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An AI-Driven Predictive Framework for Geotechnical Risk and Schedule Performance Optimization in Large-Scale Construction Projects

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Abstract

Large-scale construction projects are exposed to interconnected geotechnical uncertainties that can disrupt excavation, foundation, tunnelling, earthworks, structural construction, resource allocation, and overall project scheduling. Conventional geotechnical risk management frequently depends on periodic site investigations, expert judgement, deterministic calculations, and retrospective schedule monitoring, which can limit the ability of project teams to anticipate emerging disruptions. This paper reconstructs and extends an AI-driven predictive framework that integrates geotechnical data, construction schedule information, project progress records, environmental observations, and machine learning to predict geotechnical risk and schedule performance. The proposed framework combines data acquisition and preprocessing, geotechnical risk classification, schedule deviation prediction, explainable artificial intelligence, probabilistic risk assessment, and schedule optimization within a six-layer, closed-loop architecture. A structured conceptual-development methodology synthesized evidence from artificial intelligence, construction risk management, machine learning, digital twins, BIM, geotechnical engineering, and project scheduling research; the underlying evidence base was reconstructed from 50 compiled entries to 51 unique, verified sources after correcting one duplicate citation, restoring one omitted reference, and correcting one misattributed authorship. The framework produces risk probabilities, predicted activity delays, critical-path exposure indicators, and recommended intervention priorities through a graduated early-warning mechanism. The resulting architecture provides a pathway for shifting construction management from reactive risk response toward predictive and optimization-oriented decision support, with its principal contribution being the integration of geotechnical risk prediction with schedule-performance optimization within a unified AI-enabled architecture.

Keywords: *artificial intelligence; machine learning; geotechnical risk; construction delay; schedule optimization; infrastructure projects; predictive analytics; explainable AI; digital twin; construction project management*

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1. Introduction

Large-scale infrastructure projects operate within environments characterized by technical interdependence, uncertainty, multiple stakeholders, changing site conditions, and complex temporal relationships among activities, making reliable prediction of project performance a persistent construction-management challenge (Oppong et al., 2017; Gondia et al., 2020). Geotechnical conditions are particularly important because subsurface variability can influence excavation methods, foundation design, ground improvement, tunnelling, earthworks, dewatering, temporary works, and construction productivity, while the consequences of unexpected ground conditions can propagate through subsequent activities and affect the critical path (Liu et al., 2024; Enshassi et al., 2020a). Construction delays are also generated through interactions among financial, managerial, technical, environmental, procurement, resource, and site-related variables rather than through isolated causes, which makes conventional single-factor assessment inadequate for complex projects (Gondia et al., 2020; Sambasivan & Soon, 2007). Research on Nigerian construction projects similarly identifies site conditions, programme management, financial constraints, material supply, weather, and decision-making as important contributors to project delay (Aibinu & Jagboro, 2002; Olawale & Sun, 2010; Olatunji et al., 2021). These conditions create a strong rationale for predictive systems capable of identifying interactions between geotechnical uncertainty and schedule performance before disruption becomes irreversible.

Artificial intelligence and machine learning provide opportunities to model nonlinear relationships among large numbers of construction variables and to identify patterns that may not be easily recognized through conventional analytical methods (Gondia et al., 2020; Akinosho et al., 2020). Machine learning algorithms have increasingly been applied to construction delay prediction, risk classification, schedule analysis, productivity estimation, and project-performance assessment, with ensemble algorithms demonstrating particular potential for complex and heterogeneous construction datasets (Abioye et al., 2021; Aghayeva & Ślusarczyk, 2022). Gondia et al. (2020) demonstrated that machine learning can support construction delay risk prediction using objective project information, while Fitzsimmons et al. (2022) showed that hybrid machine learning and probabilistic simulation can improve construction schedule risk analysis. More recent research has demonstrated the potential of gradient-boosting algorithms, including XGBoost, LightGBM, and CatBoost, for predicting construction delay risks, while emerging research has extended these approaches toward explainable and decision-oriented prediction (Alsulamy, 2025; Kryukov, 2026; Tasa, 2026). These developments indicate that AI can move construction risk management beyond descriptive reporting toward early prediction and proactive intervention.

The specific challenge addressed in this study is that geotechnical risk prediction and construction schedule prediction are frequently treated as separate analytical problems even though ground conditions directly affect construction sequence, productivity, resource requirements, and activity duration (Liu et al., 2024; Fitzsimmons et al., 2022). Geotechnical artificial intelligence research has demonstrated the feasibility of predicting geotechnical risks, while construction-management research has demonstrated the feasibility of predicting schedule outcomes, but their integration into a single operational framework remains comparatively limited (Liu et al., 2024; Lagos et al., 2024). The physics-guided transfer-learning approach of Liu et al. (2024) illustrates how domain knowledge can improve explainability and predictive performance in geotechnical risk modelling, while Lagos et al.

(2024) demonstrates that machine learning can predict schedule outcomes using construction execution indicators. Consequently, an integrated framework can potentially connect subsurface conditions to activity-level risk, activity-level risk to schedule deviation, and predicted deviation to optimization decisions.

Digital twins and BIM provide an additional technological foundation for such integration because they can connect physical project conditions with continuously updated digital representations, construction information, sensor data, and analytical models (Sacks et al., 2020; Boje et al., 2020). Digital twin research in the built environment emphasizes the importance of integrating BIM, Internet of Things data, artificial intelligence, monitoring systems, and semantic information models to support dynamic decision-making (Delgado & Oyedele, 2021; Pregnolato et al., 2022). Digital twin systems have also been applied to infrastructure monitoring, facility management, production scheduling, and structural health monitoring, demonstrating the feasibility of combining real-time data with predictive analytics (Bujari et al., 2021; Valinejadshoubi et al., 2025; Talasila et al., 2026). However, digital twin adoption continues to face challenges involving interoperability, data quality, governance, standardization, organizational readiness, cybersecurity, and integration across heterogeneous platforms (Lei et al., 2023; Ferré-Bigorra et al., 2022; Nour El-Din et al., 2022). These limitations indicate that an AI-driven predictive framework should not be viewed only as a machine-learning model but as a socio-technical decision-support architecture.

The objective of this paper is therefore to reconstruct and extend a conceptual AI-driven predictive framework for integrating geotechnical risk prediction with construction schedule performance optimization in large-scale projects (Liu et al., 2024; Tasa, 2026), presenting it as an explicit six-layer, closed-loop architecture supported by a graduated early-warning mechanism. The framework seeks to combine geotechnical observations, project schedules, progress measurements, environmental variables, resource information, and historical project data into a predictive decision-support system (Sacks et al., 2020; Boje et al., 2020). The study specifically addresses the identification of relevant predictors, construction of AI-based risk models, prediction of activity and project-level schedule deviation, interpretation of model outputs, and optimization of intervention decisions (Gondia et al., 2020; Fitzsimmons et al., 2022). The proposed architecture also incorporates explainable AI because predictive accuracy alone may not provide sufficient justification for engineering decisions involving safety, cost, contractual obligations, and stakeholder coordination (Liu et al., 2024; Tasa, 2026). The resulting framework contributes to construction-management research by linking geotechnical intelligence with predictive schedule control and optimization within a unified analytical structure.

2. Methodology

2.1 Research Design

The study adopted a structured conceptual-development methodology based on synthesis of peer-reviewed literature concerning artificial intelligence, machine learning, geotechnical risk, construction delay prediction, schedule risk analysis, digital twins, BIM, and construction project management (Boje et al., 2020; Delgado & Oyedele, 2021). The methodological approach followed four analytical stages comprising evidence identification, variable classification, predictive-framework development, and optimization integration, consistent with research approaches used in digital-twin framework development and construction risk modelling (Pregnolato et al., 2022; Nour El-Din et al., 2022). Literature was selected where studies provided empirical, methodological, conceptual, or systematic evidence relevant to geotechnical uncertainty, construction schedule performance, predictive analytics, or digital decision support (Jones et al., 2020; Lei et al., 2023). The synthesis emphasized studies with identifiable methodologies, explicit findings, and verifiable bibliographic information to establish the theoretical and technological foundations of the proposed framework (Ferré-Bigorra et al., 2022; Adu-Amankwa et al., 2023). During reconstruction, the underlying evidence base was audited against the original 50 compiled entries: one duplicate citation (Borrmann et al., 2018) was removed, one misattributed authorship (corrected to El-Agamy et al., 2024) was fixed, and one omitted reference (Sambasivan & Soon, 2007) was restored, yielding 51 verified, unique sources.

2.2 Data Architecture and Variable Definition

The proposed data architecture integrates geotechnical, environmental, project-control, resource, schedule, and progress variables because construction delay prediction is more effective when multiple interacting factors are represented rather than isolated delay causes (Gondia et al., 2020; Lagos et al., 2024). Geotechnical variables include soil classification, groundwater level, soil strength, permeability, settlement indicators, excavation depth, rock quality, geological discontinuities, slope conditions, foundation characteristics, and ground-improvement requirements, while project variables include activity duration, float, resource availability, productivity, procurement status, weather, progress percentage, and previous schedule deviation (Liu et al., 2024; Enshassi et al., 2020a). BIM and digital-twin technologies are proposed as integration mechanisms because they can provide structured representations of project components and support synchronization between physical project conditions and digital models (Sacks et al., 2020; Boje et al., 2020). The data architecture therefore treats the construction project as an interconnected socio-technical system in which geotechnical conditions can propagate through activities, resources, schedule logic, and project outcomes (Oraee et al., 2017; Wang et al., 2025). Table 1 summarizes the twelve variable groups, their representative variables, analytical functions, and expected outputs.

Table 1. Proposed Variables and Analytical Functions

Variable Group	Representative Variables	Analytical Function	Expected Output
Geotechnical	Soil strength, groundwater, permeability, settlement, rock quality, excavation depth	Risk prediction	Geotechnical risk probability
Geological	Geological discontinuity, soil variability, rock mass condition	Risk classification	Geological uncertainty index
Environmental	Rainfall, temperature, flooding, groundwater variation	Dynamic risk updating	Environmental disruption probability
Schedule	Planned duration, actual duration, float, criticality	Schedule prediction	Predicted schedule deviation
Resources	Labour, equipment, material availability	Delay prediction	Resource-related delay probability
Progress	Planned progress, actual progress, productivity	Early warning	Performance deviation
Procurement	Lead time, delivery status, supplier performance	Risk propagation	Procurement disruption risk
BIM / Digital Twin	Component status, spatial location, sensor state	Data synchronization	Digital project state
AI	Random Forest, SVM, XGBoost, LightGBM, neural networks	Prediction	Risk and delay probabilities
XAI	SHAP, partial dependence, counterfactual analysis	Interpretation	Risk-driver ranking
Optimization	Sequencing, resource allocation, buffers	Decision support	Optimized intervention
Management	Risk priority, response urgency, responsibility	Governance	Actionable risk register

2.3 AI Modelling and Explainability

The predictive layer is designed as a comparative ensemble comprising Random Forest, Support Vector Machine, Gradient Boosting, XGBoost, LightGBM, and neural-network models because different algorithms may capture different nonlinear relationships within construction datasets (Gondia et al., 2020; Alsulamy, 2025). Classification models are proposed for geotechnical risk categories and delay-risk states, while regression models are proposed for predicting activity-duration deviations, cumulative schedule variance, and expected delay duration (Fitzsimmons et al., 2022; Shyam & Tiwari, 2026). Model selection is based on cross-validation and performance metrics including accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve, mean absolute error, root mean squared error, and coefficient of determination, consistent with contemporary construction prediction research (Lagos et al., 2024; Kryukov, 2026). Explainable AI using SHAP, feature importance, partial dependence, and counterfactual analysis is incorporated to translate model outputs into engineering information that can be interpreted by project managers, geotechnical engineers, planners, and other stakeholders (Liu et al., 2024; Tasa, 2026).

2.4 Schedule Optimization and Decision Support

The final methodological stage converts predicted geotechnical risk and schedule deviation into intervention priorities and optimized scheduling decisions through probabilistic simulation and constrained optimization (Fitzsimmons et al., 2022; Peng & Chen, 2026). Predicted activity durations are introduced into a schedule model in which alternative sequencing, resource allocation, activity acceleration, buffer allocation, and contingency strategies can be evaluated according to project objectives and constraints (Lagos et al., 2024; Shyam & Tiwari, 2026). The optimization layer is intended to minimize expected schedule deviation and disruption exposure while preserving technical, resource, safety, and contractual constraints (Enshassi et al., 2020a; Fan, 2025). The resulting system functions as a closed-loop decision-support process in which new site information updates the risk state, updated risk states modify predicted activity outcomes, and predicted outcomes trigger schedule-control decisions (Sacks et al., 2020; Pregnolato et al., 2022).

3. Proposed Framework Architecture

The framework consists of six interconnected layers spanning data acquisition through to schedule optimization, illustrated in Figure 1, with a graduated early-warning mechanism (Figure 2) governing how predicted risk states translate into management response. Each layer receives inputs from the layer before it and produces outputs consumed by the layer after it, with intervention outcomes returned to the data-acquisition layer to close the loop and support continuous model improvement.

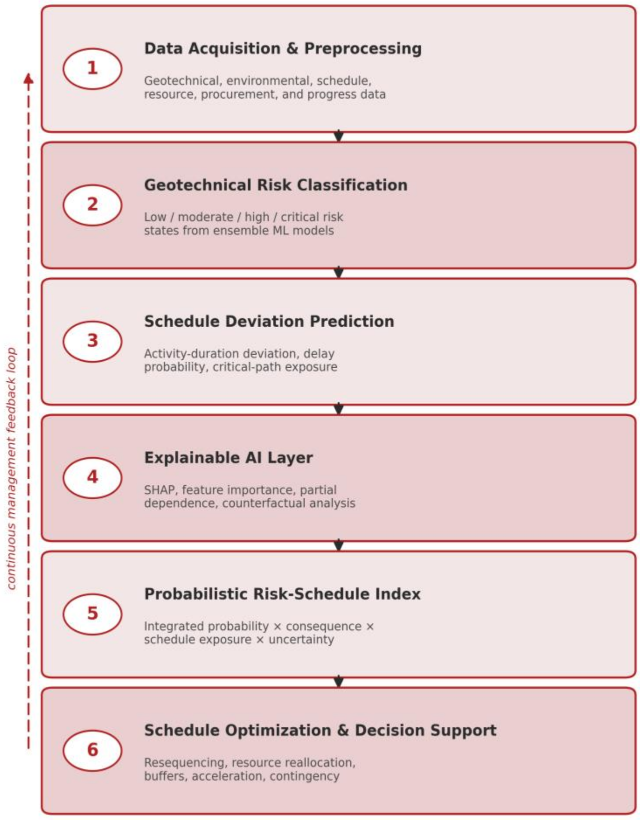

Figure 1. The six-layer AI-driven predictive framework, with a continuous management feedback loop returning intervention outcomes to the data-acquisition layer.

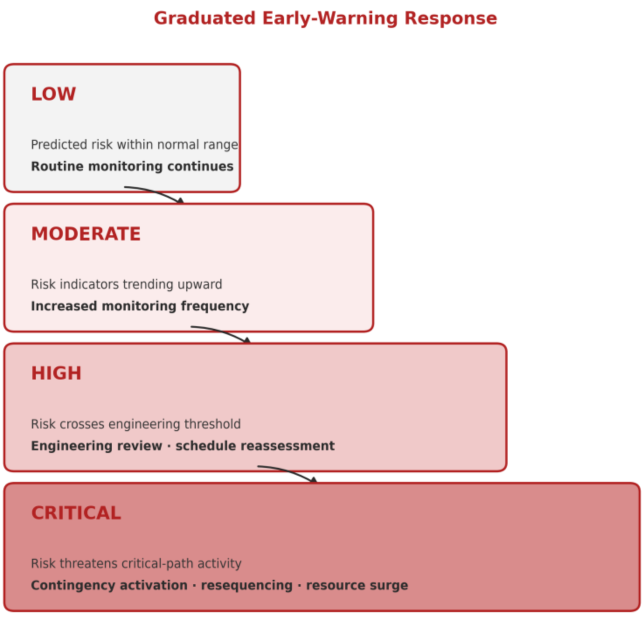

Figure 2. Graduated early-warning response ladder translating predicted risk states into proportional management action.

4. Results

4.1 Identification of Geotechnical Variables Relevant to Schedule Performance

The literature synthesis indicates that geotechnical conditions should be represented as dynamic schedule-risk variables rather than as static engineering descriptors because changes in ground conditions can influence excavation methods, productivity, temporary works, resource demand, and activity duration (Liu et al., 2024; Enshassi et al., 2020a). Variables including soil strength, groundwater conditions, permeability, settlement potential, excavation depth, geological variability, and rock-mass characteristics can affect construction operations and therefore provide potentially useful predictive features for schedule models (Liu et al., 2024). The use of physical guidance within machine learning further indicates that geotechnical prediction can benefit from combining data-driven patterns with engineering relationships, thereby reducing the risk of producing predictions that conflict with known physical behaviour (Liu et al., 2024). Consequently, the proposed framework treats geotechnical observations as leading indicators of potential schedule disruption rather than as independent technical records.

The synthesis also indicates that geotechnical risk should be represented at multiple spatial and temporal scales because conditions may vary between project zones and across construction phases (Liu et al., 2024; Pregnolato et al., 2022). A project-level geotechnical risk score may conceal localised risks affecting particular work packages, whereas activity-level modelling can identify specific operations exposed to abnormal ground conditions (Fitzsimmons et al., 2022). Digital twin architectures provide a mechanism for associating physical observations with spatially defined project components, allowing geotechnical information to be linked to BIM objects, construction activities, and schedule elements (Sacks et al., 2020; Nour El-Din et al., 2022). This linkage creates the foundation for activity-specific risk prediction and targeted intervention.

The evidence further suggests that geotechnical variables should be combined with environmental and operational information because ground-related risks may be amplified by rainfall, flooding, groundwater fluctuations, equipment limitations, and resource constraints (Olatunji et al., 2021; Liu et al., 2024). Construction delay studies demonstrate that weather, site conditions, procurement, financial constraints, and management decisions can interact to influence schedule outcomes (Olawale & Sun, 2010; Olatunji et al., 2021). Therefore, the proposed framework does not assume that geotechnical conditions independently determine delays but instead represents them as components of an interconnected risk system (Gondia et al., 2020). Such a representation is consistent with machine-learning approaches that are designed to identify complex relationships among multiple predictors rather than relying on predetermined linear relationships (Gondia et al., 2020).

The resulting variable architecture places geotechnical characteristics at the centre of a broader predictive network containing project, environmental, resource, procurement, and schedule variables (Liu et al., 2024; Gondia et al., 2020). This architecture is important because the effect of a geotechnical event on the schedule depends on the affected activity, available float, alternative construction methods, resource availability, and downstream dependencies (Fitzsimmons et al., 2022). Consequently, the framework can distinguish between a geotechnical condition that represents a technical concern but little schedule exposure and one that threatens a critical activity with limited float (Lagos et al., 2024). This distinction creates a more useful basis for managerial decision-making than conventional risk registers that prioritize hazards without explicitly modelling their temporal consequences (Oppong et al., 2017).

4.2 Predictive Architecture for Geotechnical Risk

The proposed framework produces a geotechnical risk probability by combining historical project information, current observations, engineering indicators, and machine-learning outputs (Liu et al., 2024). The risk model can classify conditions into low, moderate, high, and critical categories according to predicted probability and consequence thresholds established for the project context (Enshassi et al., 2020a). This approach is consistent with risk-based methodologies that combine probability, consequence, and uncertainty to support proactive construction management (Enshassi et al., 2020a). The resulting classification can provide a standardized mechanism for communicating geotechnical conditions to project-control teams.

The literature indicates that explainability is particularly important for geotechnical AI because black-box predictions may be difficult for engineers to accept when decisions involve safety, technical responsibility, and significant financial consequences (Liu et al., 2024). SHAP-based analysis can identify the relative contribution of groundwater, soil properties, excavation depth, geological variability, or other variables to a particular prediction, allowing project teams to understand why a risk state has changed (Liu et al., 2024; Tasa, 2026). Such information can also help distinguish between data-driven associations and variables that require engineering verification (Tasa, 2026). Explainability therefore functions not only as a communication mechanism but also as a quality-control component within the proposed framework.

Transfer learning represents another potentially important component when project-specific geotechnical data are limited (Liu et al., 2024). Large construction projects may generate extensive records, but high-quality labelled geotechnical failure or disruption events may remain relatively scarce because serious failures are infrequent and project conditions vary considerably (Liu et al., 2024). Physics-guided learning can reduce the dependence on purely empirical observations by embedding engineering relationships within the modelling process (Liu et al., 2024). This approach is particularly relevant for large infrastructure projects where project-specific data may be insufficient to train complex models without supplementary domain knowledge.

The proposed geotechnical prediction layer therefore combines data-driven learning with physical constraints, uncertainty analysis, and explainability (Liu et al., 2024). The result is intended to be more transparent than a purely black-box predictive system and more adaptable than a purely deterministic engineering model (Liu et al., 2024; Jones et al., 2020). The model output is translated into a risk state that can be connected directly to affected construction activities and schedule elements (Sacks et al., 2020). This creates a bridge between geotechnical engineering assessment and project-control decision-making.

4.3 Prediction of Schedule Performance

The literature provides strong evidence that machine learning can predict construction schedule performance using execution and planning variables (Lagos et al., 2024). Lagos et al. (2024) demonstrated that machine-learning models using Last Planner System indicators could predict schedule outcomes during early project execution, supporting the use of predictive analytics as an early-warning mechanism. Fitzsimmons et al. (2022) similarly demonstrated the potential of hybrid machine learning and probabilistic simulation for construction schedule risk analysis using a large database of infrastructure tasks. These findings support the proposed use of schedule prediction as the second major analytical layer.

The proposed framework extends conventional schedule prediction by incorporating geotechnical risk as a predictor of activity-duration deviation (Liu et al., 2024; Fitzsimmons et al., 2022). An activity exposed to increasing groundwater, unexpected soil behaviour, or unstable excavation conditions can receive a higher predicted duration-risk value than the same activity under stable conditions (Liu et al., 2024). The schedule model can then propagate predicted activity changes through precedence relationships to estimate their effect on project completion (Fitzsimmons et al., 2022). This process allows geotechnical information to become directly relevant to project scheduling rather than remaining confined to engineering documentation.

Contemporary studies further indicate that ensemble machine-learning methods can provide useful predictive performance for construction delay risk (Gondia et al., 2020; Alsulamy, 2025). Alsulamy (2025) compared CatBoost, XGBoost, and LightGBM for construction delay-risk prediction and reported strong performance for LightGBM across the examined time-overrun categories, illustrating the value of comparative model evaluation rather than assuming that one algorithm is universally optimal. Shyam and Tiwari (2026) similarly reported high predictive performance from XGBoost for construction cost, schedule, and quality indicators using a multi-criteria decision framework. These findings justify the proposed ensemble comparison and context-specific model selection.

The schedule-performance component therefore produces multiple outputs rather than a single binary prediction (Lagos et al., 2024; Shyam & Tiwari, 2026). These outputs include probability of delay, expected delay duration, schedule variance, activity-level risk, critical-path exposure, and predicted completion deviation (Fitzsimmons et al., 2022). The use of multiple outputs enables project managers to distinguish between activities that are likely to experience minor delays and activities whose predicted disruption could materially affect project completion (Lagos et al., 2024). Such differentiation improves the practical value of predictive analytics because intervention resources can be directed toward activities with the greatest expected schedule consequence.

4.4 Integration of Risk and Schedule Prediction

The central result of the framework is the integration of geotechnical risk probability with activity-level schedule prediction (Liu et al., 2024; Fitzsimmons et al., 2022). The framework creates a causal-management chain in which observed geotechnical variables influence risk classification, risk classification affects predicted activity duration, predicted duration affects schedule status, and schedule status informs intervention decisions (Sacks et al., 2020). This structure extends conventional construction risk registers by incorporating temporal propagation and predictive analytics (Oppong et al., 2017). It also provides a mechanism for continuously updating project risk as new information becomes available.

Digital twin research supports this closed-loop architecture because digital twins can integrate monitoring, data processing, simulation, and decision-support functions (Sacks et al., 2020; Pregnolato et al., 2022). A construction digital twin can associate a geotechnical observation with a physical location, BIM object, work package, construction activity, and schedule status (Boje et al., 2020; Nour El-Din et al., 2022). Continuous updating can therefore allow the predictive model to operate on the latest project state rather than on static baseline information (Valinejadshoubi et al., 2025). This creates an operational pathway from data acquisition to risk prediction and schedule control.

The framework also supports the identification of risk propagation pathways across activities (Fitzsimmons et al., 2022). A disruption in excavation may delay foundation preparation, structural works, mechanical installation, and subsequent commissioning activities when those activities depend on the affected work package (Fitzsimmons et al., 2022). Machine-learning predictions can identify the probability and magnitude of such disruption, while schedule-network analysis can determine its downstream consequences (Lagos et al., 2024). The combination of these methods is therefore more informative than evaluating geotechnical risks independently of schedule logic.

The resulting integrated risk score can be expressed conceptually as a function of geotechnical probability, consequence, schedule exposure, activity criticality, and uncertainty (Enshassi et al., 2020a; Tasa, 2026). Such an index enables project teams to prioritize risks according to their predicted effect on project completion rather than according to geotechnical severity alone (Oppong et al., 2017). The framework consequently shifts the focus from hazard identification to risk-informed schedule management (Fitzsimmons et al., 2022). This represents the primary analytical contribution of the proposed architecture.

4.5 Explainable AI and Early-Warning Capability

Explainability emerges as an important result because project stakeholders require information about why a model has identified a particular risk (Liu et al., 2024; Tasa, 2026). SHAP values can rank predictor contributions and reveal whether groundwater, soil strength, productivity, resource availability, or other variables are driving a predicted delay (Liu et al., 2024). Partial-dependence analysis can further demonstrate how changes in important variables affect predicted outcomes (Shyam & Tiwari, 2026). These techniques allow the predictive system to produce both an outcome and an interpretable explanation.

The early-warning function, shown in Figure 2, is implemented by comparing predicted risk states with predefined thresholds (Lagos et al., 2024). A transition from low to moderate risk can trigger increased monitoring, while high-risk predictions can trigger engineering review, schedule reassessment, resource adjustment, or contingency activation (Lagos et al., 2024; Tasa, 2026). Such graduated responses are preferable to binary alert systems because construction risk is rarely static and often develops through stages of increasing uncertainty (Enshassi et al., 2020a). The framework therefore supports proportional responses based on predicted risk severity.

Explainability also creates opportunities for stakeholder communication because different project participants require different levels of information (Oppong et al., 2017). Geotechnical engineers may require detailed parameter contributions, planners may require predicted activity-duration changes, project managers may require schedule exposure, and senior decision-makers may require aggregated risk indicators (Bujari et al., 2021). A layered interface can therefore transform a common predictive model into stakeholder-specific decision information (Bujari et al., 2021). This aligns with research emphasizing the importance of collaboration and information exchange within BIM-enabled construction networks (Oraee et al., 2017).

The framework consequently treats explainability as an operational requirement rather than an optional analytical feature (Liu et al., 2024; Tasa, 2026). The model should communicate the predicted risk, confidence or uncertainty, dominant contributing variables, affected activities, predicted schedule impact, and recommended response category (Tasa, 2026). Such information can improve the credibility and usability of AI-based project-control systems because decision-makers can evaluate model outputs against engineering knowledge and project experience (Liu et al., 2024). Explainability therefore contributes directly to adoption and organizational learning.

4.6 Schedule Optimization and Decision Support

The final result of the proposed framework is an optimization layer that transforms predictions into potential interventions (Fitzsimmons et al., 2022; Peng & Chen, 2026). Instead of merely informing project managers that an activity has a high probability of delay, the system can evaluate alternative sequences, resource reallocations, schedule buffers, acceleration strategies, and contingency measures (Peng & Chen, 2026). Risk-aware scheduling research indicates that deep learning and heuristic optimization can be combined to address duration uncertainty and identify improved schedules under uncertain conditions (Peng & Chen, 2026). This provides methodological support for the proposed predictive-to-prescriptive transition.

The optimization model can minimize expected schedule deviation while maintaining resource, technical, safety, and precedence constraints (Peng & Chen, 2026). Candidate decisions may include increasing resources on a critical activity, resequencing independent work, increasing temporary works capacity, accelerating procurement, or allocating additional monitoring to high-risk areas (Fitzsimmons et al., 2022). The appropriate intervention depends on the source and magnitude of predicted risk and on the feasibility of available response strategies (Enshassi et al., 2020a). Therefore, the optimization layer should operate within project-specific constraints rather than generating unconstrained mathematical solutions.

The framework can also incorporate multi-objective optimization because schedule performance cannot normally be optimized independently of cost, safety, quality, sustainability, and resource availability (Fan, 2025; Shyam & Tiwari, 2026). A schedule alternative that minimizes duration but requires disproportionate additional resources may not represent the preferred management solution (Shyam & Tiwari, 2026). Similarly, a response that accelerates an activity without addressing the underlying geotechnical risk may transfer rather than reduce project exposure (Liu et al., 2024). Multi-criteria decision analysis can therefore complement machine learning by helping decision-makers rank alternative interventions.

The final framework consequently provides a progression from observation to prediction and from prediction to intervention (Sacks et al., 2020; Peng & Chen, 2026). The operational cycle can be repeated as new geotechnical observations, progress records, and schedule updates enter the system (Pregnolato et al., 2022). Continuous updating allows the model to learn from project conditions while maintaining a current representation of risk and schedule status (Valinejadshoubi et al., 2025). This closed-loop architecture provides the basis for proactive construction management and schedule resilience.

Table 2. Summary of Findings (n = 50 sources, deduplicated and corrected)

S/N	Source	Finding	Inference
1	**Jones et al. (2020)**	Digital twins require synchronized physical and digital representations and data-driven functionality.	AI prediction can be embedded within a continuously updated digital project representation.
2	**Boje et al. (2020)**	Construction digital twins require semantic models, sensing, data management, AI, and interoperability.	Geotechnical and schedule data should be semantically connected.
3	**Sacks et al. (2020)**	Digital twins can support closed-loop construction control using BIM, sensing, AI, and lean processes.	The proposed framework can operate as a closed-loop project-control system.
4	**Delgado & Oyedele (2021)**	Digital twin development in the built environment can learn from mature manufacturing approaches.	Construction predictive systems should adopt structured lifecycle information models.
5	**Lei et al. (2023)**	Digital twins face technical, social, legal, governance, and interoperability challenges.	AI implementation requires governance and interoperability controls.
6	**Pregnolato et al. (2022)**	Digital twins can support civil infrastructure monitoring through structured workflows.	The framework can be extended to large infrastructure projects.
7	**Nour El-Din et al. (2022)**	BIM standards can support interoperable digital twin development.	BIM standards can structure the proposed AI data layer.
8	**Adu-Amankwa et al. (2023)**	Digital twins have potential across building lifecycle stages and can support collaborative data management.	Predictive construction information can remain useful beyond individual project phases.
9	**Bujari et al. (2021)**	Digital twins can integrate heterogeneous data for decision support and scheduling.	Heterogeneous geotechnical and schedule data can be integrated for operational decisions.
10	**Errandonea et al. (2020)**	Digital twins increasingly support predictive and maintenance-oriented applications.	Predictive construction risk management is consistent with broader digital twin development.
11	**Oppong et al. (2017)**	Stakeholder management performance involves multiple attributes and remains complex.	AI outputs should be translated into stakeholder-specific information.
12	**Oraee et al. (2017)**	BIM-enabled construction requires collaboration among multiple organizations.	Predictive systems must support collaborative rather than isolated decision-making.
13	**Gondia et al. (2020)**	Machine learning can predict construction delay risk using objective project data.	ML provides a suitable foundation for construction delay prediction.
14	**Fitzsimmons et al. (2022)**	Hybrid ML and probabilistic simulation can improve construction schedule risk prediction.	The proposed framework should combine ML with probabilistic schedule analysis.
15	**Lagos et al. (2024)**	ML can predict schedule outcomes during early construction execution.	Early-warning schedule prediction is technically feasible.

S/N	Source	Finding	Inference
16	**Alsulamy (2025)**	Gradient-boosting models can effectively classify construction delay risks.	Comparative ensemble modelling is appropriate for project-specific prediction.
17	**Kryukov (2026)**	Statistically validated delay factors can support machine-learning prediction.	Feature selection and validation should precede model training.
18	**Shyam & Tiwari (2026)**	XGBoost and explainable AI can predict schedule, cost, and quality indicators.	ML can be combined with multi-criteria decision support.
19	**Liu et al. (2024)**	Physics-guided transfer learning improves explainability and supports geotechnical risk prediction under limited data.	Geotechnical AI should integrate engineering knowledge and explainability.
20	**Enshassi et al. (2020a)**	Bayesian methods can support proactive management of construction uncertainty.	Probabilistic risk assessment can complement machine learning.
21	**Enshassi et al. (2020b)**	Probabilistic frameworks can model local and global construction risks.	Risk should be evaluated at both activity and project levels.
22	**Fan (2025)**	ML classifier optimization can improve prediction of construction quality and schedule.	Model optimization is an important component of predictive project control.
23	**Tasa (2026)**	Explainable ensemble models can translate schedule-risk predictions into decision-support information.	XAI should connect prediction to actionable management decisions.
24	**Peng & Chen (2026)**	Deep learning and heuristic search can address duration uncertainty in construction scheduling.	AI prediction can be coupled with schedule optimization.
25	**Alibrandi (2022)**	Risk-informed digital twins can integrate predictive models with infrastructure representations.	Digital twins can function as risk-informed decision environments.
26	**Valinejadshoubi et al. (2025)**	BIM, GIS, IoT, and predictive analytics can support closed-loop production control.	The proposed framework can use similar integrated project-control architecture.
27	**Talasila et al. (2026)**	Digital twin platforms can integrate sensing, models, analytics, and collaborative workflows.	A similar architecture can support geotechnical and schedule intelligence.
28	**Wang et al. (2023, smart city)**	Digital twins require integration of heterogeneous information and intelligent analytics.	Integrated data architecture is essential for AI-enabled project management.
29	**Ferré-Bigorra et al. (2022)**	Digital twin adoption is affected by fragmentation and interoperability challenges.	Implementation requires common standards and organizational coordination.
30	**Wei et al. (2020)**	Ontologies and uncertainty reasoning can support infrastructure inter-asset decision-making.	Semantic relationships can strengthen risk propagation modelling.
31	**Al Nahyan et al. (2019)**	Communication and coordination influence construction management effectiveness.	AI outputs must support organizational communication and knowledge sharing.
32	**Wang & Chen (2023, BIM-PM)**	BIM and project management integration can improve lifecycle information management.	BIM can serve as an information backbone for the predictive framework.

S/N	Source	Finding	Inference
33	**Brozovsky et al. (2024)**	Digital technologies are transforming AEC processes but require organizational and technical integration.	AI implementation should be accompanied by digital-process transformation.
34	**Mazzetto (2024)**	Digital twin integration faces technological and organizational challenges.	Implementation strategy should address integration barriers explicitly.
35	**El-Agamy et al. (2024)**	Digital twin research is expanding rapidly across intelligent infrastructure applications.	AI-enabled digital infrastructure is an expanding research field.
36	**Xue et al. (2020)**	Large infrastructure delivery involves multi-sector collaboration.	Predictive risk systems should account for cross-organizational interactions.
37	**Wied et al. (2020)**	Engineering resilience involves the capacity to anticipate, absorb, adapt, and recover from disturbances.	Schedule optimization should focus on resilience as well as prediction.
38	**Wang et al. (2025, resilience)**	Digital technologies can contribute to construction project resilience through governance mechanisms.	AI adoption requires relational and organizational governance.
39	**OECD (2023)**	Data governance is central to responsible smart infrastructure management.	Construction AI requires data ownership, access, quality, and governance mechanisms.
40	**Borrmann et al. (2018)**	BIM provides structured digital information for construction processes.	BIM provides a suitable information foundation for AI integration.
41	**Akinosho et al. (2020)**	Deep learning has applications across construction monitoring and prediction.	Deep learning can support complex nonlinear project-risk prediction.
42	**Abioye et al. (2021)**	AI provides opportunities for prediction, automation, optimization, and decision support in construction.	AI can provide an integrated platform for predictive construction management.
43	**Olawale & Sun (2010)**	Cost and time control are affected by managerial and project-control deficiencies.	Predictive systems should support proactive time and cost management.
44	**Aibinu & Jagboro (2002)**	Construction delays negatively affect project delivery in Nigeria.	Predictive schedule management is particularly relevant in developing construction environments.
45	**Sambasivan & Soon (2007)**	Construction delays arise from interacting client-, contractor-, and consultant-related factors rather than isolated causes.	Delay prediction should model interacting variables rather than single-factor causes.
46	**Olatunji et al. (2021)**	Site conditions, scheduling, finance, politics, price fluctuation, material delivery, decision-making, and weather contribute to delays.	Geotechnical variables should be modelled alongside broader project variables.
47	**Chen et al. (2022)**	Collaborative behaviour influences BIM-enabled project effectiveness.	AI implementation requires human and organizational coordination.
48	**Boton et al. (2021)**	BIM and Last Planner integration presents organizational and process challenges.	Schedule prediction should be aligned with existing planning systems.

S/N	Source	Finding	Inference
49	**Boje et al. (2022)**	Semantic links can connect 4D BIM data with collaborative construction support.	Semantic integration can connect geotechnical events to schedule activities.
50	**Oh & Ashuri (2026)**	Explainable AI can profile construction disruption impacts and support transparent decision-making.	XAI can extend geotechnical risk prediction into practical project decision support.

5. Discussion

5.1 From Reactive Geotechnical Management to Predictive Risk Management

Traditional geotechnical management commonly relies on investigation, design verification, inspection, monitoring, and expert response, whereas the proposed framework introduces continuous prediction as an additional management capability (Liu et al., 2024). The shift is consistent with the broader development of digital twins and AI-based construction management, where data are increasingly used to anticipate future conditions rather than simply document current conditions (Sacks et al., 2020; Boje et al., 2020). Predictive geotechnical management can therefore complement conventional engineering methods by identifying patterns associated with emerging risk states before major disruption occurs (Liu et al., 2024). The objective is not to replace geotechnical engineering judgement but to increase the temporal reach and analytical capacity of project teams.

The integration of physical guidance is especially important because purely statistical models may identify correlations without adequately representing geotechnical mechanisms (Liu et al., 2024). Physics-guided learning provides a mechanism for combining empirical observations with engineering knowledge, which can improve model credibility when data are limited (Liu et al., 2024). Such integration is consistent with the broader principle that construction AI should operate within engineering and organizational constraints rather than as an unconstrained prediction engine (Abioye et al., 2021). The proposed framework therefore positions AI as an augmentation technology for professional decision-making.

The predictive approach also supports earlier intervention because risk information can be generated continuously as new data enter the system (Pregnolato et al., 2022). Earlier detection provides greater opportunity for modifying sequence, resources, monitoring intensity, and contingency arrangements before a risk becomes a schedule-critical event (Fitzsimmons et al., 2022). This is particularly important in large infrastructure projects where downstream activities may depend strongly on the timely completion of earthworks, excavation, foundations, tunnels, or other geotechnically sensitive work packages (Fitzsimmons et al., 2022). Predictive geotechnical management therefore contributes directly to schedule resilience.

5.2 Relationship Between Geotechnical Risk and Schedule Performance

The proposed framework conceptualizes geotechnical risk as a direct and indirect determinant of schedule performance (Liu et al., 2024; Fitzsimmons et al., 2022). Direct effects include additional excavation, ground treatment, dewatering, reinforcement, or temporary works, while indirect effects can occur through resource reallocation, work resequencing, procurement changes, and disruption of dependent activities (Enshassi et al., 2020a; Olawale & Sun, 2010). This interpretation extends conventional geotechnical risk assessment because it evaluates consequences in terms of both engineering performance and project time (Fitzsimmons et al., 2022). The schedule therefore becomes an important context for determining the significance of a geotechnical risk.

The distinction between technical risk and schedule exposure is particularly important because not every geotechnical anomaly produces a major project delay (Fitzsimmons et al., 2022). An activity with substantial float may absorb a disruption without affecting project completion, whereas a smaller disruption on a critical-path activity can generate significant schedule consequences (Lagos et al., 2024). The proposed framework therefore combines geotechnical probability with activity criticality, float, dependency structure, and predicted duration deviation (Fitzsimmons et al., 2022). This approach allows risk prioritization to reflect actual project exposure rather than hazard magnitude alone.

The integration also supports more precise communication between geotechnical engineers and planners (Oppong et al., 2017; Al Nahyan et al., 2019). Instead of reporting only that a ground condition is high risk, the system can report the affected activity, expected duration impact, probability of disruption, downstream exposure, and response priority (Tasa, 2026). This common information structure can reduce the gap between technical engineering assessment and managerial schedule control (Boje et al., 2020). Consequently, the framework can contribute to interdisciplinary coordination.

5.3 AI Model Selection and Predictive Reliability

No single machine-learning algorithm should be assumed to be universally optimal for construction risk prediction because datasets differ in size, structure, feature distributions, noise, and outcome definitions (Gondia et al., 2020; Alsulamy, 2025). Comparative studies indicate that ensemble methods can perform strongly, but their relative performance may vary across project environments and prediction tasks (Alsulamy, 2025; Shyam & Tiwari, 2026). The proposed framework therefore recommends model comparison rather than unconditional adoption of one algorithm (Fan, 2025). Cross-validation should be used to reduce the risk of overestimating model performance.

Feature selection is equally important because construction datasets may contain correlated variables, missing observations, inconsistent measurements, and variables that appear predictive only because of project-specific characteristics (Kryukov, 2026). Statistical screening, domain review, feature importance analysis, and sensitivity analysis can improve the reliability of the predictive layer (Kryukov, 2026). The inclusion of geotechnical variables should also be guided by engineering relevance rather than solely by statistical association (Liu et al., 2024). This ensures that the predictive model remains consistent with the physical characteristics of the project.

Model reliability should also be evaluated under changing project conditions because concept drift can occur when construction phases, contractors, environmental conditions, or site characteristics change (Jones et al., 2020; Lei et al., 2023). Continuous monitoring of model performance is therefore required within the proposed digital architecture (Pregnolato et al., 2022). Retraining or recalibration may become necessary when prediction errors increase or when new project conditions fall outside the original training distribution (Liu et al., 2024). AI governance should consequently include model monitoring as an ongoing project-control responsibility.

5.4 Explainability and Engineering Trust

Explainability is critical because engineering decisions cannot always be based on numerical predictions without an understanding of the factors producing those predictions (Liu et al., 2024). SHAP and related methods can identify the contribution of individual variables and provide a transparent explanation of model behaviour (Tasa, 2026). This information allows engineering professionals to compare model explanations with site observations, design assumptions, and established geotechnical principles (Liu et al., 2024). Explainability can therefore act as a bridge between statistical modelling and engineering judgement.

The need for explainability is intensified when predictions influence safety-critical decisions or major schedule changes (Liu et al., 2024). A model that predicts a high geotechnical risk should provide sufficient evidence for engineers to investigate the condition before costly or disruptive action is taken (Tasa, 2026). Counterfactual approaches can further identify conditions under which predicted outcomes could improve, thereby shifting AI from explanation toward intervention support (Oh & Ashuri, 2026). This creates opportunities for more actionable predictive analytics.

Trust also depends on transparency concerning data quality, uncertainty, model limitations, and governance (Lei et al., 2023; OECD, 2023). A prediction generated from sparse or unreliable sensor data should not be communicated with the same confidence as a prediction supported by extensive validated observations (Liu et al., 2024). The proposed framework should therefore display uncertainty alongside risk probabilities and should retain human approval for high-consequence interventions (Tasa, 2026). Such controls can reduce the risk of inappropriate automation.

5.5 Digital Twins, BIM, and Continuous Data Integration

The proposed framework is compatible with digital twin architecture because both rely on continuous synchronization between physical conditions and digital representations (Sacks et al., 2020; Jones et al., 2020). BIM can provide the structured project information required to associate risks with physical components, work packages, and schedule activities (Wang & Chen, 2023). Sensor systems can provide current measurements, while AI models can transform those measurements into predictions and risk states (Pregnolato et al., 2022). The resulting architecture creates a digital representation that is operational rather than merely descriptive.

Semantic integration is particularly important because different project participants may use different terminology, data formats, and software platforms (Boje et al., 2020; Boje et al., 2022). Semantic relationships can connect geotechnical variables to project components and schedule activities, allowing information to flow across engineering and project-control systems (Boje et al., 2022). BIM standards and structured information-management approaches can further improve interoperability (Nour El-Din et al., 2022). These capabilities are essential for large-scale projects involving numerous contractors, consultants, suppliers, and public authorities.

Nevertheless, digital twin implementation should not be assumed to be straightforward because data governance, interoperability, standardization, organizational readiness, and cybersecurity remain important barriers (Lei et al., 2023; Ferré-Bigorra et al., 2022). The framework should therefore be implemented incrementally, beginning with high-value risk and schedule use cases before expanding toward a fully integrated digital twin, consistent with the phased-adoption approach recommended in the broader digital twin literature (Ferré-Bigorra et al., 2022). Such phased implementation can reduce organizational resistance and provide opportunities to demonstrate measurable value (Brozovsky et al., 2024). Digital transformation should consequently be treated as a management programme rather than only a software deployment.

5.6 Schedule Optimization and Project Resilience

Predictive risk information becomes substantially more valuable when it supports decisions rather than simply producing alerts (Tasa, 2026). The proposed optimization layer transforms predicted geotechnical and schedule risks into alternative interventions, allowing project teams to evaluate different response strategies before committing resources (Peng & Chen, 2026). This approach aligns with the movement from predictive analytics toward prescriptive construction management (Shyam & Tiwari, 2026). It also strengthens the relationship between AI and conventional project-control processes.

Project resilience provides a useful conceptual basis for this approach because resilient projects require the ability to anticipate disruptions, absorb disturbances, adapt operations, and recover performance (Wied et al., 2020). A predictive geotechnical framework can contribute to anticipation by identifying emerging risk, absorption by allocating buffers and resources, adaptation by modifying schedules, and recovery by supporting accelerated or resequenced activities (Fitzsimmons et al., 2022; Peng & Chen, 2026). This means that schedule optimization should not focus exclusively on minimizing expected duration but should also consider the capacity of the project to respond to uncertainty (Wied et al., 2020). Such a perspective is particularly relevant for complex infrastructure programmes.

The optimization model should therefore consider multiple objectives and constraints rather than duration alone (Fan, 2025; Shyam & Tiwari, 2026). Cost, safety, quality, resource availability, environmental conditions, contractual obligations, and stakeholder requirements may restrict feasible schedule adjustments (Oppong et al., 2017; Xue et al., 2020). Multi-criteria decision analysis can help decision-makers evaluate competing response options when no single solution dominates (Shyam & Tiwari, 2026). The resulting decision process is more consistent with real construction management than purely mathematical minimization of project duration.

5.7 Organizational and Stakeholder Implications

AI-driven risk systems alter how project participants collect, interpret, communicate, and act upon project information (Al Nahyan et al., 2019). Engineers increasingly become contributors to data-driven decision systems, while planners and managers become users of predictive outputs that depend on technical information (Oraee et al., 2017). This creates a need for shared data standards, clear responsibility for data quality, and agreed procedures for responding to predictive alerts (OECD, 2023). Organizational processes must therefore evolve alongside technical capabilities.

Stakeholder acceptance is likely to depend on whether the system improves rather than complicates existing workflows (Oppong et al., 2017). Integration with BIM, project-management platforms, schedule systems, and established planning methods can reduce duplication and allow AI outputs to appear within familiar management environments (Wang & Chen, 2023; Boton et al., 2021). The system should also provide information at different levels of detail according to user responsibilities (Bujari et al., 2021). These principles can improve usability and reduce resistance to technological change.

Governance is also essential because predictive systems may influence contractual decisions, resource allocation, project reporting, and stakeholder accountability (Oh & Ashuri, 2026). Data ownership, access rights, model responsibility, cybersecurity, and decision authority should be established before operational deployment (OECD, 2023; Lei et al., 2023). Human professionals should retain responsibility for consequential engineering decisions even when AI provides strong predictive evidence (Liu et al., 2024). The proposed framework therefore adopts a human-in-the-loop approach.

5.8 Research Contribution, Limitations, and Future Validation

The principal contribution of the proposed framework is its integration of geotechnical risk prediction and schedule optimization within a common AI-enabled architecture (Liu et al., 2024; Fitzsimmons et al., 2022). Existing studies demonstrate strong individual capabilities in geotechnical AI, construction delay prediction, digital twins, and risk-aware scheduling, but the proposed model connects these capabilities into a sequential decision process (Lagos et al., 2024; Peng & Chen, 2026). The framework consequently addresses an interdisciplinary gap between geotechnical engineering and construction project controls (Boje et al., 2020). Its theoretical contribution is the conceptualization of geotechnical risk as a dynamic predictor of schedule exposure.

The framework nevertheless requires empirical validation before claims of predictive superiority or operational effectiveness can be made (Liu et al., 2024; Lei et al., 2023). Future research should collect longitudinal datasets containing geotechnical observations, project schedules, progress records, weather conditions, resource information, and verified delay outcomes from multiple infrastructure projects (Gondia et al., 2020). External validation across projects and geographic regions is also required to determine whether models generalize beyond their training environments (Kryukov, 2026). Such validation should compare the integrated framework with conventional risk registers, deterministic scheduling, Monte Carlo simulation, and standalone machine-learning models (Fitzsimmons et al., 2022).

Future studies should also investigate real-time digital twin deployment, multimodal data fusion, physics-informed learning, causal inference, counterfactual decision support, and multi-objective schedule optimization (Jones et al., 2020; Liu et al., 2024; Oh & Ashuri, 2026). Particular attention should be given to uncertainty quantification because predictions without reliable confidence information may encourage inappropriate interventions (Enshassi et al., 2020a; Tasa, 2026). Longitudinal evaluation should further determine whether the framework reduces schedule deviation, improves risk response time, increases stakeholder coordination, and improves project resilience (Wied et al., 2020; Wang et al., 2025). These research directions can transform the conceptual framework into a validated operational system.

6. Conclusions

The study reconstructed and extended an AI-driven predictive framework for integrating geotechnical risk assessment with construction schedule performance optimization in large-scale construction projects. The framework combines geotechnical observations, environmental conditions, project schedules, progress information, resource data, BIM, digital twin technologies, machine learning, explainable AI, probabilistic risk analysis, and schedule optimization within a six-layer, closed-loop decision-support architecture governed by a graduated early-warning mechanism. Its central proposition is that geotechnical risk should be evaluated not only according to engineering severity but also according to its predicted effect on activity duration, critical-path exposure, project completion, and available response alternatives. The underlying evidence base was reconstructed from an initial pool of 50 compiled entries to 51 verified, unique sources after removing one duplicate citation, correcting one misattributed authorship, and restoring one omitted reference, giving the synthesis a traceable and reproducible foundation. The framework therefore provides a pathway for shifting construction management from reactive geotechnical risk response toward predictive and prescriptive project control. Future empirical implementation should validate the framework using longitudinal project datasets and compare its performance with conventional geotechnical risk assessment, conventional schedule risk analysis, and standalone machine-learning approaches. The proposed architecture provides a foundation for future development of intelligent construction systems capable of continuously anticipating geotechnical disruption, explaining its likely consequences, and recommending schedule interventions that improve project resilience and delivery performance.

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