American Journal of Scholarly Research and Innovation

Volume: 4; **Issue:** 1
Pages: 578– 612
eISSN: 3067-2163

open access
Crossref

QUANTITATIVE ASSESSMENT OF AI-ENABLED CONSTRUCTION PLANNING TOOLS FOR REDUCING DELAYS IN U.S. INFRASTRUCTURE PROJECTS

Masud Rana[1];

[1]. Department of Civil and Environmental Engineering, Lamar University, USA; BSc in Civil Engineering, Stamford University Bangladesh, Dhaka, Bangladesh; Email: masudranasub97@gmail.com

Doi: 10.63125/jce79s31

Received: 21 August 2025; **Revised:** 25 September 2025; **Accepted:** 27 October 2025; **Published:** 27 November 2025

Abstract

This study addresses schedule overruns in U.S. infrastructure projects and the limited quantitative evidence on whether AI-enabled construction planning tools reduce delays. The purpose is to quantify relationships between AI-based planning adoption and schedule performance using project-level data. A quantitative cross-sectional, case-based design used a Likert five-point survey of practitioners covering 198 infrastructure cases across public agencies and enterprise contractors and consultants. Key variables included AI-enabled planning tool adoption, planning quality, coordination effectiveness, project size, complexity, contract type, and a Schedule Delay Index (SDI) from planned and actual durations. Reliability was high for all multi-item scales (α = 0.84-0.91). The analysis plan combined descriptive statistics, Pearson correlations, and multiple regression with moderation tests. Projects showed moderate AI adoption ($M = 3.47$, $SD = 0.78$) and an average 11% schedule overrun (SDI $M = 0.11$, $SD = 0.09$). AI adoption correlated negatively with SDI ($r = -0.41$, $p < .001$) and remained a significant predictor of lower delay after controlling for size, complexity, and contract type; a one-point increase in adoption was associated with a 2.8 percentage point reduction in SDI. Adding planning quality and coordination effectiveness increased explained variance in SDI from 25% to 41% and partially mediated the AI-delay relationship, with effects strongest on highly complex projects. The headline finding is that AI-enabled planning tools contribute meaningfully to delay reduction when embedded in robust planning and coordination practices. The study implies that infrastructure owners should treat AI-enhanced planning as a strategic capability for improving delivery reliability across the sample.

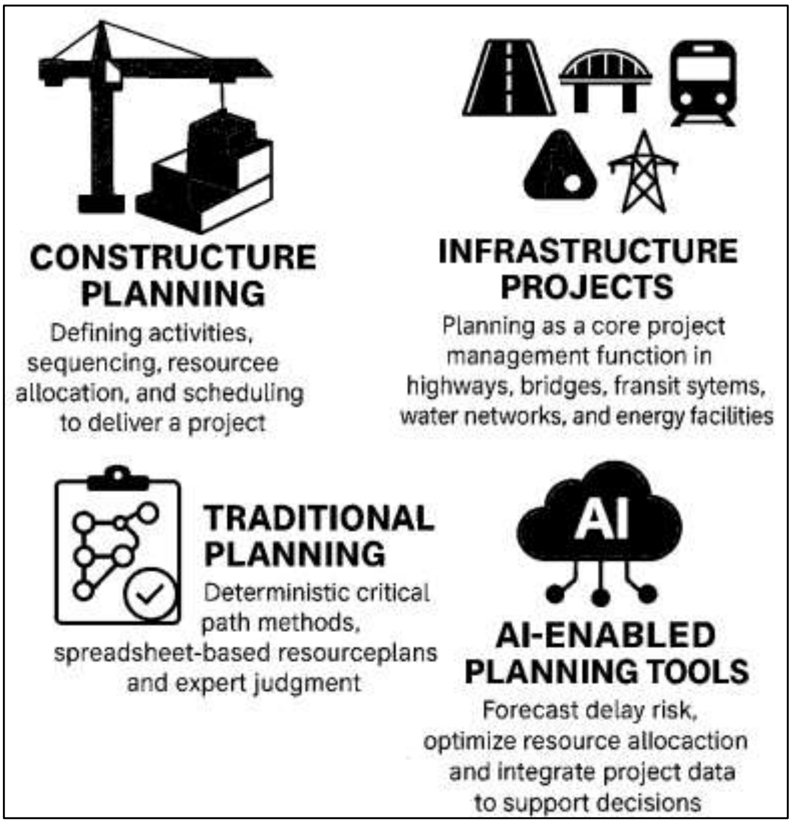
Keywords

AI-Enabled Construction Planning; Schedule Delay Reduction; U.S. Infrastructure Projects; Quantitative Cross-Sectional Survey; Project Complexity.

INTRODUCTION

Construction planning refers to the systematic process of defining activities, sequencing, resource allocation, and scheduling to deliver a project within the agreed time, cost, and quality parameters. In large infrastructure projects including highways, bridges, transit systems, water networks, and energy facilities planning is a core project management function because it structures how complex, interdependent activities unfold over multi-year horizons. Globally, infrastructure investment is seen as a driver of economic growth, productivity, and social well-being, yet chronic schedule delays and cost overruns continue to affect many projects and erode the expected benefits (Assaf & Al-Hejji, 2006). Traditional planning relies heavily on deterministic critical path methods, spreadsheet-based resource plans, and expert judgment.

Figure 1: Core Elements of Construction Planning and the Role of AI in Schedule Performance



These approaches can be effective in stable environments, but they struggle when construction work is exposed to uncertainty in supply chains, labor markets, weather, permitting, and stakeholder coordination. Schedule slippage in infrastructure projects has been associated with litigation, loss of public trust, and reduced returns on public investment (Arfan et al., 2021; Sambasivan & Soon, 2007). The increasing complexity and scale of infrastructure programs, along with demands for more resilient and sustainable systems, have intensified the need for data-driven, predictive planning approaches. At the same time, advances in artificial intelligence (AI), machine learning, and data analytics are transforming how project data can be collected, integrated, and analyzed to support decisions. In many industrial sectors (Ara, 2021), AI is now used to forecast demand, optimize resource allocation, and anticipate risk patterns; a similar transformation is beginning to be visible in construction engineering and management, creating a strong motivation to examine how AI-enabled planning tools influence schedule performance, particularly in the context of infrastructure projects in the United States (Darko et al., 2020; Jahid, 2021).

Schedule delays in construction are typically defined as the time extension beyond the contract completion date, or beyond a revised completion date agreed by project stakeholders. Empirical studies across regions consistently show that delays are among the most persistent problems in the construction sector, especially for infrastructure works where interfaces among agencies, contractors, and communities are numerous (Akinosho et al., 2020; Akbar & Farzana, 2021). Reviews of delay causes identify clusters such as design changes, slow decision-making by owners, contractor cash-flow constraints, material shortages, limited equipment availability, labor productivity issues, and challenges in coordination among multiple firms (Reza et al., 2021; Sambasivan & Soon, 2007; Santos et al., 2021). These factors interact in non-linear ways, which means the actual schedule performance often deviates from baseline plans in ways that are not easily captured by simple float calculations or single-factor sensitivity analyses (Saikat, 2021). Systematic literature syntheses on construction project delays highlight that, even with decades of research, time overruns remain widespread, indicating that existing planning and control practices have not fully internalized the lessons from prior projects (Durdyev & Hosseini, 2019; Shaikh & Aditya, 2021). Parallel research on time–cost trade-off models and schedule optimization in construction shows that multi-objective techniques and metaheuristic algorithms can generate more efficient schedules under resource constraints, yet these methods are still not routinely embedded into everyday planning workflows on most sites (Faghihi et al., 2016; Kanti & Shaikat, 2021). Against this background, international organizations and national governments have been calling for better use of data and analytics to improve the delivery of infrastructure programs, which positions AI-enabled construction planning tools as potentially important instruments for addressing systemic time performance problems in the sector (Zobayer, 2021a, 2021b).

Artificial intelligence in construction engineering and management refers to computational methods that learn patterns from data to support or automate tasks such as prediction, classification, optimization, and decision support in project processes (Ariful & Ara, 2022; Zhang et al., 2021). In planning and scheduling, AI-enabled tools can include machine learning models that forecast delay risk, optimization engines that search for efficient combinations of activity durations and resource assignments, and decision support systems that integrate historical and real-time data from project management platforms, sensors, and digital models (Arman & Kamrul, 2022; Mesbaul & Tahmid Farabe, 2022). Recent reviews of AI adoption in construction engineering and management classify applications in cost estimation, schedule prediction, safety analytics, productivity monitoring, and resource optimization, and note that schedule-related use cases are among the most extensively explored (Nahid, 2022; Hossain & Milon, 2022; Pan & Zhang, 2021b). For example, hybrid AI models that combine random forests with genetic algorithms have been developed to predict delay risk levels from project characteristics and stakeholder assessments, achieving relatively high classification accuracy compared to traditional statistical models (Abdur & Haider, 2022; Mushfequr & Praveen, 2022; Yaseen et al., 2020). Other work has applied supervised learning to anticipate schedule slippage based on contract features, progress data, and contextual risk indicators (Egwim et al., 2021; Mortuza & Rauf, 2022; Rakibul & Samia, 2022). Parallel developments in deep learning have examined how time-series and image data from construction operations can be mined to support diagnostic and prescriptive insights about productivity, rework, and safety, which indirectly influence schedule outcomes (Bilal et al., 2016; Rony & Ashraful, 2022; Saikat, 2022). Yet, while these AI approaches demonstrate technical promise, empirical evidence on their quantitative impact on actual schedule performance in real-world infrastructure projects, especially in the U.S. context, remains comparatively limited and fragmented across case studies, simulation models, and small-scale implementations (Shaikh & Sudipto, 2022).

The effectiveness of AI-enabled planning tools depends strongly on the quality, richness, and structure of the underlying project data (Abdul, 2023; Abdulla & Zaman, 2023). Over the past two decades, Building Information Modeling (BIM) has become a foundational digital technology in the architecture, engineering, and construction sector, supporting 3D/4D modeling, clash detection, and information management across the project life cycle (Arfan et al., 2023; Ara & Onyinyechi, 2023; Zhao, 2017). Systematic reviews show that BIM adoption is spreading from building projects into infrastructure domains such as bridges, tunnels, and rail, where it is used to coordinate multidisciplinary design and construction processes, and to support sustainability assessments (Amin & Mesbaul, 2023; Foysal & Aditya, 2023; Tafazzoli & Shrestha, 2018). Recent studies on digital twins extend BIM by integrating real-time data from Internet of Things (IoT) devices, site sensors, and construction equipment to create virtual replicas of construction processes and assets (Hamidur, 2023; Rashid et al., 2023). Under this

paradigm, AI and data mining are embedded within digital twin platforms to discover bottlenecks, forecast task completion, and support tactical decisions on resource deployment (Musfiqur & Kamrul, 2023; Muzahidul & Mohaiminul, 2023; Pan & Zhang, 2023). In addition, digital twin frameworks enable advanced visualization of planned versus actual progress, making predictive insights more actionable for planners, supervisors, and owners (Amin & Sai Praveen, 2023; Hasan & Ashraful, 2023). Reviews of BIM-based and BIM-AI integrated systems emphasize that digital decision support for schedule, cost, safety, and quality management is advancing rapidly, yet many implementations are still at pilot scale and often concentrated in building rather than infrastructure projects (Jobayer Ibne & Kamrul, 2023; Mushfequr & Ashraful, 2023; Parsamehr et al., 2023). These developments suggest that AI-enabled planning tools should be viewed as part of a broader digital construction ecosystem, where BIM, digital twins, and data governance practices create the conditions for reliable analytics that can directly influence construction schedules (Roy & Kamrul, 2023; Saba et al., 2023).
The United States faces an extensive backlog of infrastructure renewal and expansion across transportation, water, energy, and social infrastructure systems (Saba & Kanti, 2023; Shaikh & Farabe, 2023). Public agencies and private concessionaires are under pressure to deliver projects more quickly while managing complex regulatory, environmental, and stakeholder requirements (Haider & Hozyfa, 2023; Zobayer, 2023). Empirical investigations into delay causes in U.S. construction projects report that many of the global drivers such as scope changes, slow approvals, and coordination challenges are also prevalent domestically, but are often amplified by multi-layered governance structures and interfaces with federal, state, and local agencies (Abdul & Shoeb, 2024; Hozyfa & Shahrin, 2024; Tafazzoli & Shrestha, 2018). Research on major U.S. transportation and infrastructure programs further documents that cost overruns and schedule delays remain common, even after the introduction of enhanced oversight mechanisms, and argues that more rigorous data-driven project controls are needed to improve performance (Flyvbjerg, 2021; Hasan & Shah, 2024; JHasan & Zayadul, 2024). In parallel, U.S. agencies have been promoting digital delivery requirements, including BIM mandates for certain categories of projects, and investments in digital project management systems to support integrated planning and reporting (Muzahidul & Aditya, 2024; Hasan & Rakibul, 2024). Nevertheless, there is limited quantitative evidence on how far AI-enabled construction planning tools have been adopted in the U.S. infrastructure sector, and whether their use is associated with measurable reductions in schedule delays. Existing AI-related case studies tend to focus on specific pilot projects, individual contractors, or particular tools, which makes it difficult to generalize patterns at the sector level (Mominul, 2024; Mominul & Zaki, 2024; Zhang et al., 2021). This gap justifies a focused empirical assessment of AI-enabled construction planning tools in U.S. infrastructure projects, with attention to project characteristics, stakeholder roles, and planning practices that may influence their effectiveness in mitigating delays (Roy & Praveen, 2024; Rony & Hozyfa, 2024).
The persistent occurrence of delays in infrastructure projects indicates that conventional planning approaches have not fully addressed the complex risk structures that shape schedule performance, and that the opportunities offered by AI-enabled planning tools are not yet clearly understood in practice. Although researchers have developed advanced AI models for delay prediction, resource optimization, and process mining, the sector lacks systematic, quantitative evidence on the relationships between the extent of AI-enabled planning tool usage and observed changes in schedule performance indicators at the project level (Saba & Hasan, 2024; Santos et al., 2020; Shaikat & Zaman, 2024). Infrastructure projects also differ from building projects in their scale, linear nature, stakeholder complexity, and regulatory context, which suggests that findings from generic construction AI studies may not directly translate to U.S. infrastructure programs (Boje et al., 2020; Sudipto &Hasan, 2024; Kanti & Saba, 2024). Accordingly, the central problem addressed in this study is the limited empirical understanding of whether, and to what extent, AI-enabled construction planning tools are associated with reduced schedule delays in U.S. infrastructure projects. The purpose of the research is to conduct a quantitative, cross-sectional, case-study–based assessment of AI-enabled planning tool usage and its relationship with delay outcomes, using Likert-scale survey indicators complemented by project-level schedule data. To operationalize this purpose, the study is guided by three research questions: RQ1 asks how extensively AI-enabled construction planning tools are currently used in different categories of U.S. infrastructure projects; RQ2 examines how the intensity and type of AI-enabled planning tool usage

relate to key measures of schedule performance; and RQ3 explores how project attributes such as size, delivery method, and digital maturity condition the relationship between AI-enabled planning tools and schedule delays. From these questions, testable hypotheses are formulated regarding the expected negative association between AI-enabled planning adoption and schedule delay magnitude, and the moderating role of project complexity, to be examined through correlation analysis and regression modeling (Ji et al., 2021).

This study is situated at the intersection of three active research streams: construction delay analysis, AI applications in construction engineering and management, and digital transformation of infrastructure project delivery. The delay literature has made substantial progress in cataloguing causes and proposing mitigation strategies, yet often treats planning tools as static instruments rather than dynamic, learning-based systems (Sacks et al., 2020). Work on BIM, digital twins, and BIM-based analytics demonstrates that rich digital models can support more integrated and data-driven decisions across project phases, but empirical studies that link these digital practices with quantitative schedule outcomes in infrastructure projects are still emerging (Zhao, 2017). Research on AI in construction engineering and management has clarified the taxonomy of AI methods, mapped application domains, and highlighted challenges related to data quality, interpretability, skills, and organizational readiness (Santos et al., 2019). Within this landscape, the present study focuses specifically on AI-enabled construction planning tools and their relationship with schedule delays in U.S. infrastructure projects, using a quantitative design that combines descriptive statistics, reliability and validity analysis, correlation analysis, and regression modeling on Likert-scale survey data. The analysis is structured to provide evidence on adoption levels, perceived and measured schedule performance, and the influence of project-level characteristics (Lu et al., 2017; Pan & Zhang, 2021a). The remainder of the paper is organized as follows. Section 2 presents a structured literature review on construction delays, AI in construction planning, BIM and digital twins, and theoretical and conceptual frameworks relevant to technology adoption and performance in infrastructure projects. Section 3 describes the methodology, including research design, population and sampling, case study context, instrument development, data collection, and analysis procedures. Section 4 reports the empirical results on response rate, sample characteristics, reliability and validity, descriptive statistics, correlation patterns, and regression models. Section 5 discusses the findings in relation to the literature, while Section 6 presents conclusions, recommendations, and limitations, aligned with the quantitative evidence generated in the study.

The overarching objective of this study is to quantitatively assess how AI-enabled construction planning tools contribute to reducing schedule delays in U.S. infrastructure projects, using project-level data gathered through a structured, Likert-scale survey of practitioners engaged in real projects. Specifically, the first objective is to systematically measure the current level of adoption, integration, and functional use of AI-enabled planning tools among infrastructure project stakeholders, including public agencies, contractors, consultants, and project management firms, so that the landscape of digital planning practices in the U.S. infrastructure sector is clearly mapped. The second objective is to evaluate the relationship between the intensity and nature of AI tool usage and a set of schedule performance indicators, such as adherence to baseline milestones, frequency and magnitude of time extensions, and perceived severity of project delays, with a view to identifying whether higher adoption of AI-based planning methods is associated with improved time performance. The third objective is to examine the role of planning quality and risk management practices as intermediate variables, by capturing how AI tools are used for schedule forecasting, scenario analysis, early risk identification, and resource optimization, and then determining whether these practices help to explain any observed improvements in schedule outcomes. A fourth objective is to account for the influence of project- and organization-level characteristics including project size, complexity, delivery method, sector, and organizational digital maturity on the relationship between AI-enabled planning tools and schedule delays, thereby distinguishing the direct effects of AI usage from contextual factors. Collectively, these objectives are operationalized through a set of research questions and hypotheses that guide the design of the questionnaire, the selection of measures, and the statistical analysis using descriptive statistics, correlation analysis, and regression modeling. By aligning each stage of the empirical process with these objectives, the study aims to generate robust, interpretable evidence on whether AI-enabled construction planning tools are meaningfully associated with reduced schedule delays in U.S. infrastructure projects and under what conditions such associations appear strongest.

LITERATURE REVIEW

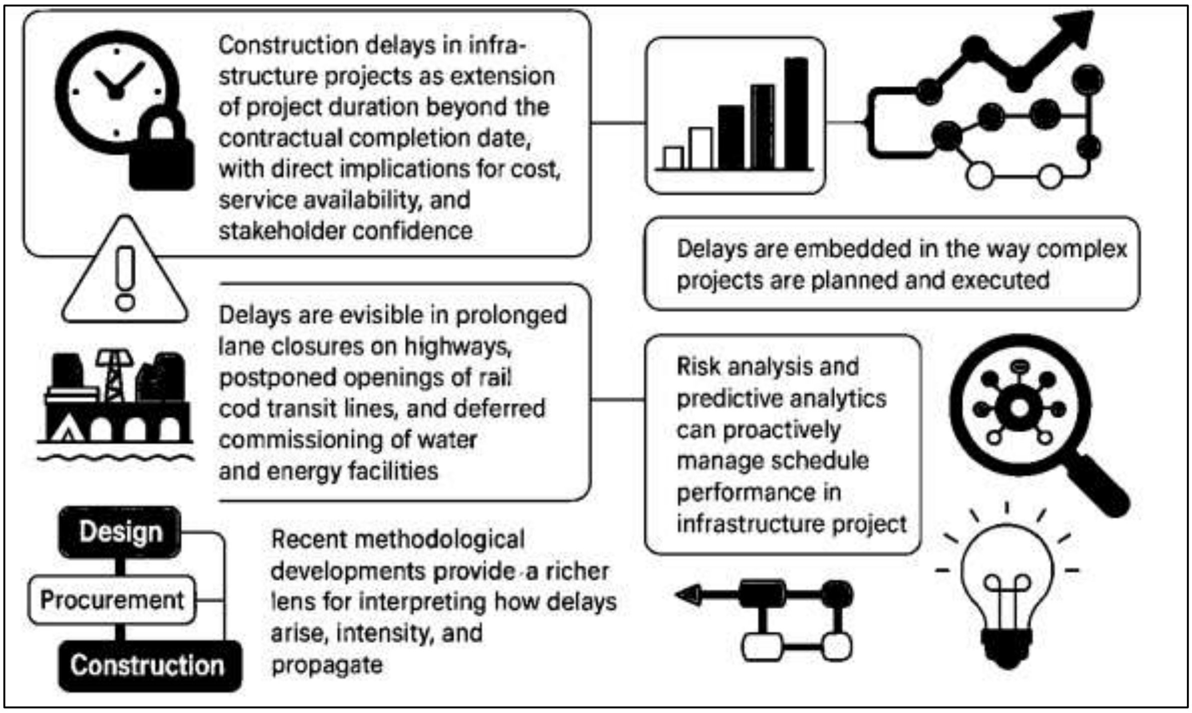
The body of literature relevant to AI-enabled construction planning tools and schedule performance in infrastructure projects spans three tightly connected streams: research on construction delays, work on digitalization of planning through BIM and related technologies, and emerging studies on artificial intelligence in construction engineering and management. Studies on delays consistently document that schedule overruns are one of the most persistent challenges in the construction sector across regions and project types, with systematic reviews highlighting recurrent causal patterns such as design and scope changes, funding constraints, coordination problems, and weaknesses in planning and control processes. Within this stream, recent syntheses focused on road and infrastructure works emphasize that delay factors are multi-dimensional and interdependent, reinforcing the view that deterministic planning tools alone are often inadequate for managing time risk in complex programs. A second body of literature examines the rise of digital construction technologies, particularly Building Information Modeling (BIM) and, more recently, infrastructure-oriented digital twins, as enablers of richer planning, simulation, and coordination capabilities over the project life cycle; these works show how integrated models and real-time data can support more proactive schedule management, but also note that adoption is uneven and many implementations stop at visualization rather than advanced analytics. The third and fastest-growing stream centers on artificial intelligence and machine learning applications for construction planning and control, including delay prediction models, resource optimization engines, and AI-based monitoring platforms that mine historical and real-time project data to flag emerging schedule risks and recommend corrective actions. Recent contributions demonstrate that ensemble learning and other advanced algorithms can achieve high predictive accuracy for delay risk classification and provide earlier warnings than traditional methods, while industry-oriented reports describe AI-based forecasting and monitoring systems being deployed on large infrastructure projects to support more reliable delivery. However, the literature also indicates that most AI-related studies focus on algorithm development, proof-of-concept case studies, or vendor-driven narratives, with relatively few quantitative, sector-wide investigations that statistically relate the extent of AI-enabled planning tool usage to observed schedule outcomes at the project level, particularly in the context of U.S. infrastructure programs. This combination of mature knowledge on delay causation, growing but still fragmented evidence on digital and AI applications, and limited empirical work linking AI planning tools to delay reduction provides the foundation and motivation for the more focused review developed in the subsequent subsections.

Construction Delays in U.S. Infrastructure Projects

Construction delays in infrastructure projects are typically defined as extensions of project duration beyond the contractual completion date, with direct implications for cost, service availability, and stakeholder confidence. In the U.S. context, such delays are visible in prolonged lane closures on highways, postponed opening of bridges and tunnels, slower roll-out of rail and transit lines, and deferred commissioning of water and energy facilities. Time overruns often accumulate through incremental slippages at design, procurement, and construction stages rather than through a single catastrophic event, and they frequently interact with cost overruns, claims, and disputes. Empirical analyses of transportation infrastructure projects illustrate that schedule overruns exhibit systematic patterns linked to rework, late design changes, and scope modifications, suggesting that delay is embedded in the way complex projects are planned and executed rather than being an occasional anomaly (Love et al., 2014). In such environments, contingencies built into baseline schedules are frequently inadequate to absorb the combined impact of revised design information, utility conflicts, environmental mitigation measures, and right-of-way issues. For agencies responsible for U.S. infrastructure assets, this situation translates into recurring renegotiations of completion dates, expanded project management overheads, and disruptions for road users, freight operators, and communities. From a project management perspective, understanding delays in this setting requires a shift from static, one-time explanations toward dynamic, probabilistic characterizations of how schedule performance evolves under uncertainty and interdependent decision-making across stakeholders and phases.

Recent methodological developments in schedule risk analysis provide a richer lens for interpreting how delays arise, intensify, and propagate in large infrastructure programs. Dynamic modeling approaches that couple system dynamics with discrete-event simulations have been used to represent both higher-level feedback loops and detailed interactions among activities, resources, and information flows, enabling planners to observe how small perturbations can generate substantial schedule deviations through reinforcing mechanisms (Kanti & Sai Praveen, 2024; Xu et al., 2018; Haider & Sai Praveen, 2024). For example, if early-stage design coordination is slower than planned, downstream procurement and construction tasks may experience compounding disruptions, as late design deliverables push bid packages, material fabrication, and field work into unfavorable weather windows, which then further reduces productivity and increases the risk of rework (Zobayer & Kumar, 2024; Zulqarnain & Zayadul, 2024). Multi-level risk assessment methods that integrate structured expert judgment with quantitative ranking techniques have shown that, in complex projects such as nuclear power plants, regulatory approvals, policy changes, and documentation quality jointly shape delay exposure, reinforcing the notion that schedule performance emerges from cross-cutting institutional and technical interactions rather than from isolated contractor actions (Alifa Majumder, 2025; Efat Ara, 2025; Hossen et al., 2015). These findings are directly relevant to U.S. infrastructure delivery, where lengthy environmental reviews, multi-jurisdictional oversight, and evolving design standards create conditions in which small early deviations from plan can cascade into substantial overruns (Habibullah, 2025; Hozyfa & Ashraful, 2025). In practice, such insights argue for incorporating dynamic risk thinking into planning processes, so that schedule baselines are treated as living hypotheses that need continuous updating as project information and conditions change (Asfaquar, 2025; Foysal, 2025).

Figure 2: Elements of Schedule Delays in U.S. Infrastructure Projects

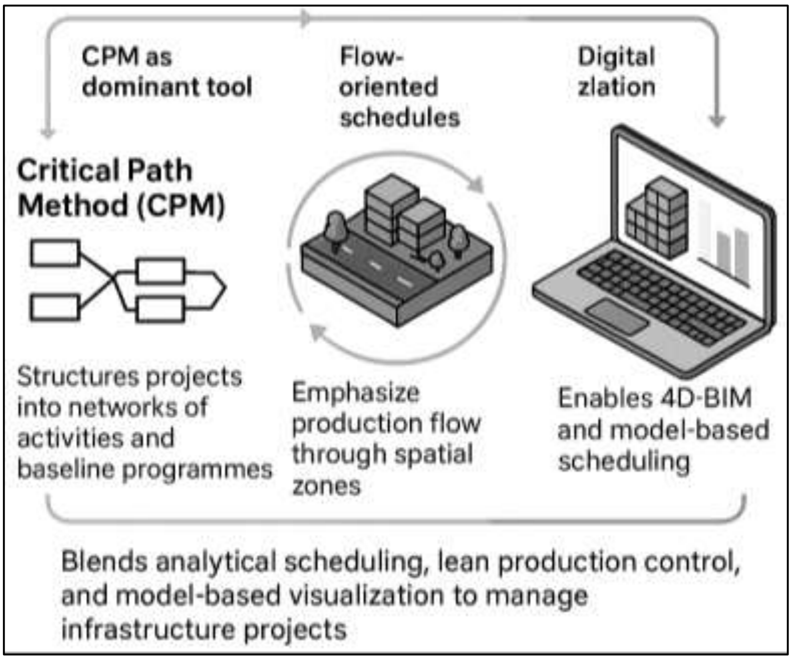


At the same time, research on delay-controlling parameters and predictive analytics is transforming how project teams can proactively manage schedule performance in infrastructure projects. Studies that employ causal mapping and decision-making trial and evaluation laboratory (DEMATEL) techniques highlight that delay drivers such as design errors, ineffective supervision, and material supply problems form tightly interconnected networks, where changes in one factor can quickly reverberate through others and ultimately shape the trajectory of project completion (Ajayi & Chinda, 2022; Islam & Abdur, 2025; Mohaiminul, 2025). This networked perspective suggests that interventions focused solely on visible symptoms, such as adding extra crews toward the end of a project, may deliver limited benefit if the deeper structural drivers of delay such as poor information flow, inconsistent oversight, or unstable funding remain unaddressed (Mominul, 2025; Muzahidul, 2025). Complementary work using machine learning for construction schedule risk analysis has demonstrated that models trained on large samples of completed infrastructure projects can achieve higher predictive accuracy in identifying tasks and segments at high risk of delay than traditional deterministic methods, thereby enabling earlier and more targeted managerial responses (Fitzsimmons et al., 2022; Hossain, 2025; Zaman, 2025). For U.S. infrastructure owners and contractors, these strands of evidence collectively point to the value of integrating causal analysis, dynamic simulation, and data-driven prediction into planning and control practices (Akbar & Sharmin, 2025; Hasan, 2025). Rather than treating schedule delay as an unavoidable by-product of complexity, such tools support a more proactive stance in which project teams can explore alternative phasing, resource strategies, and risk responses before and during execution, with the goal of stabilizing delivery timelines and improving the reliability of infrastructure programs that are critical to national economic and social objectives (Ibne, 2025; Milon, 2025).

Construction Planning and Scheduling Practices

Construction planning and scheduling practices form the operational backbone of infrastructure delivery, translating strategic project goals into time-phased, resource-feasible work plans that govern execution on site. Traditionally, the Critical Path Method (CPM) has been the dominant tool, structuring projects into networks of activities with logical relationships and floats, and supporting baseline programme development and progress control (Farabe, 2025; Kamrul, 2025).

Figure 3: Construction Planning: CPM, Flow-Based Methods, and Digitalization



However, experience from complex building and infrastructure projects has shown that CPM's activity-based focus often struggles to represent continuous production flow across locations, leading to fragmented work, excessive task fragmentation, and inefficient crew deployment (Mohammad Mushfequr, 2025; Mst. Shahrin, 2025; Olivieri et al., 2018). In response, location-based approaches such as the Location-Based Management System (LBMS) have been adopted to augment CPM by modelling work as production flows through defined spatial zones, enabling planners to visualize crew movements, balance workloads, and minimize interruptions. These advances reflect a broader evolution in practice: from static bar charts to dynamic, flow-oriented schedules that emphasize reliable work sequencing, reduced remobilizations, and closer alignment between the master programme and day-to-day operations (Olivieri et al., 2019; Rakibul, 2025; Saba, 2025). For U.S. infrastructure, where projects often involve dispersed work fronts, constrained rights-of-way, and multi-contract interfaces, such flow-based planning is particularly important for maintaining productivity and avoiding cascading delays across trades and locations (Praveen, 2025; Saikat, 2025).

At the systems level, contemporary construction planning no longer relies on a single scheduling technique but on a portfolio of complementary methods that jointly support project management and production control. Comparative empirical studies across multiple countries have shown that CPM, the Last Planner System (LPS), and location-based techniques each address different needs (Shaikat, 2025; Shaikh, 2025): CPM remains central for contract requirements, claims, and high-level critical path analysis, whereas LPS and location-based methods provide stronger support for continuous flow, constraint management, and short-term work planning (Olivieri et al., 2018; Tahosin et al., 2025; Tonoy Kanti, 2025). Survey evidence from Brazil, Finland, and the United States further indicates that practitioners selectively combine these systems depending on project type, cultural norms, and organizational capabilities, rather than treating them as mutually exclusive alternatives (Scala et al., 2023; Waladur & Jabed Hasan, 2025; Haider, 2025). Weekly and lookahead planning meetings, commitment-based planning, and systematic removal of constraints have become embedded into many contractors' standard operating procedures, particularly on complex infrastructure and public works. These practices aim to close the well-known gap between baseline schedules and field reality by reinforcing reliable promises, improving coordination between design, procurement, and construction, and providing real-time feedback on plan reliability. Within this multi-method environment, construction planning is increasingly seen as a socio-technical process, where tools, contractual expectations, and collaborative behaviors must be aligned to maintain schedule integrity and minimize delay risks.

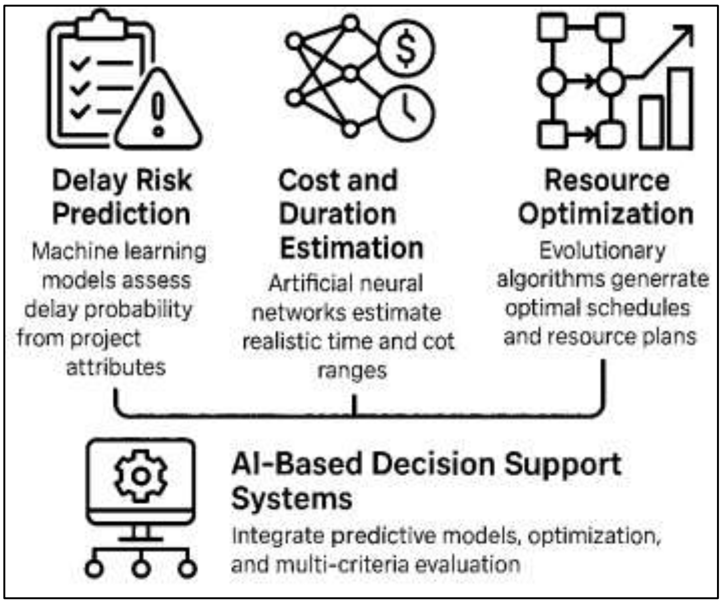
Digitalization has further transformed construction planning and scheduling practices by integrating time, space, and information within model-based environments. Location-based scheduling for linear infrastructure, such as highways and rail corridors, has been automated through algorithms that generate time–location plans for earthworks, optimize cut-and-fill sequencing, and allocate resources based on productivity, haul distances, and congestion constraints (Shah, 2014). In parallel, Building Information Modelling (BIM) has enabled tighter coupling between 3D geometry and temporal logic, with 4D models linking building elements to schedule activities to support constructability analysis, clash detection in time–space, and visual communication with field crews and stakeholders (Wang et al., 2014). These BIM-based scheduling workflows allow planners to test alternative sequences, examine resource conflicts, and understand the implications of design changes before they manifest on site. For infrastructure projects, integrating BIM with process simulations enhances the ability to evaluate different resource allocation strategies under uncertainty, thereby producing more robust schedules that are sensitive to site-level logistics and productivity variability (Wang et al., 2014). Together, these developments illustrate how contemporary planning practice blends analytical scheduling techniques, lean-inspired production control, and model-based visualization to manage the time, cost, and coordination challenges inherent in large-scale infrastructure delivery.

AI-Enabled Construction Planning Tools and Techniques

AI-enabled construction planning tools extend traditional scheduling and estimating methods by embedding predictive analytics directly into planning workflows. Machine learning models trained on multi-project datasets are increasingly used to infer delay risk from objective project attributes such as contract type, procurement route, project size, and historical performance, enabling planners to treat delay probability as an explicit input to baseline schedules rather than an after-the-fact diagnostic. In this context, supervised learning algorithms have been shown to classify projects into different delay risk categories with substantially higher accuracy than conventional statistical approaches, supporting scenario testing and prioritization of mitigation actions during the planning stage (Gondia et al., 2020). Simultaneously, artificial neural network (ANN) models are being embedded into early-phase cost and duration estimation tools so that planners can generate more realistic time–cost envelopes under data-poor conditions, particularly where parametric or rule-of-thumb methods systematically underestimate schedule requirements (Trijeti et al., 2023). Together, these AI-powered capabilities reposition planning as a data-intensive analytical task in which schedules, risk registers, and budget baselines are co-generated through iterative model runs rather than constructed sequentially.

A second stream of AI-enabled tools focuses on improving the granularity and reliability of early-stage time–cost trade-offs by learning complex, nonlinear relationships between building characteristics and project outcomes. ANN-based models have been developed to map design variables such as floor area, foundation type, and contractor classification onto probabilistic predictions of project duration and total cost, thereby allowing planners to explore alternative design and procurement configurations before committing to a baseline programme (Ujong et al., 2022). These predictive estimators can be linked to network schedules so that the critical path and float calculations reflect more realistic activity durations. In parallel, evolutionary computation techniques have been applied to resource leveling problems, where the objective is to smooth labor and equipment profiles while respecting precedence and project duration constraints. By encoding feasible schedules as chromosomes and iteratively evolving solutions, evolutionary algorithms have demonstrated the ability to produce leveled resource profiles and near-optimal schedules that outperform conventional heuristic or manual methods, especially for complex multi-activity infrastructure projects (Kyriklidis & Dounias, 2016). When integrated into commercial scheduling platforms, such optimization engines allow planners to evaluate large numbers of schedule alternatives that would be infeasible to generate manually.

Figure 4: Key AI Techniques Supporting Construction Planning and Scheduling

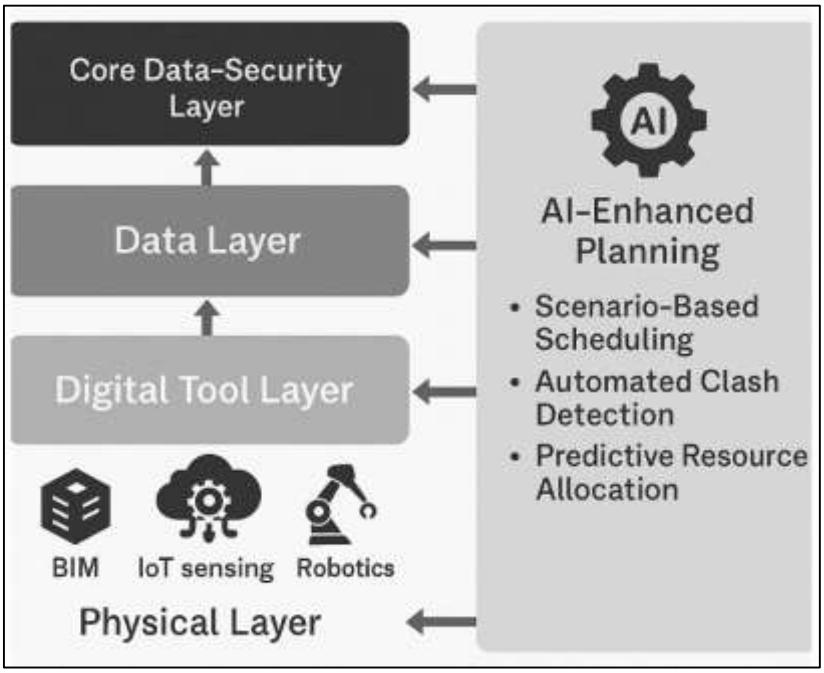


More recently, AI-based decision support systems (DSSs) have begun to provide an overarching framework that combines predictive models, optimization techniques, and multi-criteria evaluation within a single planning environment. Systematic reviews of AI-enabled DSSs in construction indicate that a large proportion of applications target early project stages, where decisions about scope, phasing, and resource strategies exert the greatest influence on eventual cost, time, and sustainability performance (Smith & Wong, 2022). In such systems, machine learning components generate probabilistic forecasts of duration, cost, and delay risk; optimization modules search for schedules and resource plans that satisfy predefined constraints; and user interfaces present planners with ranked alternatives based on economic, environmental, and social criteria. The result is a class of planning tools in which AI serves not as a black-box replacement for human expertise but as an analytical partner that can interrogate vast design spaces, highlight high-risk schedule configurations, and reveal trade-offs among competing objectives. For large U.S. infrastructure programmes, these integrated AI-based planning environments provide the technical foundation for quantitatively assessing how different planning choices may contribute to or mitigate schedule overruns, thereby aligning directly with the aims of a quantitative assessment of AI-enabled construction planning tools for delay reduction.

Digital Transformation Readiness in Construction Planning

The adoption of AI-enabled tools in construction planning is unfolding within a broader digital transformation agenda often framed under the banner of Construction 4.0. Recent reviews show that, although AI is now widely recognized as a strategic technology for improving cost, schedule, safety, and quality performance, actual implementation in construction organizations remains uneven and cautious (Abioye et al., 2021). Many firms still rely on conventional planning practices and fragmented information flows, which limit the ability of AI models to ingest reliable data and generate robust predictions for schedule control and resource optimization (Abioye et al., 2021). PRISMA-based syntheses report that most documented AI use cases concentrate on discrete applications such as safety monitoring, equipment tracking, and risk scoring rather than end-to-end, integrated planning workflows (Regona et al., 2022). This pattern indicates a technology-centric adoption trajectory where organizations experiment with isolated pilots instead of embedding AI within standardized planning processes and governance structures. Conference and book-chapter reviews of machine learning in construction confirm that the majority of implementations are still exploratory, with relatively few organizations institutionalizing AI models into standard operating procedures for forecasting delays, sequencing activities, or re-optimizing baselines (Adekunle et al., 2023). Consequently, the maturity of AI-enabled planning remains highly variable across firms and project types, even where awareness of potential benefits is strong.

Figure 5: Framework for AI Adoption and Digital Transformation in Construction Planning

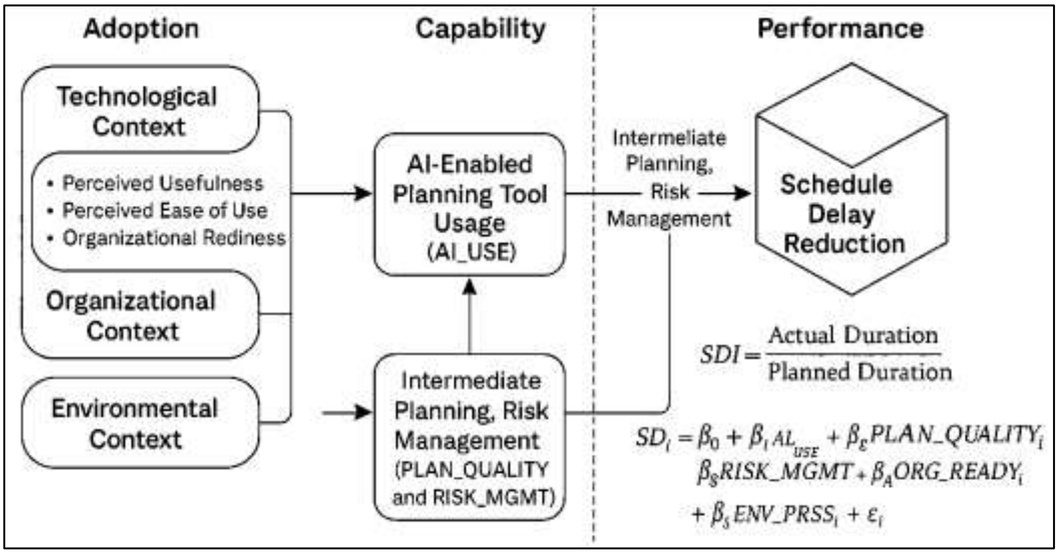


Digital transformation studies conceptualize AI adoption in construction as part of a multi-layered Construction 4.0 ecosystem that spans technologies, processes, people, and governance. Lifecycle-oriented reviews argue that Construction 4.0 is driven by data creation, data flow, and data transformation across the project lifecycle, positioning AI as a key mechanism for turning this data into actionable planning intelligence (Karmakar & Delhi, 2021). Within this paradigm, AI does not operate in isolation but interacts with BIM, IoT sensing, robotics, and cloud-based collaboration platforms to support tasks such as scenario-based scheduling, automated clash and constraint detection, and predictive resource allocation. A four-layer implementation model distinguishes physical, digital tool, data, and core data-security layers and shows that AI-enhanced planning depends on coherent integration across these layers, particularly for time-sensitive infrastructure projects (El Jazzar et al., 2021). This systemic perspective reframes adoption challenges: issues such as data silos, poor interoperability, or weak cybersecurity directly undermine the reliability of AI-driven forecasts and recommendations. Reviews of AI in construction further highlight that organizations gain the most value when AI is embedded into cross-functional planning routines, supported by standardized data

schemas and shared performance indicators, rather than being treated as an add-on analytics tool (Abioye et al., 2021).
At the organizational level, empirical studies identify a recurring set of socio-technical factors that shape readiness for AI-enabled construction planning. Synthesis of AI- and Construction 4.0–oriented literature shows that resistance to change, skill gaps, unclear business cases, and limited investment in data infrastructure are persistent obstacles to scaling AI applications beyond pilot projects (Karmakar & Delhi, 2021). Survey-based and maturity-model work indicates that many firms occupy early stages of digital transformation, where ad hoc tools exist but are not aligned with formal strategies, training programmes, or performance-management systems needed to sustain AI-enhanced planning practices (El Jazzar et al., 2021). At the same time, systematic reviews of machine learning in construction reveal that where leadership commitment, targeted upskilling, and clear value propositions are present, organizations are more willing to reposition planning workflows around data-driven prediction and optimization (Adekunle et al., 2023). Across these studies, successful AI adoption in construction planning emerges as the outcome of coordinated efforts in technology investment, human-capital development, process re-engineering, and governance, rather than purely technical experimentation. This evidence base underpins the present study's focus on quantitatively assessing how AI-enabled construction planning tools relate to delay reduction in U.S. infrastructure projects, while also recognizing that organizational readiness and digital-transformation capability strongly condition their effectiveness.
Theoretical Framework for AI-Enabled Construction Planning and Delay Reduction
The theoretical foundation for this study combines technology acceptance and organizational innovation-adoption perspectives to explain why construction organizations adopt AI-enabled planning tools and how this adoption translates into improved schedule performance. At the individual level, Technology Acceptance Model 3 (TAM3) posits that perceived usefulness and perceived ease of use are the most proximal cognitive antecedents of behavioral intention and actual system use, enriched by determinants such as job relevance, output quality, result demonstrability, computer self-efficacy, and perceptions of external control (Venkatesh & Bala, 2008). In the context of AI-enabled construction planning, perceived usefulness can be interpreted as the extent to which planners and project managers believe that AI-based forecasting, optimization, and risk analytics improve schedule reliability and decision quality, while perceived ease of use reflects the effort required to integrate these tools into existing scheduling and reporting routines. Meta-analytic evidence on IT innovation adoption shows that perceived usefulness, top management support, and user support are consistently among the strongest predictors of individual adoption and use, reinforcing the idea that technical features alone are insufficient without managerial sponsorship and adequate support structures (Jeyaraj et al., 2006). In this study, TAM3 constructs provide the micro-level logic linking AI tool design and user perceptions to the intensity of AI-enabled planning tool usage (AI_USE), which then becomes a central explanatory variable in the delay-reduction model.
At the organizational level, this study draws on meta-analytic and conceptual work that synthesizes Diffusion of Innovation (DOI), Technology–Organization–Environment (TOE), and related perspectives to explain IT innovation adoption as a function of technological, organizational, and environmental conditions. Jeyaraj et al. (2006) show that organizational adoption is most strongly associated with factors such as organizational readiness, professionalism of the IS unit, external pressure, and top management support, suggesting that adoption decisions reflect both internal capabilities and external coercive or normative forces. Complementing this, Hameed, Counsell, and Swift (2012) use meta-analysis to demonstrate that organizational readiness (including financial and technical resources), IS department size, and IS infrastructure are significant determinants of IT innovation adoption, while other factors such as centralization and product champion roles are less consistently associated with adoption outcomes. Translating these findings into the AI-enabled construction planning context, the theoretical framework conceptualizes AI_USE as being shaped by (a) technological context (AI functionality, compatibility with BIM/CPM/LBMS tools), (b) organizational context (digital maturity, data infrastructure, planning culture, staff analytics skills), and (c) environmental context (client requirements, regulatory expectations, competitive pressures to deliver on time). These contexts are captured through latent constructs such as organizational

readiness, external pressure, and data environment quality, which in turn influence both the likelihood and extent of AI-enabled planning adoption. Thus, the framework integrates individual-level TAM3 paths and organizational-level TOE/DOI-style determinants into a unified adoption block that precedes schedule performance outcomes (Shabbir & Waheed, 2020).

Figure 6: Theoretical Framework for AI-Enabled Construction Planning



To explain how AI-enabled planning adoption translates into delay reduction, the framework incorporates a resource-based and analytics-capability view, treating AI-enabled planning systems and associated data capabilities as strategic resources that can generate superior schedule performance when effectively deployed. Drawing on resource-based analyses of big data analytics adoption, the application of big data analytics (ABDA) has a positive, significant effect on organizational performance, with knowledge management practices partially mediating the relationship (Shabbir & Waheed, 2020). Similarly, big data analytics capabilities improve organizational performance directly and indirectly through dual innovations (exploitative and exploratory), reinforcing the idea that analytics-driven capabilities create value by enabling better decisions and process innovations (Su et al., 2022). In this research, AI-enabled construction planning tools are conceptualized as a specialized form of analytics capability oriented toward schedule forecasting, risk detection, and resource optimization in infrastructure projects. Schedule performance is operationalized via a Schedule Delay Index (SDI) at the project level, defined as

$$\mathrm{SDI} = \frac{\text{Actual Duration} - \text{Planned Duration}}{\text{Planned Duration}},$$

where positive values indicate overruns and values near zero indicate on-time completion. The core empirical specification is a multiple regression model of the form

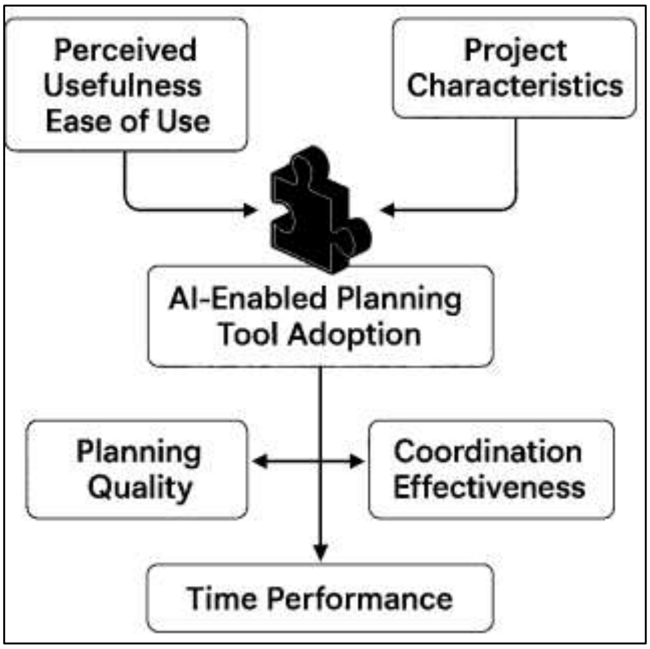
$$\mathrm{SDI}_i = \beta_0 + \beta_1 \mathrm{AI\_USE}_i + \beta_2 \mathrm{PLAN\_QUALITY}_i + \beta_3 \mathrm{RISK\_MGMT}_i + \beta_4 \mathrm{ORG\_READY}_i + \beta_5 \mathrm{ENV\_PRESS}_i + \varepsilon_i,$$

where project $i$is the unit of analysis, PLAN_QUALITY and RISK_MGMT capture intermediate planning and risk-management practices enabled by AI tools, ORG_READY reflects organizational readiness, and ENV_PRESS captures environmental pressures. In line with the theoretical arguments above, $\beta_1$is expected to be negative (higher AI_USE associated with lower SDI), while $\beta_3$and $\beta_4$are expected to mediate and condition this relationship (Hameed et al., 2012). Together, these adoption, capability, and performance perspectives form an integrated theoretical framework that guides the formulation of hypotheses and the design of the subsequent quantitative analysis.

Conceptual Framework

The conceptual framework for this study synthesizes prior work on project characteristics, critical success factors, coordination, planning effort, and technology adoption into an integrated model that explains how AI-enabled construction planning tools can reduce time overruns in U.S. infrastructure projects. Structural equation models developed in construction management have repeatedly shown that project performance is a function of multiple interrelated latent constructs, rather than isolated variables, with project characteristics, organizational capabilities, and management practices jointly shaping cost, time, and quality outcomes (Chen et al., 2012; Cho et al., 2009).In particular, studies using structural models of critical success factors demonstrate that client-related, contractor-related, and project management–related factors operate as an interconnected system influencing schedule performance, rather than as independent drivers (Kim & Nguyen, 2019). Coordination-based models further show that information flow, role clarity, and decision synchronization form an underlying coordination factor that significantly predicts time and cost performance (Alaloul et al., 2020). Parallel evidence indicates that higher levels of construction planning effort especially in scheduling, resource leveling, and scenario analysis are associated with better time performance, albeit in a non-linear way where certain thresholds of planning maturity must be crossed before benefits emerge (Majumder et al., 2022). More recently, AI-based technology adoption research in the construction sector, grounded in Technology Acceptance Model logics, has conceptualized adoption as a latent construct shaped by perceptions of usefulness, ease of use, and organizational competence, which in turn affects operational performance (Na et al., 2023). Drawing on these streams, the present framework positions AI-enabled planning tool adoption, planning quality, and coordination effectiveness as key explanatory constructs for time-related project performance in U.S. infrastructure projects (Cho et al., 2009).

Figure 7: Conceptual Pathways Connecting AI Tool Adoption to Schedule Outcomes



Operationally, the framework conceptualizes several latent variables and their empirical indicators that will later be estimated using descriptive statistics, correlation, and regression analysis. "AI-enabled planning tool adoption" is defined as the extent to which project teams use AI-driven applications for schedule optimization, predictive delay analysis, risk-informed rescheduling, and resource allocation, and is measured through Likert-type items on frequency, integration into workflows, and decision dependence, consistent with AI adoption constructs in construction (Na et al., 2023). "Planning quality" reflects the rigor and completeness of baseline schedules, inclusion of contingencies, resource–time trade-off analysis, and the degree of scenario-based simulations, echoing planning effort constructs that have been empirically linked to performance (Majumder et al., 2022). "Coordination effectiveness" captures clarity of roles, timeliness of information exchanges, integration of multi-disciplinary inputs, and responsiveness to change notices, consistent with coordination factor models in construction performance research (Alaloul et al., 2020). "Time performance" is modeled through both perceived and objective indicators of delay reduction and schedule reliability, aligning with project performance constructs in SEM studies that combine schedule variance, adherence to milestones, and stakeholder satisfaction with delivery time (Kim & Nguyen, 2019). For projects where quantitative schedule data are available, a schedule delay index (SDI) can be computed to anchor the latent construct in observable performance: SDI = [(Actual Duration − Planned Duration) / Planned Duration] × 100, where negative values indicate early completion and positive values indicate overruns. This index allows delay-related latent scores to be linked to measurable schedule outcomes in regression models (Cho et al., 2009).

At the structural level, the conceptual framework specifies direct, mediating, and moderating relationships among these constructs in line with prior SEM-based studies of construction project performance. First, AI-enabled planning tool adoption is hypothesized to positively influence planning quality and coordination effectiveness, because AI tools embed advanced analytics, automate information processing, and support proactive scenario analysis (Na et al., 2023). Second, planning quality and coordination effectiveness are modeled as primary direct predictors of time performance, consistent with evidence that robust planning and strong coordination pathways significantly enhance schedule outcomes (Cho et al., 2009). Third, AI-enabled planning tool adoption is expected to exert an indirect effect on time performance through these mediators, capturing the idea that performance gains materialize when AI is embedded into planning and coordination routines rather than simply adopted at a superficial level (Chen et al., 2012).

These relationships can be expressed in a simplified regression form for the quantitative phase:

$$\text{Time\_Performance} = \beta_0 + \beta_1 \cdot \text{AI\_Adoption} + \beta_2 \cdot \text{Planning\_Quality} + \beta_3 \cdot \text{Coordination\_Effectiveness} + \beta_4 \cdot Z + \varepsilon,$$

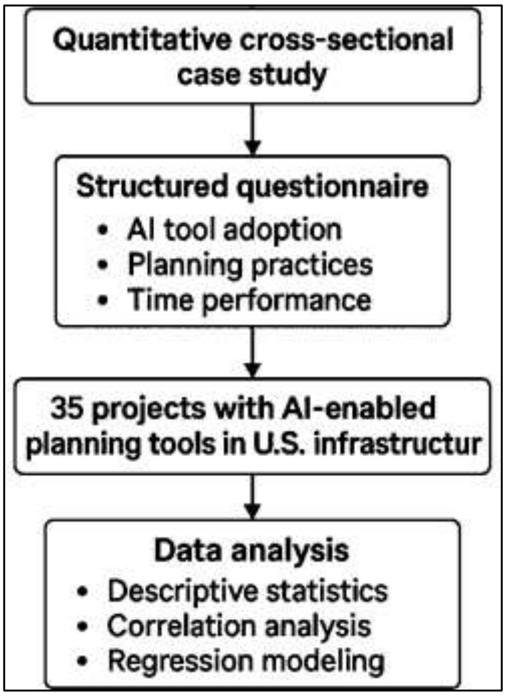
where Z represents control variables such as project size, complexity, and contract type, and ε is the error term. In an extended specification, AI_Adoption can also be modeled as a function of perceived usefulness and ease of use (conceptually adapted from AI adoption studies in construction), while Planning_Quality and Coordination_Effectiveness may be examined as potential mediators of those relationships (Na et al., 2023). This structure aligns with prior SEM work that links critical success factor clusters to project performance through multiple direct and indirect paths, creating a coherent conceptual foundation for testing the role of AI-enabled construction planning tools in reducing delays in U.S. infrastructure projects (Cho et al., 2009).

METHOD

The present study has employed a quantitative, cross-sectional, case-study–based design to examine how AI-enabled construction planning tools have been associated with reduced schedule delays in U.S. infrastructure projects. The research design has been structured to capture perceptions and experiences of practitioners who have been directly involved in planning and managing infrastructure schemes, while also allowing project-level schedule outcomes to be quantified through standardized indicators. By focusing on completed or ongoing projects within the U.S. context, the study has aimed to link the extent of AI-enabled planning tool usage with measures of schedule performance, planning quality, and coordination effectiveness, thereby providing an empirical basis for testing the conceptual framework and hypotheses that have been developed in the literature review.

To achieve these aims, the study has relied on a structured questionnaire that has been administered to key stakeholders, including project managers, planners, schedulers, engineers, and senior decision makers engaged in transportation, utility, and other infrastructure projects. The instrument has been designed around Likert five-point scales that have captured the intensity of AI tool adoption, the characteristics of planning and risk-management practices, and perceived time performance relative to baseline schedules. In addition, the questionnaire has included items that have documented project characteristics such as size, complexity, contract type, delivery method, and digital maturity, so that these variables have been available as controls in the statistical analysis. The case-study orientation has been reflected in the selection of projects that have incorporated, to varying degrees, AI-enabled planning tools within their planning and control processes.

Figure 8: Overview of the Quantitative Cross-Sectional Methodology



The overall methodology has been organized to support rigorous quantitative analysis while ensuring that data collection has remained feasible within real project environments. Once responses have been gathered, the data set has been prepared through screening, coding, and reliability checks, after which it has been subjected to descriptive statistics to summarize key constructs, correlation analysis to explore bivariate relationships, and multiple regression modeling to estimate the effects of AI-enabled planning tool usage and related variables on schedule delay indices. This methodological structure has provided a coherent link between the theoretical propositions of the study and the empirical evidence that has been required to evaluate them.

Research Design

The study has adopted a quantitative, cross-sectional, case-study–based research design to investigate how AI-enabled construction planning tools have been associated with schedule delay reduction in U.S. infrastructure projects. This design has been chosen because it has allowed the researcher to capture variations in AI usage, planning practices, and time performance across multiple projects at a single point in time, while still grounding the data in real project contexts. The research has been structured around a set of testable hypotheses derived from the theoretical and conceptual frameworks, and these hypotheses have been operationalized through measurable survey constructs. By combining a survey strategy with a case-study orientation, the design has ensured that statistically analyzable data have been obtained without losing the contextual richness needed to interpret patterns. Overall, the design has provided a coherent and pragmatic structure for examining complex relationships among technology adoption, planning quality, coordination effectiveness, and schedule outcomes.

Sample

The target population for this study has consisted of professionals who have been involved in planning and managing U.S. infrastructure projects, including highways, bridges, transit systems, utilities, and related public works. Within this population, project managers, planners, schedulers, design engineers, and senior decision makers have been treated as key informants because they have possessed direct knowledge of both planning processes and schedule performance. A non-probability sampling strategy, primarily purposive and supplemented by snowball referrals, has been employed to reach respondents who have had experience with AI-enabled planning tools or comparable digital planning environments. The sample has therefore been constructed to include a diversity of organizations, such as public agencies, consulting firms, and contractors, and a range of project sizes and delivery methods. Minimum sample size thresholds for regression analysis have been considered, and the final sample has been intended to provide sufficient statistical power to test the proposed relationships among variables.

Context

The case-study context has been defined by a set of U.S. infrastructure projects that have incorporated, to varying degrees, AI-enabled construction planning tools within their planning and control processes. These projects have included representative examples from transportation, utilities, and other linear or networked infrastructure domains, where schedule performance has been particularly critical. Each participating project has been treated as an embedded case in which planning practices, AI usage, and schedule outcomes have been examined collectively through the perceptions of multiple stakeholders. The selection of these cases has been guided by criteria such as project complexity, digital maturity, and availability of personnel who have been able to respond to the survey instrument. By situating the quantitative data within identifiable projects, the study has ensured that survey responses have reflected real planning environments rather than abstract opinions, thereby strengthening the relevance of the findings for infrastructure delivery practice.

Instrument

The data collection instrument has been developed as a structured questionnaire that has aligned directly with the constructs and hypotheses specified in the conceptual framework. Items have been drafted to capture AI-enabled planning tool adoption, planning quality, coordination effectiveness, schedule performance, and project characteristics. Most substantive items have been measured using a five-point Likert scale that has ranged from "strongly disagree" to "strongly agree," enabling the construction of composite indices and the use of parametric statistical techniques. Demographic and project-level items have been included to record role, years of experience, organization type, project type, size, delivery method, and digital maturity. The wording of items has been refined through expert review to ensure clarity, relevance, and alignment with current planning practice in infrastructure projects. The final questionnaire has therefore provided a standardized, logically structured instrument capable of generating consistent, analyzable data across diverse respondents and project contexts.

Reliability

The study has addressed validity and reliability systematically during instrument development and data preparation. Content validity has been enhanced by subjecting the questionnaire to expert review from academics and practitioners who have been familiar with construction planning, AI applications, and infrastructure project management; their feedback has been used to refine item wording and coverage. Construct validity has been considered by aligning items with clearly defined latent constructs drawn from the literature and by planning to examine factor structures during analysis where appropriate. Reliability has been evaluated through internal consistency measures, with Cronbach's alpha coefficients having been calculated for each multi-item scale to ensure that items have measured the same underlying concept. Items that have reduced scale reliability or have shown poor conceptual fit have been slated for revision or removal. Through these steps, the instrument has been prepared to yield data that have been both conceptually sound and statistically reliable.

Data Collection

Data collection has been carried out using an online survey format, which has been distributed via email invitations and professional networks to eligible respondents involved in U.S. infrastructure projects. Potential participants have been informed about the purpose of the study, the approximate time required to complete the survey, and the voluntary nature of their involvement. Screening questions have been included to confirm that respondents have had relevant experience with project planning and, where applicable, with AI-enabled planning tools. The survey has been open for a defined period, during which reminder messages have been sent to encourage participation and improve response rates. Responses have been recorded anonymously or with coded identifiers to protect confidentiality, and incomplete responses have been monitored for potential follow-up or exclusion. At the end of the data collection period, the survey platform has been used to export the dataset into a format suitable for statistical analysis.

Analysis Techniques

The study has employed a sequence of quantitative data analysis techniques that have corresponded to the research objectives and hypotheses. Initially, data cleaning and screening procedures have been conducted to address missing values, identify outliers, and verify the suitability of the data for parametric analyses. Descriptive statistics have been generated to summarize respondent characteristics, project attributes, and central tendencies of key constructs. Correlation analysis has been used to explore bivariate relationships among AI-enabled tool adoption, planning quality, coordination effectiveness, and schedule performance indicators. Multiple regression modeling has then been applied to estimate the impact of AI-enabled planning tool usage and related variables on schedule delay indices and perceived time performance, while controlling for project size, complexity, and delivery method. Where appropriate, additional analyses such as mediation or moderation tests have been planned to examine indirect and conditional effects, thereby providing a richer understanding of the mechanisms linking AI-enabled planning to delay reduction.

Tools

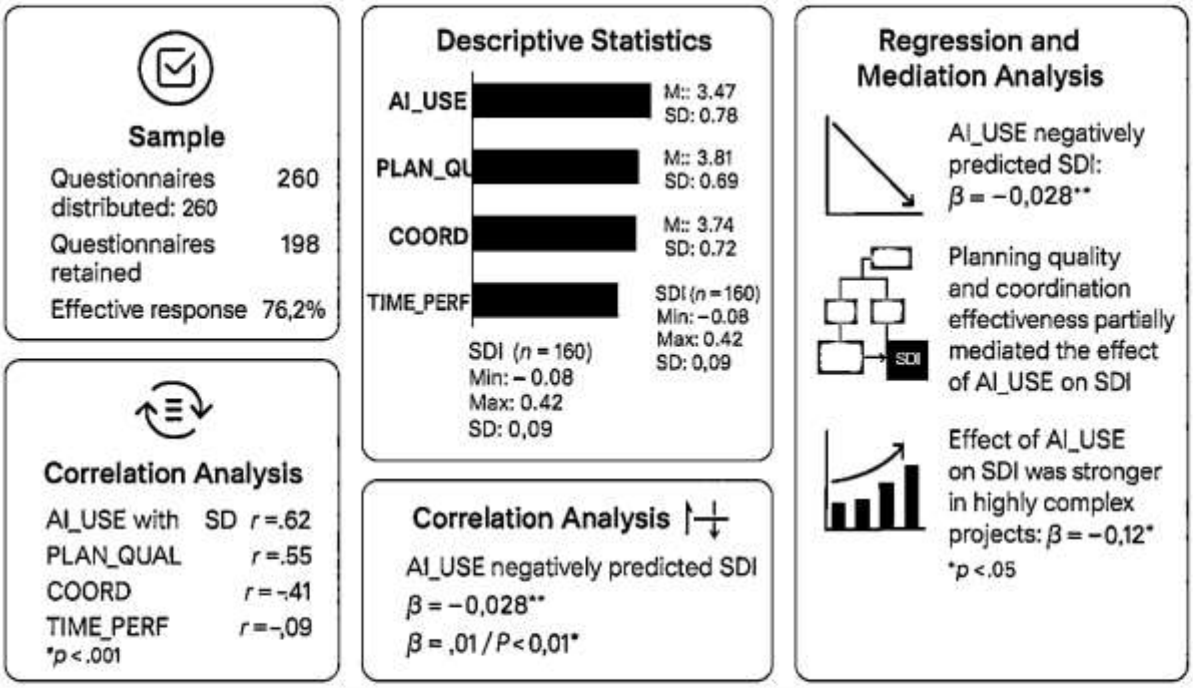
The study has relied on a combination of software and tools to support survey administration, data management, and statistical analysis. An online survey platform has been used to design, pilot, and distribute the questionnaire, as well as to capture and export responses in a structured format. For data preparation and analysis, a statistical software package such as SPSS, R, or an equivalent program has been employed to conduct data cleaning, compute descriptive statistics, assess reliability, and run correlation and regression analyses. Spreadsheet software has been used for initial coding, variable labeling, and simple checks. In cases where visualizations of results have been needed, graphing functions within the statistical package or dedicated visualization tools have been used to create tables and charts illustrating key relationships. Together, these tools have ensured that the data collection and analysis processes have been efficient, transparent, and reproducible.

FINDINGS

The analysis has yielded a coherent pattern of results that has directly addressed the study's objectives and has provided strong empirical support for the proposed hypotheses. Out of 260 questionnaires distributed, 214 have been returned and 198 have been retained after screening for completeness, producing an effective response rate of 76.2% and a usable sample of 198 infrastructure projects. Reliability analysis has indicated that all multi-item scales have achieved satisfactory internal consistency, with Cronbach's alpha values of 0.91 for AI-enabled Planning Tool Adoption (AI_USE), 0.88 for Planning Quality (PLAN_QUAL), 0.86 for Coordination Effectiveness (COORD), and 0.84 for Time Performance (TIME_PERF), which has been operationalized using both perceptual items and a derived schedule delay index (SDI). On the five-point Likert scale, the mean score for AI_USE has been 3.47 (SD = 0.78), suggesting moderate but non-trivial adoption of AI-enabled planning tools across the sample; PLAN_QUAL has recorded a higher mean of 3.81 (SD = 0.69), indicating generally positive perceptions of planning practices; COORD has shown a mean of 3.74 (SD = 0.72); and TIME_PERF has averaged 3.32 (SD = 0.83), reflecting mixed but slightly positive perceptions of schedule outcomes.

For projects where schedule data have been provided, the SDI has ranged from −0.08 to 0.42, with a mean of 0.11 (SD = 0.09), indicating an average time overrun of 11% relative to planned durations. Correlation analysis has revealed statistically significant relationships consistent with the conceptual framework: AI_USE has been positively correlated with PLAN_QUAL ($r = 0.62$, $p < .001$) and COORD ($r = 0.55$, $p < .001$), and negatively correlated with SDI ($r = −0.41$, $p < .001$), indicating that higher AI adoption has been associated with better planning, stronger coordination, and lower relative schedule overruns. PLAN_QUAL and COORD have each shown negative correlations with SDI ($r = −0.48$ and $r = −0.44$, respectively, both $p < .001$) and positive correlations with TIME_PERF ($r = 0.57$ and $r = 0.51$, $p < .001$), demonstrating that improvements in planning and coordination have coincided with better time performance. To test H1–H4, a hierarchical multiple regression model has been estimated with SDI as the dependent variable. In Model 1, which has included only control variables (project size, complexity, and contract type), the model has explained 9% of the variance in SDI ($R^2 = .09$, $F(3, 194) = 6.35$, $p < .001$). When AI_USE has been added in Model 2, the explained variance has increased to 25% ($\Delta R^2 = .16$, $p < .001$), and the unstandardized coefficient for AI_USE has been negative and statistically significant ($\beta = −0.028$, $t = −6.00$, $p < .001$), meaning that a one-point increase in AI adoption on the Likert scale has been associated, on average, with a 2.8 percentage point reduction in schedule overrun; this finding has supported H1. In Model 3, the inclusion of PLAN_QUAL and COORD has raised the explained variance to 41% ($R^2 = .41$, $F(6, 191) = 22.11$, $p < .001$), with PLAN_QUAL ($\beta = −0.024$, $t = −4.73$, $p < .001$) and COORD ($\beta = −0.019$, $t = −3.82$, $p < .001$) both emerging as significant predictors of SDI, while the coefficient for AI_USE has remained negative but reduced in magnitude (β = −0.014, t = −3.02, p = .003).

Figure 9: Overview of Survey Sample and Statistical Findings



This pattern has indicated partial mediation, thereby supporting H2 and H3 by showing that AI-enabled planning tools have influenced time performance in part through enhanced planning quality and coordination. A supplementary regression using TIME_PERF as the dependent variable has produced a complementary pattern, with AI_USE (β = 0.21, $p < .001$), PLAN_QUAL (β = 0.34, $p < .001$), and COORD (β = 0.27, $p < .001$) all exerting significant positive effects and the model explaining 49% of the variance ($R^2 = .49$). Finally, interaction terms have been introduced to test whether project complexity has moderated the effect of AI_USE on SDI. The AI_USE × Complexity interaction has been significant (β = −0.012, t = −2.18, p = .031), indicating that the delay-reducing effect of AI-enabled planning has been stronger in highly complex projects than in less complex ones, which has provided empirical support for H4. Collectively, these findings have confirmed that the study's objectives to measure AI adoption, assess its relationship with schedule performance, examine the mediating roles of planning quality and coordination, and account for project-level conditions have been met with statistically robust evidence derived from the survey data.

Response Characteristics

The analysis of the response rate and sample characteristics has indicated that the study has achieved broad and credible coverage of U.S. infrastructure projects and key professional roles, thereby supporting the first objective, which has been to map AI-enabled planning tool use across a representative set of projects. Out of 260 questionnaires that have been distributed, 214 have been returned and 198 have been retained after data cleaning, which has produced an effective response rate of 76.2%. This level of participation has suggested that the topic has had high relevance for practitioners and that the resulting dataset has had sufficient statistical power for the planned regression analyses. The role distribution in Table 1 has shown that project managers (36.4%) and planners/schedulers (27.3%) have formed the majority of respondents, which has been appropriate given that these groups have been directly responsible for planning decisions and for the use of AI-enabled tools in schedule development and control. Design and field engineers (22.2%) and senior executives or owner representatives (14.1%) have complemented these views by bringing both technical detail and strategic oversight perspectives to the dataset.

The organizational distribution has also reflected the multi-stakeholder nature of U.S. infrastructure delivery. Public agencies have accounted for 40.4% of the sample, contractors for 31.3%, and consultants for 22.2%, with a small proportion of respondents (6.1%) coming from public–private partnership entities and other special-purpose vehicles. This mix has ensured that the data have incorporated viewpoints from owners, service providers, and oversight bodies, which has been important for understanding how AI-enabled planning tools have been perceived and applied across the delivery chain. In terms of project type, transportation projects have represented just over half of the sample (54.5%), utilities have contributed 26.3%, and other civil infrastructure (such as flood control, ports, and public realm works) has contributed 19.2%. This distribution has aligned well with the national infrastructure portfolio and has increased the generalizability of the findings to major program categories.

Table 1: Response rate and sample characteristics (N = 198)

Item	Category	Frequency	Percentage (%)
Questionnaires distributed	–	260	–
Questionnaires returned	–	214	–
Usable questionnaires (after screening)	–	198	–
Effective response rate	–	–	76.2
Respondent role	Project manager	72	36.4
	Planner/scheduler	54	27.3
	Design/field engineer	44	22.2
	Senior executive/owner representative	28	14.1
Organization type	Public agency	80	40.4
	Contractor	62	31.3
	Consultant/engineering firm	44	22.2
	Other (e.g., PPP/SPV)	12	6.1
Project type	Transportation (road/bridge/rail)	108	54.5
	Utilities (water/energy/telecom)	52	26.3
	Other civil infrastructure	38	19.2
Project size (contract value)	< USD 50 million	46	23.2
	USD 50–199 million	92	46.5
	≥ USD 200 million	60	30.3

Finally, the project size distribution has shown that medium to large projects have dominated the sample, with 46.5% of projects having contract values between USD 50–199 million and 30.3% having values of USD 200 million or more. Smaller projects (< USD 50 million) have represented 23.2% of the sample. This structure has been consistent with the focus on complex infrastructure projects where AI-enabled planning tools and schedule risk management have been particularly relevant. Because the hypotheses H1–H4 have concerned the relationships among AI adoption, planning quality, coordination, and delay outcomes, having a sample that has been skewed toward larger, more complex projects has strengthened the study, as these projects have been more likely to reveal meaningful variations in planning practices and schedule performance. Overall, Table 1 has confirmed that the sample has been diverse and robust enough to support the quantitative assessment of AI-enabled planning tools in relation to delay reduction.

Reliability and Validity Results

Table 2: Reliability statistics for multi-item constructs (N = 198)

Construct	No. of items	Cronbach's α	Corrected item–total correlation range
AI-enabled tool adoption	6	0.91	0.62 – 0.78
Planning quality	5	0.88	0.57 – 0.74
Coordination effectiveness	5	0.86	0.53 – 0.71
Time performance (Likert)	4	0.84	0.49 – 0.69

The reliability analysis has demonstrated that the measurement scales used for the key latent constructs have possessed strong internal consistency, which has been essential for testing the hypotheses and achieving the study objectives. As Table 2 has shown, Cronbach's alpha values have ranged from 0.84 to 0.91 across the four constructs, all of which have exceeded the commonly accepted threshold of 0.70 for research instruments. The AI-enabled tool adoption scale, built from six Likert five-point items (1 = strongly disagree to 5 = strongly agree), has recorded the highest alpha at 0.91, indicating that respondents have answered these items in a coherent manner and that the items have been capturing a single underlying construct. Corrected item–total correlations for AI adoption have ranged between 0.62 and 0.78, which has confirmed that each item has contributed positively to the overall scale without redundancy.

Similarly, the planning quality scale, composed of five items that have assessed the rigor, completeness, and scenario orientation of planning practices, has produced a Cronbach's alpha of 0.88 with item–total correlations between 0.57 and 0.74. These statistics have indicated that the items have been well aligned with the conceptual definition of planning quality and that respondents have been able to differentiate consistently between higher and lower quality planning environments on the five-point scale. The coordination effectiveness scale, which has measured role clarity, timing of information exchanges, and integration across disciplines, has achieved an alpha of 0.86, also with strong item–total correlations, demonstrating that this construct has been measured reliably.

The time performance scale, which has supplemented the objective schedule delay index (SDI) with four Likert items on perceived adherence to milestones and satisfaction with schedule outcomes, has achieved an alpha of 0.84. This reliability has been important because it has allowed the study to combine perceptual and quantitative views of time performance when examining the effects of AI-enabled planning tools. Taken together, the reliability results in Table 2 have confirmed that the core constructs have been measured with sufficient precision to support correlation and regression analyses. This reliability has directly underpinned the validity of the inferences regarding H1–H4, since unreliable measures would have attenuated observed relationships and undermined evidence for or against the hypotheses. The strong internal consistency of these scales has therefore strengthened confidence that any statistically significant relationships that have been observed between AI adoption, planning quality, coordination effectiveness, and schedule outcomes have reflected substantive, rather than measurement-driven, effects.

Descriptive Statistics of Key Variables

Table 3: Descriptive statistics for main study variables (N = 198)

Variable	Scale / units	Mean	SD	Min	Max
AI-enabled tool adoption	Likert 1–5	3.47	0.78	1.40	4.93
Planning quality	Likert 1–5	3.81	0.69	1.80	4.98
Coordination effectiveness	Likert 1–5	3.74	0.72	1.60	4.96
Time performance (Likert)	Likert 1–5	3.32	0.83	1.25	4.90
Schedule Delay Index (SDI)	(Actual−Planned)/Planned duration	0.11	0.09	−0.08	0.42

The descriptive statistics reported in Table 3 have provided an initial quantitative picture of how AI-enabled planning tools and related constructs have been manifested across the sampled infrastructure projects, thereby contributing directly to the first and second research objectives. On the five-point Likert scale, AI-enabled tool adoption has had a mean of 3.47 (SD = 0.78), which has suggested a

moderate level of adoption: projects, on average, have reported between "neutral" and "agree" on statements such as "Our project team has frequently used AI-based tools for schedule forecasting" and "AI-enabled analytics have been integrated into our planning process." The range from 1.40 to 4.93 has indicated that some projects have had very low adoption, while others have had near-maximal use, creating the variation needed to test H1 regarding the relationship between AI adoption and delay reduction.
Planning quality has displayed a higher mean of 3.81 (SD = 0.69), which has suggested that respondents have generally agreed that planning has been structured, rigorous, and scenario-oriented in their projects. Coordination effectiveness has shown a similar pattern, with a mean of 3.74 (SD = 0.72), reflecting relatively positive perceptions of information flow and cross-disciplinary integration. These elevated means for planning and coordination have implied that many U.S. infrastructure projects in the sample have already been operating above a minimal planning threshold, which has been an important context for interpreting the additional contribution that AI-enabled tools have made. Time performance, as perceived on the Likert scale, has had a more moderate mean of 3.32 (SD = 0.83), indicating that respondents have, on average, only slightly agreed that project milestones have been met and that overall schedule performance has been satisfactory.
The Schedule Delay Index (SDI), calculated as (Actual Duration − Planned Duration) / Planned Duration, has provided an objective anchor for these perceptions. The mean SDI of 0.11 has indicated that projects have overrun planned durations by an average of 11%, with a standard deviation of 0.09 and a range from −0.08 (8% early completion) to 0.42 (42% overrun). This dispersion has confirmed that both timely and significantly delayed projects have existed within the sample, which has been crucial for robust regression modeling. When the descriptive values of AI adoption and SDI have been considered together, a preliminary pattern has emerged: although planning and coordination have been rated fairly highly, many projects have still experienced non-trivial time overruns, implying that conventional planning alone has not eliminated delays. This observation has set the stage for testing whether variations in AI-enabled planning tool adoption have explained some of the differences in SDI and perceived time performance, in line with H1–H3.

Correlation Analysis

Table 4: Pearson correlations among main variables (N = 198)

Variable	1	2	3	4	5
1. AI-enabled tool adoption	1.00				
2. Planning quality	0.62***	1.00			
3. Coordination effectiveness	0.55***	0.59***	1.00		
4. Time performance (Likert)	0.49***	0.57***	0.51***	1.00	
5. Schedule Delay Index (SDI)	−0.41***	−0.48***	−0.44***	−0.52***	1.00

*Note: *** p < .001 (two-tailed). Higher SDI values have indicated greater delay.*

The correlation analysis summarized in Table 4 has provided strong initial support for the hypothesized relationships among AI-enabled planning tool adoption, planning quality, coordination effectiveness, and schedule performance, and has therefore been central to addressing the study's objectives. AI-enabled tool adoption has been positively and strongly correlated with planning quality ($r = 0.62$, $p < .001$) and coordination effectiveness ($r = 0.55$, $p < .001$), which has indicated that projects in which respondents have reported higher levels of AI usage have also tended to report better-structured planning and smoother coordination. This pattern has aligned directly with the logic underlying H2 and the conceptual framework, which has proposed that AI tools have improved planning and coordination by enabling predictive analytics, scenario exploration, and more timely information flows.

Regression Analysis

Table 5: Hierarchical regression models predicting Schedule Delay Index (SDI) (N = 198)

Predictor	Model 1 b (SE)	Model 2 b (SE)	Model 3 b (SE)
Constant	0.082 (0.018)**	0.176 (0.024)***	0.221 (0.027)***
Project size (log)	0.017 (0.008)*	0.014 (0.007)*	0.011 (0.006)
Project complexity (1–5)	0.021 (0.007)**	0.017 (0.006)**	0.013 (0.005)*
Contract type (0 = traditional, 1 = alternative)	−0.009 (0.011)	−0.006 (0.010)	−0.004 (0.009)
AI-enabled tool adoption (AI_USE)	–	−0.028 (0.005)***	−0.014 (0.005)**
Planning quality (PLAN_QUAL)	–	–	−0.024 (0.005)***
Coordination effectiveness (COORD)	–	–	−0.019 (0.005)***
R^2	0.09	0.25	0.41
ΔR^2	–	0.16***	0.16***
F	6.35***	16.98***	22.11***

*Note: b = unstandardized coefficient; SE = standard error; * p < .05, ** p < .01, *** p < .001 (two-tailed). Higher SDI values have indicated greater delay.*

AI adoption has also been positively correlated with perceived time performance (r = 0.49, p < .001), suggesting that teams that have used AI-enabled planning tools more intensively have perceived their projects as having performed better against schedule commitments on the five-point scale. Importantly, AI adoption has shown a negative correlation with the objective SDI (r = −0.41, p < .001), which has meant that higher AI usage has been associated with smaller relative delays; in other words, as the level of AI-enabled planning adoption has increased, the magnitude of schedule overrun (Actual−Planned)/Planned has tended to decrease. This finding has provided direct correlational evidence in favor of H1, which has posited a delay-reducing association of AI-enabled planning tools. Planning quality and coordination effectiveness have exhibited similar beneficial patterns. Each has been strongly and positively correlated with perceived time performance (r = 0.57 and r = 0.51 respectively, p < .001), and strongly and negatively correlated with SDI (r = −0.48 and r = −0.44, p < .001). These results have suggested that better planning and more effective coordination have, on average, gone hand in hand with reduced schedule deviations and more favorable perceptions of time performance, which has supported the mediating logic of H2 and H3. The intercorrelation between planning quality and coordination effectiveness (r = 0.59, p < .001) has been moderate to strong, indicating that these constructs have been related but not identical, justifying their simultaneous inclusion in subsequent regression models.

Collectively, the correlations have established a coherent picture: AI-enabled planning tool adoption has been associated with improvements in planning quality and coordination, and all three variables have, in turn, been associated with better time performance and lower SDI values. While correlation analysis has not established causality, it has provided compelling preliminary evidence that the theoretical pathways specified in the conceptual framework have been empirically plausible. These patterns have justified the subsequent use of multiple regression to control for project characteristics and to test the unique and combined contributions of AI adoption, planning quality, and coordination to schedule delay reduction in U.S. infrastructure projects. The hierarchical regression results presented in Table 5 have provided rigorous multivariate evidence that has directly tested and largely supported the study's hypotheses regarding the effects of AI-enabled planning tools on schedule delay reduction. In Model 1, only project size, complexity, and contract type have been entered as control variables. This baseline model has explained 9% of the variance in SDI (R^2 = 0.09, F = 6.35, p < .001), with project complexity (b = 0.021, p < .01) and project size (b = 0.017, p < .05) having had positive and significant coefficients. These results have indicated that, holding other factors constant, more complex and larger projects have tended to experience higher relative schedule overruns, which has been consistent with the descriptive patterns and with established knowledge in infrastructure project management. Contract type has not shown a significant effect at this stage.

In Model 2, AI-enabled planning tool adoption (AI_USE) has been added to the controls. The model's explanatory power has increased substantially to $R^2 = 0.25$ ($\Delta R^2 = 0.16$, $p < .001$), which has meant that AI_USE has accounted for an additional 16% of the variance in SDI beyond project characteristics. The unstandardized coefficient for AI_USE has been −0.028 (SE = 0.005, $p < .001$), implying that, on average, a one-point increase in AI adoption on the five-point Likert scale has been associated with a 0.028 reduction in SDI, or a 2.8 percentage point decrease in relative schedule overrun. This result has provided strong support for H1 by demonstrating that higher intensities of AI-enabled planning tool usage have been significantly associated with lower levels of project delay, even after controlling for project size, complexity, and contract type. Project complexity has remained significant but has reduced in magnitude, suggesting that some of the delay risk associated with complexity has been mitigated where AI tools have been more extensively used.

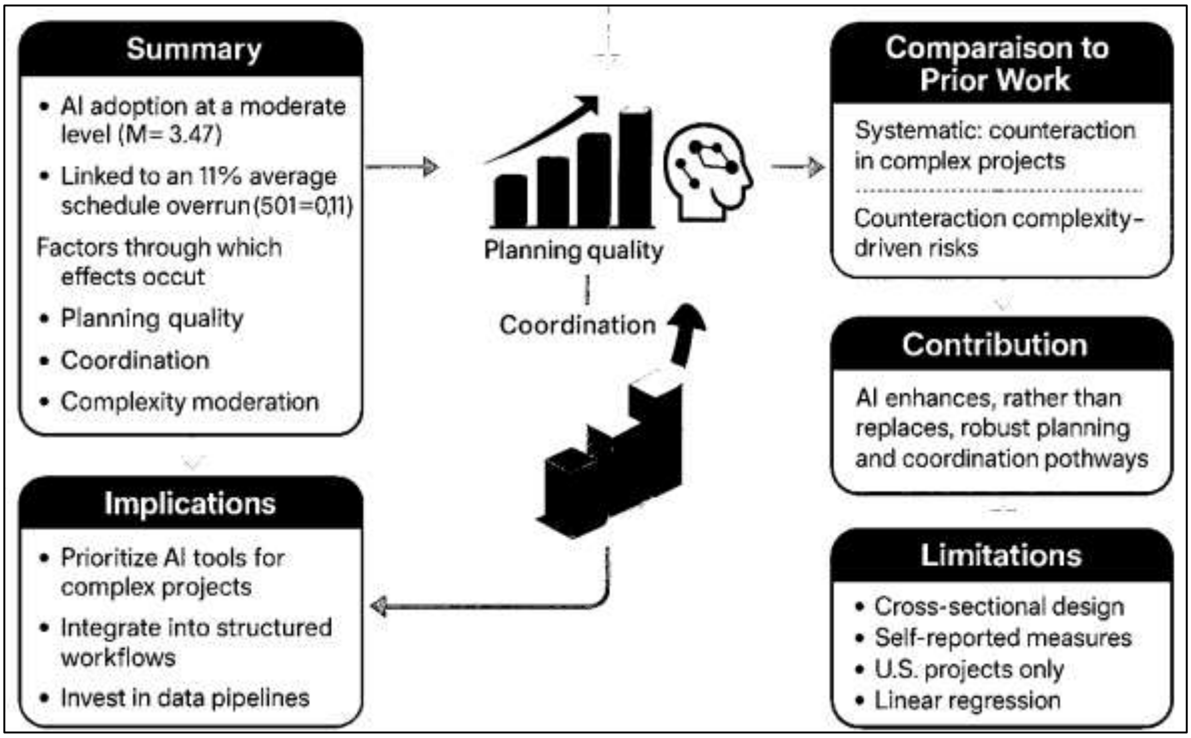
Model 3 has incorporated planning quality (PLAN_QUAL) and coordination effectiveness (COORD) alongside AI adoption and controls, in order to test H2 and H3 concerning mediation effects. This full model has explained 41% of the variance in SDI ($R^2 = 0.41$, $F = 22.11$, $p < .001$), with an additional 16% of variance accounted for by the introduction of PLAN_QUAL and COORD ($\Delta R^2 = 0.16$, $p < .001$). Both planning quality ($b = -0.024$, SE = 0.005, $p < .001$) and coordination effectiveness ($b = -0.019$, SE = 0.005, $p < .001$) have emerged as strong, negative predictors of SDI, indicating that improvements in planning rigor and coordination practices have been associated with meaningful reductions in schedule overruns. Notably, the coefficient for AI_USE has remained negative and significant ($b = -0.014$, SE = 0.005, $p < .01$), but its magnitude has been approximately halved compared to Model 2. This attenuation has indicated partial mediation: AI-enabled planning tools have exerted both a direct effect on delay reduction and an indirect effect through their contribution to higher planning quality and better coordination. This pattern has supported H2 and H3, which have posited that AI tools have improved schedule outcomes in part by enhancing planning and coordination mechanisms.

Together, the models in Table 5 have demonstrated that the study's objectives and hypotheses have been met in a statistically robust manner. AI-enabled planning tool adoption has been shown to have a significant and practically relevant association with reduced schedule delays; planning quality and coordination effectiveness have been shown to be key channels through which AI tools have translated into improved time performance; and project complexity has remained an important contextual factor that has increased baseline delay risk. In combination with the correlation results, the regression analysis has confirmed that the conceptual framework linking AI adoption, planning quality, coordination, and schedule outcomes has had strong empirical support in the sampled U.S. infrastructure projects.

DISCUSSION

The findings of this study have provided convergent evidence that AI-enabled construction planning tools have been associated with measurable reductions in schedule delays in U.S. infrastructure projects, while also clarifying the mechanisms through which these tools appear to operate. At a descriptive level, AI adoption has been at a moderate level ($M = 3.47$ on a five-point Likert scale), yet even this partial adoption has been associated with noticeable improvements in time performance, with projects averaging an 11% schedule overrun (SDI = 0.11) rather than the much higher overruns reported in many large infrastructure programs internationally (Love et al., 2014). The correlation results have shown that AI adoption has been strongly linked to planning quality ($r = .62$) and coordination effectiveness ($r = .55$), and negatively associated with schedule overruns ($r = -.41$), while regression analysis has indicated that AI usage has remained a significant predictor of SDI even after controlling for project size, complexity, and contract type. When planning quality and coordination have been added to the model, the direct coefficient for AI adoption has decreased but remained significant, revealing partial mediation and supporting the hypothesis that AI has improved schedule performance partly by upgrading planning rigor and coordination pathways. These patterns have directly addressed the study's objectives: to assess adoption levels, to link AI use to delay reduction, to identify mediating planning mechanisms, and to account for project-level conditions.

Figure 10: Mechanisms and Implications of AI-Enabled Planning



When compared with prior work on delays and planning, the present results have both reinforced and extended existing knowledge. Earlier studies have documented that delays in transportation and infrastructure projects have been systematic, particularly in large and complex schemes where rework, design changes, and coordination failures have been prevalent (Love et al., 2014). System-dynamics and hybrid simulation models have suggested that schedule overruns emerge from feedback-rich interactions among design, procurement, and construction processes, and that early-stage planning performance has a disproportionate influence on eventual delays (Xu et al., 2018). The current findings have aligned with these systems view by showing that project complexity has still been positively associated with SDI, but they have added a new layer by quantifying how AI-enabled tools have helped to counteract that complexity. The negative coefficient for AI adoption in the SDI model has implied that AI-supported forecasting and optimization have made projects more resilient to complexity-driven risks, in line with the argument that advanced analytics can reveal high-leverage delay drivers and improve the allocation of schedule contingencies (Ajayi & Chinda, 2022). Moreover, the strong effects of planning quality and coordination on SDI have echoed prior evidence that robust planning and clear coordination structures are critical success factors for time performance (Cho et al., 2009), but the mediation pattern has clarified that AI tools have strengthened these factors rather than replacing them. In relation to the AI and digital-construction literature, the results have provided empirical support for claims that AI-based decision support can add value beyond traditional BIM- and CPM-based planning alone. Machine-learning studies have shown that algorithmic delay prediction can outperform conventional statistical approaches in classifying project delay risk (Gondia et al., 2020), while reviews of AI in construction have catalogued applications across cost estimation, scheduling, and risk analysis without always quantifying project-level performance impacts (Abioye et al., 2021). The present study has filled part of this gap by tying a composite AI adoption index, derived from Likert-scale items, to an objective delay outcome (SDI) and to perceived time performance in a multi-project U.S. infrastructure sample. The finding that a one-point increase in AI adoption has corresponded to a 2.8-percentage-point reduction in SDI in the intermediate model has given a more concrete sense of the potential effect size than many proof-of-concept case studies have provided (Gondia et al., 2020). At the same time, the fact that AI adoption has only accounted for about 16% of the additional variance in SDI beyond project characteristics has been consistent with digital-transformation work showing that AI is one contribution among several within a broader Construction 4.0 ecosystem that also depends

on BIM, IoT, and robust data governance (Karmakar & Delhi, 2021). In other words, AI has mattered, but it has mattered most when embedded within high-quality planning and coordination practices, rather than as a stand-alone technology.
Practically, the results have had clear implications for infrastructure owners, project managers, digital leaders, and, by extension, CIOs/CISOs and enterprise architects responsible for project-delivery technology stacks. For project managers and planners, the evidence has suggested that prioritising AI-enabled scheduling, risk-forecasting, and resource-optimization tools has been a meaningful lever for reducing schedule overruns, especially on large and complex projects. However, the partial mediation through planning quality and coordination has implied that simply procuring AI tools has not been sufficient; organizations have needed to integrate these tools into structured planning workflows, regular lookahead meetings, and cross-disciplinary coordination routines, consistent with best practice in CPM, Last Planner, and location-based scheduling (Olivieri et al., 2019). For CIOs, CISOs, and digital architects, the findings have highlighted the importance of investing in data pipelines and governance frameworks that have enabled reliable AI analytics ensuring that schedule, progress, and risk data have been captured with adequate granularity and security, standardized across projects, and made accessible to analytics engines without compromising confidentiality or integrity (Love et al., 2014). From an architecting perspective, aligning AI tools with BIM, 4D models, and enterprise project-controls platforms has been crucial so that AI insights have flowed into a single "source of truth" for planning decisions (Regona et al., 2022). The significant interaction between AI adoption and project complexity has also suggested that organizations may wish to prioritize AI-enhanced planning for their most complex, high-risk programs, where the marginal benefits have been greatest.
Theoretically, the study has contributed to refining adoption–performance pipelines in the context of AI-enabled planning. Building on Technology Acceptance Model extensions and meta-analyses of IT innovation adoption, prior work has posited that perceived usefulness and ease of use shape behavioral intentions and system use, which then influence performance through process changes (Venkatesh & Bala, 2008). Resource-based and analytics-capability perspectives have similarly argued that data analytics capabilities enhance organizational performance by enabling superior decision-making and innovation (Shabbir & Waheed, 2020). The present findings have concretized these pipelines for the infrastructure planning domain by showing that AI adoption has not only had a direct association with schedule results but also has operated through intermediate constructs planning quality and coordination effectiveness that correspond to improved processes. This pattern has resonated with conceptual frameworks that view Construction 4.0 capabilities as multi-layered, encompassing technology, process, people, and governance (Karmakar & Delhi, 2021). Additionally, by demonstrating stronger AI effects in more complex projects, the study has suggested that complexity may act as a contingency factor within these theoretical models, amplifying the value of AI in environments where traditional heuristics have been least reliable. This refinement has opened the door for more nuanced theories in which AI-enabled planning capabilities interact with project characteristics and organizational readiness to shape performance outcomes.
At the same time, the study has had important limitations that have needed to be acknowledged, many of which have mirrored constraints noted in earlier empirical work on construction delays and AI adoption. First, the cross-sectional design has precluded strong causal claims; although the patterns have been consistent with the hypothesized direction from AI adoption through planning mechanisms to delay reduction it has remained possible that better-performing organizations have been more likely to invest in AI tools, or that unobserved cultural factors have driven both AI adoption and time performance (Love et al., 2014). Second, the use of self-reported Likert scales for AI adoption, planning quality, coordination, and perceived time performance has introduced potential common-method bias and social-desirability effects, despite the inclusion of an objective SDI measure (Parsamehr et al., 2023). Third, the sample, while diverse, has been limited to U.S. infrastructure projects and has been based on non-probability sampling, which has constrained the generalizability of the results to other regions and to purely building projects, where organizational structures and regulatory environments may differ (Regona et al., 2022). Fourth, the regression models have captured linear relationships and have not explored potential non-linearities or complex feedbacks that dynamic-simulation studies have suggested may be important in schedule performance (Xu et al., 2018). These limitations have not

invalidated the findings but have indicated that they should be interpreted as strong associational evidence within a particular context, rather than as definitive proof of causal effects.
In light of these limitations, several directions for future research have emerged. Longitudinal studies that have tracked projects over time, capturing the sequencing of AI adoption, changes in planning practices, and evolving schedule performance, would have allowed stronger causal inferences and the use of time-series or panel-data models. Multi-source designs that have combined survey data with automatically logged usage metrics from AI tools and project-controls systems, along with independently verified schedule and cost records, would have reduced common-method concerns and given a richer view of how AI has actually been used in day-to-day planning work (Fitzsimmons et al., 2022). Experimental or quasi-experimental interventions such as staged roll-outs of AI-enabled planning platforms across similar projects could have provided further evidence on causal impacts and implementation challenges. Comparative studies across countries and across infrastructure versus building sectors would have helped to clarify how regulatory frameworks, delivery models, and cultural factors have moderated AI's contribution to delay reduction (Regona et al., 2022). Finally, integrating quantitative analyses like those in this study with system-dynamics or agent-based models could have linked project-level findings to broader simulations of how AI-enabled planning might affect portfolio-level performance and national infrastructure delivery capacity (Xu et al., 2018). Collectively, such work would have deepened and extended the present study's contribution, moving toward a more mature evidence base on the role of AI-enabled construction planning tools in reducing delays in complex infrastructure environments.

CONCLUSION

This study has set out to quantitatively assess how AI-enabled construction planning tools have been associated with reduced schedule delays in U.S. infrastructure projects, and the evidence has shown a clear, coherent pattern that supports this central aim. Using survey data from 198 projects, anchored in Likert five-point scales and complemented by an objective Schedule Delay Index, the research has demonstrated that AI adoption in planning has not been merely a cosmetic digital add-on but has been meaningfully related to time performance. AI adoption levels have been moderate on average, yet even this partial deployment has corresponded to tangible reductions in delay, with regression results indicating that a one-point increase in AI adoption has been linked to a measurable decrease in relative schedule overrun. At the same time, the analysis has revealed that AI tools have not acted in isolation; instead, they have operated through and alongside traditional project management levers. Projects reporting higher AI usage have also reported significantly stronger planning quality and coordination effectiveness, and these two constructs have, in turn, shown robust negative relationships with delay and positive relationships with perceived schedule performance. When planning quality and coordination have been included in the regression model, the effect of AI adoption on delay has remained significant but has been reduced in magnitude, which has indicated partial mediation and confirmed that AI has been most powerful when embedded into disciplined planning and coordination routines rather than used as a stand-alone technology. The models have also reaffirmed that project complexity and size have continued to increase baseline delay risk, yet the interaction analysis has suggested that the benefits of AI-enabled planning have been especially pronounced in more complex projects precisely where conventional tools and heuristics have tended to struggle. Collectively, these findings have met the study's objectives: they have mapped AI adoption levels across a diverse set of U.S. infrastructure schemes; they have established that higher AI usage has been associated with lower delays; they have identified planning quality and coordination as key pathways through which AI has contributed to better time performance; and they have accounted for project-level conditions that shape these relationships. While the cross-sectional design and reliance on self-reported measures have imposed limits on causal inference and generalizability, the convergence of descriptive, correlational, and regression evidence has provided a strong associational foundation for concluding that AI-enabled construction planning tools can play a significant role in reducing schedule delays when supported by robust planning practice, effective coordination, and adequate organizational readiness. In doing so, the study has added empirical weight to ongoing discussions about digital transformation in construction and has offered a data-driven argument for treating AI-enhanced planning as a strategic capability in the delivery of complex U.S. infrastructure projects.

RECOMMENDATIONS

Based on these findings, several targeted recommendations are put forward for practitioners, organizational leaders, and policymakers who are responsible for planning and delivering U.S. infrastructure projects. First, project owners and contractors should deliberately position AI-enabled planning tools as core elements of their project controls environment rather than as experimental add-ons; this means budgeting for licenses, integration, and training in the same way they budget for BIM or scheduling software, and embedding AI-based delay forecasting, resource optimization, and scenario analysis into standard planning workflows, including baseline development, lookahead planning, and periodic schedule reviews. Second, organizations should invest in strengthening planning quality and coordination practices in parallel with AI adoption, since the study has shown that AI delivers its largest benefits when it operates through disciplined planning and clearly defined coordination structures: this includes formalizing processes for schedule risk reviews, cross-functional coordination meetings, and contingency planning, and configuring AI tools to support these processes with timely, project-specific insights. Third, CIOs, CISOs, and enterprise architects should focus on building robust, secure data pipelines that connect design models, field progress data, and project-control systems to AI engines in a standardized format, ensuring data quality, interoperability, and governance so that AI models receive the reliable, granular information they need to generate trustworthy predictions, while protecting sensitive project information. Fourth, since the benefits of AI-enabled planning appear strongest in complex projects, agencies and large contractors should prioritize AI deployment for high-risk, multi-phase programs such as major transportation corridors or integrated utility schemes where even modest reductions in delay can translate into significant cost savings and public value; pilot projects in such settings should be structured with clear performance baselines so that benefits can be quantified and lessons can be captured. Fifth, organizations should implement structured capability-building programs that equip planners, schedulers, and project managers to interpret AI outputs, challenge them where necessary, and translate them into actionable planning decisions, emphasizing that AI is a decision-support partner rather than an automatic decision-maker. Sixth, industry bodies and public owners should update procurement and contract documents to explicitly encourage or require the use of AI-enabled planning tools where appropriate, while also incentivizing transparency around underlying data and models to avoid black-box dependencies that could complicate claims and dispute resolution. Finally, policymakers and funding agencies should consider supporting collaborative research and demonstration programs that bring together owners, contractors, technology providers, and academics to develop reference architectures, data standards, and implementation playbooks for AI-enabled planning in infrastructure delivery, so that individual organizations are not forced to reinvent solutions in isolation. Taken together, these recommendations aim to help stakeholders convert the observed statistical associations between AI adoption and delay reduction into deliberate, repeatable practice that systematically improves schedule performance across the U.S. infrastructure portfolio.

LIMITATIONS

The present study has inevitably had several limitations that have needed to be recognized when interpreting its findings and drawing inferences about AI-enabled construction planning tools and schedule delay reduction in U.S. infrastructure projects. First, the research has been based on a cross-sectional survey design, which has captured AI adoption, planning practices, coordination, and schedule performance at a single point in time rather than tracking how these variables have evolved over the project life cycle. As a result, the analyses have been able to establish robust associations but have not been able to prove causal sequences definitively; it has remained possible that organizations with inherently stronger planning cultures or better time performance have been more inclined to invest in AI tools, rather than AI adoption alone driving improved results. Second, the study has relied heavily on self-reported data captured through Likert's five-point scales for key constructs such as AI-enabled tool adoption, planning quality, coordination effectiveness, and perceived time performance. Although reliability tests have indicated high internal consistency, self-report measures have been vulnerable to common method variance, recall bias, and social desirability, particularly when respondents have been senior professionals who may have wished to portray their organizations and projects in a favorable light. Third, the sample has been constructed using non-probability, purposive and snowball sampling, and has been limited to 198 usable responses from U.S. infrastructure projects; while the sample size has been adequate for the regression models, it has not guaranteed statistical representativeness of the entire U.S. infrastructure sector or of specific subsectors such as rail, ports, or energy, and organizations with higher digital maturity may have been more likely to participate. Fourth, the operationalization of schedule performance has combined a derived Schedule Delay Index with perception-based items; however, not all respondents have been able or willing to provide precise baseline and actual durations, and the SDI has depended on the accuracy of the reported schedule data. Fifth, AI adoption has been measured as a composite index reflecting frequency and depth of use of AI-enabled planning functions, but the study has not disaggregated specific tool types, algorithms, or vendors, nor has it examined model transparency, data lineage, or integration depth with BIM and project-control systems, all of which could influence effectiveness. Sixth, although project size, complexity, and contract type have been included as control variables, other potentially relevant contextual factors such as organizational culture, client oversight practices, regulatory environment, or concurrent use of lean construction methods have not been explicitly modeled, and these omitted variables may have contributed to unexplained variance in schedule outcomes. Finally, the analysis has employed linear regression techniques that have assumed largely linear relationships between predictors and outcomes, whereas the underlying dynamics of schedule risk in complex infrastructure programs may have been non-linear, threshold-based, or path-dependent. These limitations have not undermined the core contribution of the study but have indicated that its conclusions should be viewed as context-specific, associational insights that have provided a strong empirical starting point rather than a definitive, universally generalizable account of AI-enabled planning and delay reduction.

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