao et al., 2024). RL can be adaptive and recover quickly under the disturbances, solving this drawback well of static optimization approach (Zhang & Cheng, 2024).

### 4.3 BIM Integration and Project Management Systems

BIM generates a rich information of geometric, semantic and relational data in support of an intelligent automation within the scheduling domain. By developing a BIM and machine learning-supported integrated system based on ABC principles (BIM-ML), construction activities are automatically mined from 3D models, leading to preliminary schedules with 30% less stairs group go effort needed in manual planning and an activity recognition accuracy of 85% (Al-Sinan et al., 2024) ML algorithms detected 73% of scheduling misalignment prior to becoming manifest as delays, which in turn reduced coordination failures and rework costs by 21-28% (Jaroudi et al., 2023). The implementation achieved 28-32% reduction in a constant planning time across the variety of projects, and transformer-based NLP models efficiently learned the implicit activity sequencing without explicit rule programming (Amer et al., 2021; Al-Sinan et al., 2024). The site was covered 94.30% by IoT with the sensor network, which made it possible to monitor project situations and adjusted the schedule. ML-enabled dashboards integrated this real-time data (equipment GPS, material inventory and labour tracking) with predictive alerts that predicted early warning sign of emerging risks with a precision of 80–85% and lead time 2–3 weeks ahead (Ahmad et al., 2025). Cloud-based solutions reduced the computational latency by 74.3% and phased deployment also had a higher successful implementation rate at 76.3% for staggered models, relative to comprehensive system integration (31.5%) (Ahmad et al., 2025). Pilots achieved an ROI of 3.27 :1 in 7.5 months and developed organizational capabilities. Organizations monitored by BIM-ML-IoT dashboards reduced planning time and equipment downtime by 45-52% and 38-40%, respectively (Holovchenko, 2024).

## 5. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

### 5.1 Data Scarcity:

46% of project file rejection (Fitzsimmons et al., 2022) suggests that industry-wide data governance issues persist. Improved model training and validation could be achieved if standardized data collection protocols became the norm, as well as industry data repositories.

### 5.2 Geographic/Contextual Variation

A description was made of selected international projects (identifying the lower levels of interval grant amounts) in which 18% had greater intervention values. The transferability of ML models between geographic areas, economic settings and construction sectors is unclear and needs to be further investigated (Johansson, 2024).

### 5.3 Model Interpretability

The black-box characteristic of GBM makes it less preferable to project managers who wish to receive interpretative decisions. Future work that integrates high-performance models together with interpretability mechanisms (e.g., SHAP values and attention mechanisms) will improve practical acceptance (Datta et al., 2024).

### 5.4 Real-Time Implementation

To achieve the benefits of viewing results from a historical perspective using complete project data, real time implementation requires development across IoT sensors, cloud computing infrastructure and the standardization of Project Management Information System (PMIS). However, such an infrastructure is not always presents in the construction industry (Ahmad et al., 2025).

### 5.5 Transfer Learning

Cross-project model erosion (15–25% $R^2$ reduction) requires transfer learning studies. Domain adaptation and fine-tuning methods might help make models more readily applicable across different construction sectors and in different geographies.

## 6. CONCLUSION

Traditional deterministic and stochastic approaches, such as Critical Path Method (CPM) and Program Evaluation and Review Technique (PERT), though widely used historically in project scheduling, have limitations in managing complexity with inherent uncertainty. In this article, we have discussed the potential of ML in meeting these challenges by being adaptive and making decisions (prediction) for intelligent resource allocation, scheduling, etc.

The body of literature reviewed between 2015 and 2025 shows that supervised learning models, such as Random Forest, Support Vector Regression, or Artificial Neural Networks, are superior to traditional regression methods for predicting time and cost. Deep learning-based models like LSTM and optimization-based approaches (such as Genetic Algorithm and Reinforcement Learning) improve the accuracy, along with capturing sequential dependencies of project activities, better resource utilization and reduced schedule variance (Seyişoğlu et al., 2024; Shinde, 2024).

ML integrated with BIM and Project Management Information Systems (PMIS) integration efforts have the potential to automate schedule generation and risk forecasting, shifting from traditional project control to proactive – adaptive management (Jaroudi et al., 2023; Nabeel, 2024). Notwithstanding, some limitations persist: data scarcity, no interoperability, no unified frameworks, and a lack of explanation often preclude the practical deployment of models in real-world environments (Taheri, 2024).

Future research will require standardized open datasets, hybrid ML frameworks, and XAI mechanisms for further development of ML-enabled project scheduling. As predictive analytics, optimaization, and digital twin technology merge in research, project management is expected to become a smart, adaptive scheduling system, improving accuracy, cost effectiveness and resilience.

## DECLARATION OF USE OF AI

We **utilised** Grammarly for **proofreading** grammar and Gemini to assist **with formatting citations** according to APA standards. All AI-generated suggestions were critically reviewed and validated to ensure accuracy and academic integrity.

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