

The Impact of Integrating Big Data and Artificial Intelligence Algorithms on Enhancing Time Efficiency Throughout the Life Cycle of Architectural and Urban Planning Projects

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ABSTRACT

The contemporary construction and urban development industry faces persistent structural challenges, including substantial schedule deviations, declining productivity, and delays in information feedback, which stem from the rigidity of traditional project management methods and data discontinuities across project life cycle phases. To address these fundamental constraints, the present study investigates the impact of the systematic integration of big data and artificial intelligence (AI) algorithms on enhancing time efficiency throughout the life cycle of architectural and urban planning projects. The research methodology adopts an empirical-analytical approach at two scales, namely complex architectural buildings and large-scale urban infrastructure projects. Accordingly, the effects of implementing intelligent systems were evaluated across four phases: pre-design, planning, construction monitoring, and critical path optimization. The statistical findings demonstrated that integrating generative design based on multi-objective genetic algorithms with predictive solar radiation and climate models reduced the time required to generate and optimize architectural design alternatives by 79.2% compared with conventional parametric methods, decreasing the conceptual decision-making period from 120 hours to 25 hours. During the planning phase, the application of hybrid machine learning models, with an area under the receiver operating characteristic curve exceeding 0.92, filtered out more than 92% of false-positive clashes in Building Information Modeling (BIM), preventing the loss of 1,616 specialist person-hours. Furthermore, during on-site construction, integrating real-time computer vision data streams with Internet of Things (IoT) positioning sensors reduced the reporting delay for construction-site nonconformities from an average of 3.2 working days to 16.2 minutes, representing a 97.2% acceleration in the supervisory feedback cycle. Inferential analyses based on Earned Value Management (EVM) indicators and paired-samples t-tests at the 95% confidence level confirmed that the Schedule Performance Index (SPI) improved to a stable level of 1.04 during the construction phases.

Keywords: Artificial Intelligence, Big Data, Earned Value Management, Critical Path Optimization.

1. Introduction

The architecture, engineering, construction, and urban development sectors are undergoing a fundamental transition from fragmented, experience-driven project management toward digitally integrated, data-intensive, and increasingly autonomous decision-making environments. This transition is largely driven by the persistent inefficiencies that continue to characterize construction projects, including schedule overruns, productivity losses, coordination failures, resource conflicts, delayed managerial responses, and substantial uncertainty across successive phases of the project life cycle. Although conventional project management methods provide formal mechanisms for scope, schedule, cost, resource, and risk control, they frequently operate through periodic reporting cycles and deterministic planning structures that are insufficiently responsive to the highly dynamic conditions of contemporary construction and urban development projects (Project Management, 2021). Construction projects are particularly vulnerable to time-related inefficiencies because design revisions, supply-chain disruptions, workforce constraints, weather variability, equipment downtime, spatial interference, and unforeseen site conditions continuously modify the assumptions upon which initial schedules are constructed. Consequently, static scheduling mechanisms may rapidly lose their representational accuracy once implementation begins. Scheduling optimization has therefore emerged as a central concern in construction management, with prior research emphasizing the need for computational methods capable of addressing complex activity dependencies, resource constraints, uncertainty, and multiple competing objectives (Khamooshi & Kiani, 2021). At the same time, artificial intelligence (AI) has developed from a specialized computational discipline into a broadly applicable framework for perception, prediction, reasoning, optimization, and autonomous decision support (Russell & Norvig, 2021). Its convergence with rapidly expanding project datasets has created a significant opportunity to reconceptualize time management not merely as periodic schedule control, but as a continuous, predictive, and adaptive process extending throughout the entire life cycle of architectural and urban planning projects.

Among the most important foundations of this transformation is Building Information Modeling (BIM), which has established a shared digital representation of the physical and functional characteristics of built assets and has substantially altered coordination among designers,

engineers, contractors, and project owners. BIM enables information generated during planning, design, construction, and operation to be structured within interconnected digital models, thereby improving visualization, interdisciplinary coordination, quantity extraction, construction sequencing, and information accessibility (Eastman et al., 2021). Its contribution to project management has expanded considerably beyond three-dimensional modeling, particularly through 4D and 5D applications that connect geometric information with time and cost variables (Ye et al., 2024). However, BIM alone does not automatically transform data into predictive intelligence. Traditional BIM workflows may still depend on manual model inspection, rule-based clash detection, periodic updates, and human interpretation of large volumes of project information. Consequently, the growing integration of BIM with artificial intelligence and other computational technologies has become a major research trajectory within construction informatics (Brilakis et al., 2020). Machine learning applications within BIM environments have demonstrated the potential to automate classification, identify construction risks, predict project conditions, detect inconsistencies, and support decision-making that would otherwise require extensive manual interpretation (Zabin et al., 2022). The increasing sophistication of these applications suggests that BIM should no longer be conceptualized solely as a digital modeling platform; rather, when integrated with AI and continuously updated project data, it can function as an intelligent information infrastructure capable of supporting real-time schedule optimization and life-cycle decision-making.

The significance of artificial intelligence in this domain has expanded rapidly because construction projects now generate heterogeneous datasets at unprecedented volume, velocity, and variety. These data originate from BIM models, project management platforms, sensors, cameras, drones, mobile devices, equipment telematics, geospatial databases, procurement systems, worker tracking technologies, digital documentation, and environmental monitoring systems. Such heterogeneous data environments correspond closely to the defining characteristics of big data and create opportunities for discovering patterns that are difficult to identify through conventional statistical or managerial procedures. Recent reviews indicate that AI applications are increasingly distributed throughout the construction project life cycle, including feasibility assessment, design optimization, cost estimation, schedule prediction, safety management, progress monitoring, risk

assessment, resource allocation, and operational decision support (Datta et al., 2024). The evolutionary trajectory of AI in construction project management similarly demonstrates a shift from isolated prediction tasks toward integrated decision-support systems capable of learning from historical and real-time project information (Adebayo et al., 2025). Scoping evidence further confirms that AI is becoming embedded in multiple dimensions of construction management rather than remaining restricted to experimental computer science applications (Lai et al., 2025). More recent assessments of AI applications in construction management indicate that the research frontier is increasingly concerned with multimodal information processing, deep learning, digital twins, generative systems, explainable AI, and adaptive optimization (Zhang & Jiang, 2026). Nevertheless, despite this rapid methodological evolution, the extent to which integrated big data and AI systems can systematically improve temporal productivity across interconnected project phases remains insufficiently established.

One particularly important dimension of this integration concerns the transition from periodic project observation to continuous, data-driven situational awareness. The Internet of Things (IoT) enables physical construction processes to be digitally observed through networks of interconnected sensors, positioning devices, wearable systems, and equipment-monitoring technologies. Early IoT-based construction systems demonstrated the feasibility of real-time worker positioning, monitoring, and alarm generation, establishing an important foundation for continuous site intelligence (Kanan et al., 2018). More recent research has extended this paradigm by integrating BIM, IoT, and Geographic Information Systems (GIS) for construction resource monitoring, thereby connecting model-based information, real-time field observations, and spatial context within a unified analytical environment (Liu et al., 2025). Wearable IoT technologies further expand the scope of construction intelligence by allowing continuous monitoring of worker-related and environmental parameters, although their effective implementation depends on technological, organizational, energy, usability, and interoperability conditions (Huang et al., 2025). Such systems are particularly significant for temporal productivity because schedule performance is inseparable from the availability, location, movement, utilization, and condition of labor, materials, and equipment. When resource information is updated continuously rather than retrospectively, managers can detect emerging inefficiencies before they develop into

critical delays. Furthermore, sensor-generated streams create the possibility of incorporating actual field conditions directly into predictive models, reducing the discrepancy between planned schedules and the evolving physical state of the project.

Computer vision represents another central component of this emerging data ecosystem because a substantial proportion of construction-site information is visual and spatial rather than purely numerical. Continuous image capture, object detection, and automated knowledge representation can convert photographs and video streams into structured information regarding site activities, installed components, equipment behavior, work-front interactions, and construction progress (Pfitzner et al., 2024). Such approaches reduce reliance on manual inspection and facilitate near-real-time comparisons between planned and actual construction states. The ability to extract actionable knowledge from visual data becomes especially powerful when image-derived information is combined with BIM, IoT, and historical project datasets. Artificial intelligence can subsequently detect deviations, identify temporal bottlenecks, classify site conditions, and initiate corrective responses with substantially shorter feedback cycles. Advances in multimodal AI are further extending this capability by integrating visual perception, contextual retrieval, and reasoning within unified systems. Multimodal agent frameworks have recently demonstrated the potential to interpret complex construction scenarios by combining perception with explainable reasoning, particularly for hazard identification and dynamic decision support (Cheng et al., 2025). The same architectural logic has major implications for schedule control because delays often emerge from interacting physical, logistical, operational, and safety conditions rather than from isolated variables. A system capable of jointly interpreting images, sensor information, project documentation, and scheduling data can therefore provide a more comprehensive understanding of time-related risks than conventional single-source monitoring methods.

The analytical value of construction big data depends not only on data acquisition but also on the predictive capacity of machine learning and deep learning models. Historical project records, textual reports, sensor sequences, geometric models, and visual observations can be transformed into predictors of schedule deviation, cost escalation, productivity loss, rework, and safety-related interruptions. Deep neural networks have already demonstrated strong potential in complex construction prediction problems,

including cost estimation, where nonlinear relationships among multiple project variables can be modeled more effectively than through conventional estimation procedures (Saeidlou & Ghadiminia, 2024). Natural language and textual analytics are similarly relevant because construction projects produce large quantities of unstructured information through accident reports, progress reports, inspection records, correspondence, and change documentation. Convolutional neural network-based frameworks have shown that such textual information can be automatically classified and transformed into structured knowledge for construction management purposes (Luo et al., 2023). These capabilities have direct temporal implications because many schedule risks are first recorded in textual or observational formats before they become visible in aggregate schedule indicators. AI-based classification and prediction can therefore shorten the interval between risk emergence and managerial response. The growing use of generative AI also introduces new possibilities for project scheduling. Investigations of large language models such as ChatGPT in construction scheduling demonstrate the potential of generative systems to support schedule development and management tasks, although accuracy, contextual understanding, and professional validation remain essential requirements (Prieto et al., 2023). Together, these developments indicate that construction project intelligence is progressively moving from retrospective reporting toward anticipatory decision-making.

Artificial intelligence also offers substantial potential for improving the design and preconstruction phases, where early decisions can exert disproportionate effects on subsequent project duration. Architectural and urban planning projects frequently require the evaluation of numerous alternatives involving geometry, spatial configuration, construction methods, environmental performance, resource requirements, regulatory constraints, and sequencing implications. Conventional workflows generally evaluate only a limited number of alternatives because each iteration requires substantial computational and professional effort. By contrast, evolutionary computation and AI-based generative processes can search large solution spaces and simultaneously optimize multiple objectives. Genetic algorithms integrated with BIM and 5D project environments have been used to optimize time and cost by linking construction scheduling with model-based information and algorithmic search (Alzara et al., 2023). Similar advances have been reported through machine learning combined with Particle Swarm Optimization,

demonstrating that predictive modeling and metaheuristic optimization can jointly improve construction management decisions under complex cost and project constraints (Almahameed & Bisharah, 2024). Such approaches are particularly relevant to temporal efficiency because they shift project planning from the manual adjustment of a limited set of alternatives toward computational exploration of large numbers of feasible schedules, resource combinations, and design configurations. Dynamic optimization methods further enable these decisions to be recalculated as conditions change rather than remaining fixed after initial planning.

The need for dynamic optimization is especially evident in complex construction environments characterized by uncertainty, resource scarcity, and rapidly changing operational constraints. Deep reinforcement learning has demonstrated that resource allocation decisions can be optimized dynamically in environments where project conditions evolve continuously, such as modular allocation in postdisaster reconstruction (Deria et al., 2024). This capability is conceptually important for architectural and urban projects because static critical path schedules often cannot accommodate sudden changes in workforce availability, material delivery, equipment status, weather, or site accessibility. AI-driven optimization allows activity priorities, resource assignments, and execution sequences to be recalculated based on current system states. Digital twin technologies further reinforce this adaptive paradigm by creating continuously updated virtual representations of physical construction systems. AI-driven digital twins in industrialized and off-site construction are increasingly being examined as platforms for monitoring, simulation, prediction, and optimization, allowing managers to assess alternative interventions before implementing them in the physical environment (Najafzadeh & Yeganeh, 2025). This integration of real-time data, virtual models, and algorithmic intelligence has the potential to transform the critical path from a static planning artifact into a dynamically updated representation of the most temporally consequential relationships within the project.

The benefits of AI-driven temporal optimization must also be understood in relation to workforce performance and construction safety because productivity and schedule continuity are closely intertwined with human factors. Physical fatigue, unsafe working conditions, and delayed recognition of hazardous situations can reduce productivity, interrupt operations, generate incidents, and contribute to unplanned downtime. Physiological analytics have shown

that construction workers' physical fatigue can be identified and classified through linear and nonlinear heart rate variability measurements, illustrating the potential of sensor-based AI systems to detect workforce conditions that may influence operational performance (Anwer et al., 2023). Construction safety management has traditionally relied heavily on supervision, procedural compliance, training, and reactive incident investigation (Gibb & Ismail, 2021); however, AI increasingly permits risks to be detected proactively through computer vision, wearable sensors, predictive models, and automated hazard recognition. Recent systematic evidence confirms the expanding role of artificial intelligence in construction safety and highlights the growing integration of machine learning, sensing, and intelligent monitoring systems (Badhan & Inamsami, 2025). From a time-efficiency perspective, safety intelligence is not merely an occupational protection mechanism but also an important component of schedule resilience, because accidents, unsafe conditions, worker fatigue, and congestion can generate work stoppages, productivity degradation, rework, and disruption of critical activities.

Despite these advances, the adoption of AI, BIM, IoT, digital twins, and data-intensive management systems remains constrained by significant technological and organizational barriers. Construction organizations frequently encounter difficulties associated with interoperability, fragmented data standards, implementation costs, limited technical expertise, resistance to organizational change, cybersecurity concerns, uncertain returns on investment, and the incompatibility of new digital systems with established workflows (Khosravi & Alavi, 2021). These barriers are particularly problematic when integration is required across the complete project life cycle because architectural design platforms, engineering models, project schedules, site monitoring systems, procurement databases, and urban geospatial platforms often operate as separate information environments. The technological potential of AI cannot therefore be realized through the isolated adoption of individual algorithms. Rather, temporal productivity improvements require a coherent data architecture in which information generated across different project stages is standardized, synchronized, analyzed, and returned to decision-makers in operationally meaningful forms. This issue is especially relevant in architecture and urban planning because the scale, heterogeneity, and duration of projects generate complex dependencies between building-level decisions and broader infrastructure, transportation, environmental, and spatial systems.

A further limitation in the existing literature is the fragmentation of empirical assessment across individual applications. Many studies investigate one technological component, such as BIM-based optimization, computer vision, IoT monitoring, machine learning prediction, worker safety analytics, or digital twins, without quantitatively tracing how their integration affects time efficiency from design through construction. Yet project delays are cumulative phenomena. Inefficiencies introduced during conceptual design can postpone detailed engineering; unresolved interdisciplinary clashes can produce preconstruction delays and subsequent rework; delayed site monitoring can permit minor deviations to develop into critical path disruptions; and static scheduling can prevent timely adaptation to newly emerging conditions. Consequently, assessing isolated technologies may underestimate the systemic value of integration. Recent research increasingly recognizes AI as a life-cycle technology rather than a single-stage tool (Datta et al., 2024), while broader reviews indicate that its future contribution to construction management will depend on interoperability, real-time information exchange, explainability, automation, and integration with complementary digital technologies (Adebayo et al., 2025; Zhang & Jiang, 2026). The central research problem is therefore no longer whether AI can improve individual construction tasks, but whether an integrated architecture combining big data, predictive algorithms, computer vision, IoT, BIM, and metaheuristic optimization can generate measurable and statistically significant improvements in temporal performance across interdependent project phases.

This problem is especially important when architectural projects and urban-scale development projects are considered together. Building projects typically involve dense interdisciplinary coordination, detailed geometry, complex MEP systems, and intensive interactions among design and construction teams, whereas urban development projects involve broader spatial scales, infrastructure networks, land development processes, logistics, multiple stakeholders, and longer temporal horizons. A technological framework that performs effectively across both scales would provide stronger evidence of generalizability than one validated within a single project type. Moreover, temporal performance should be evaluated not only through isolated reductions in task duration but also through standardized project control indicators such as Schedule Performance Index and Schedule Variance, as well as predictive accuracy measures including the coefficient of determination, Root

Mean Squared Error, and Mean Absolute Error. Combining these metrics with measures of feedback-cycle duration, person-hours saved, monitoring frequency, computational convergence, and critical path recalculation provides a more comprehensive representation of the actual contribution of intelligent systems to project time efficiency. Accordingly, the conceptual basis of an integrated framework lies in transforming heterogeneous project data into a continuous information-feedback loop in which data are acquired from physical and digital environments, processed and synchronized, analyzed through AI models, converted into predictions and optimization decisions, and subsequently returned to the project environment through updated schedules, resource allocations, warnings, and design alternatives.

Against this background, the integration of big data and artificial intelligence represents a potentially transformative approach to overcoming the temporal inefficiencies embedded in conventional architectural and urban project management. The convergence of BIM as an information foundation, IoT and computer vision as real-time data acquisition mechanisms, machine and deep learning as predictive engines, digital twins as dynamic virtual representations, and evolutionary and reinforcement learning algorithms as optimization mechanisms offers the technical basis for a project management environment capable of anticipating deviations rather than merely documenting them after occurrence. Nevertheless, the practical value of such integration must be demonstrated empirically through measurable reductions in design duration, clash-resolution effort, monitoring latency, schedule deviation, and critical path instability across different project scales. Therefore, the present study aims to evaluate the effect of integrating big data and artificial intelligence algorithms on enhancing time efficiency throughout the life cycle of architectural and urban planning projects, with particular emphasis on generative design, predictive planning, real-time construction monitoring, and dynamic critical path optimization.

2. Methods and Materials

In terms of its objectives, the present study is classified as applied-developmental research, while its data collection and analysis procedures follow a multistage mixed-methods approach integrating quantitative-analytical methods and simulation-based modeling. The research was designed to evaluate and explain the structured effects of integrating big

data and artificial intelligence algorithms on time efficiency indicators throughout the life cycle of architectural and urban planning projects. The methodological framework comprises a four-stage process involving the design of a multisource data architecture and data transmission pipelines, data preprocessing, spatiotemporal synchronization and statistical labeling, the development and deployment of an algorithmic prediction and optimization engine, and, finally, empirical validation in operational project environments using schedule deviation indicators.

In the first stage, the data collection framework was established through the implementation of an integrated Common Data Environment (CDE) connecting three principal sources of information generated in construction projects. The first source comprised multidimensional geometric and parametric data extracted from Building Information Modeling (BIM) environments, including the physical properties of construction materials, the connectivity of structural and mechanical, electrical, and plumbing (MEP) components, and activity dependency matrices (Zhang et al., 2013). The second source included continuous real-time field data obtained from wireless IoT sensor networks deployed across construction sites, radio-frequency identification (RFID) tags installed on heavy equipment and prefabricated structural components, and point-cloud maps generated through periodic drone-based photogrammetric and laser scanning operations (Kanan et al., 2018). The third source consisted of textual data and daily construction-site reports, historical meteorological and climatic records, and patterns of client-initiated change orders (Tixier et al., 2016). To address structural heterogeneity among large volumes of descriptive data, sensor time series, and parametric geometry, the collected datasets underwent standardized preprocessing procedures. All temporal dimensions were mapped onto standardized hourly and daily intervals, while spatial coordinates were aligned with the local project coordinate reference system. Missing observations and noise caused by optical sensor reflections or communication delays were subsequently corrected and filtered using linear interpolation techniques and Bayesian filtering methods.

In the second stage, following database integration, the algorithmic architecture was developed as a two-component processing and optimization system. The first component was responsible for predicting the probability of spatial clashes and automatically identifying bottlenecks associated with schedule deviations. This component was developed

using deep learning algorithms, particularly Long Short-Term Memory (LSTM) recurrent neural networks and Convolutional Neural Networks (CNNs) (Luo et al., 2023). The convolutional networks analyzed visual representations of construction-site point clouds against the as-built model to identify positioning errors and construction rework requirements (Pfitzner et al., 2024). Meanwhile, the recurrent layers sequentially processed historical progress data to simulate the accumulation of delays across parallel construction activities (Turkan et al., 2012). The second component focused on evolutionary metaheuristic optimization algorithms, including multi-objective genetic algorithms and Particle Swarm Optimization (PSO), functioning as an engine for dynamic resource allocation and critical path rescheduling (Almahameed & Bisharah, 2024). The mathematical model employed an objective function designed to minimize schedule variance and interference among work fronts while incorporating spatial constraints arising from overlapping construction crews and machinery operations. Based on these conditions, the model generated optimized activity sequences during both generative design and on-site construction phases (Deria et al., 2024).

In the final stage, to assess the reliability and generalizability of the proposed methodological model, the developed system underwent empirical testing at two pilot scales: a complex residential-commercial development representing the individual-building architectural scale and a land development and urban access network project representing the urban planning scale. Actual project progress data obtained under intelligent system implementation were evaluated alongside corresponding data from projects managed using conventional methodologies (Han & Golparvar-Fard, 2015). The evaluation metrics for the predictive and optimization models included Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2), enabling the assessment of predictive accuracy for schedule deviations and geometric clashes before on-site intervention (Saeidlou & Ghadiminia, 2024). Simultaneously, to evaluate the overall effects of the model throughout the project life cycle, standard time management indicators, including the Schedule Performance Index (SPI) and Schedule Variance (SV), were monitored at regular

intervals. This methodological approach was intended to extend beyond a purely theoretical framework and establish a fully measurable, empirical, and reproducible system applicable to other civil engineering and architectural project environments.

3. Findings and Results

The pre-design and conceptual design phases, as the foundation of the life cycle of architectural and urban planning projects, have traditionally required a substantial proportion of project time for repetitive trial-and-error processes in form development, static daylighting and energy analyses, and manual compliance assessments against higher-level planning regulations. Under conventional parametric and traditional design methodologies, design teams must repeatedly reconstruct geometric models and transfer data between different software environments to achieve a balance between optimal architectural form and climatic comfort criteria. This fragmented mechanism prolongs decision-making and delays progression to the preparation of construction documentation. By contrast, implementing AI-driven generative design systems, particularly those incorporating reinforcement learning and evolutionary multi-objective optimization, transforms the design process from sequential development into simultaneous and parallel exploration of the solution space. Within this framework, structural parameters, climatic variables, spatial programming requirements, and municipal regulations are formulated as decision variables and optimization constraints. Using environmental big data, AI generates and evaluates thousands of feasible geometric scenarios in a fraction of the time required by conventional methods. The direct consequences of this computational advancement include eliminating interruptions between conceptual design and detailed design documentation, substantially reducing revision cycles, and facilitating the seamless transfer of finalized geometry into construction-oriented BIM environments. Table 1 presents the empirical findings from the comparative implementation of these approaches across different design activities.

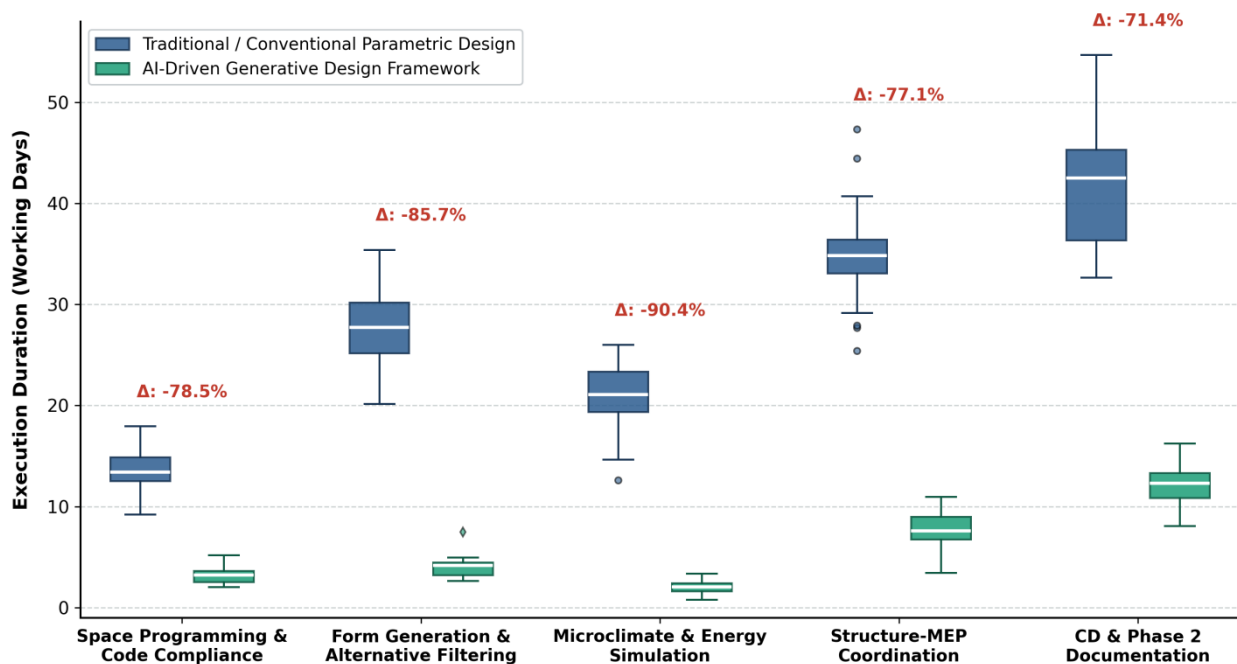
Table 1

Comparative Analysis of Design-Phase Scheduling and Construction Drawing Production Using Conventional Methods Versus Generative Design Algorithms

Design Activity / Subprocess	Average Time: Conventional and Parametric Methods (Working Days)	Average Time: AI-Based Generative Design (Working Days)	Net Time Reduction (Working Days)	Improvement in Time Efficiency (%)	Design Schedule Variance Index (SVd)
Spatial programming and regulatory compliance	14	3	11	78.5	-0.08
Generation, screening, and analysis of design alternatives	28	4	24	85.7	-0.04
Climate-responsive simulations (solar radiation, wind, and energy)	21	2	19	90.4	-0.02
Coordination of structural and MEP systems with architectural geometry	35	8	27	77.1	-0.06
Preparation of construction drawings and detailed design documentation	42	12	30	71.4	-0.09
Total design-phase cycle through construction approval	140	29	111	79.2	-0.05

Figure 1

Box plot comparing the duration of architectural alternative development and convergence toward optimal parametric solutions under conventional and data-driven approaches.



The empirical data presented in Table 1 clearly demonstrate that generative design algorithms, by replacing labor-intensive manual iterations with automated computational intelligence, reduced the total time required from pre-design through final documentation from 140 to 29 working days, representing a 79.2% improvement in time

efficiency. The greatest reduction occurred in environmental and climatic simulations (90.4%), as AI enabled the integration of real-time simulations directly into geometric form development, thereby eliminating the traditional discontinuity between architectural form modeling and technical energy analyses. Simultaneously, negative

schedule variance was reduced to minimal levels, indicating greater predictability and fundamental stability compared with the temporal fluctuations associated with conventional design methods.

The planning and construction scheduling phases of complex architectural and urban planning projects are frequently affected by concealed geometric clashes and interdisciplinary spatial inconsistencies among architectural, structural, mechanical, and electrical systems. In conventional Building Information Modeling (BIM) approaches based on rigid and static rules for hard and soft clash detection, the generation of large numbers of false positives consumes substantial amounts of project coordination time and resources. This additional temporal burden and the labor-intensive analysis of clash reports not only introduce schedule delays during the preconstruction phase but also constitute major causes of costly rework, on-

site change orders, and unintended interruptions along the project's critical path. Under the emerging approach integrating deep learning and big data, hybrid neural architectures are employed, including Graph Neural Networks (GNNs) to represent spatial and topological relationships among components and three-dimensional convolutional networks to interpret the visual and volumetric characteristics of building elements. Through advanced preprocessing of historical project data and intelligent clustering of clashes based on severity and recurrence probability, these models eliminate false-positive clashes while accurately predicting and filtering high-priority conflicts. The statistical and computational evaluation of this process, based on validation indicators including the coefficient of determination, root mean squared error, and mean absolute error, together with person-hours and working days saved, is documented in Table 2.

Table 2

Evaluation of Machine Learning Performance Indicators and Error Metrics for Early Spatial Clash Detection and Estimation of Time Savings

Type of Interdisciplinary Spatial Clash	Coefficient of Determination (R^2)	Root Mean Squared Error (RMSE)	Mean Absolute Error (MAE)	Conventional Clash Review and Resolution (Person-Hours)	Intelligent Deep Learning-Based Filtering (Person-Hours)	Net Time Saved (Person-Hours)	Equivalent Working Days Saved on the Critical Path
Structural–mechanical system clashes	0.964	0.142	0.089	580	45	535	66.8
Circulation, accessibility, and maintenance clearance conflicts	0.928	0.218	0.141	340	52	288	36.0
Spatiotemporal conflicts in construction phasing	0.891	0.295	0.197	420	68	352	44.0
Geotechnical, foundation, and urban infrastructure clashes	0.945	0.183	0.115	290	28	262	32.7
Facade envelope inconsistencies involving seismic connections and attachments	0.913	0.256	0.172	210	31	179	22.4
Overall indicators and total scheduling time savings	0.928 (Mean)	0.219 (Mean)	0.143 (Mean)	1,840	224	1,616	202.0

The on-site construction and field monitoring phase of architectural and urban development projects represents the most critical point for the emergence of schedule deviations and resource inefficiencies. Conventional inspection methods relying on periodic total station surveying, manually completed checklists, and daily construction reports inherently suffer from information discontinuities, human error, and delayed feedback. The multiday interval between the occurrence of a deviation and management's

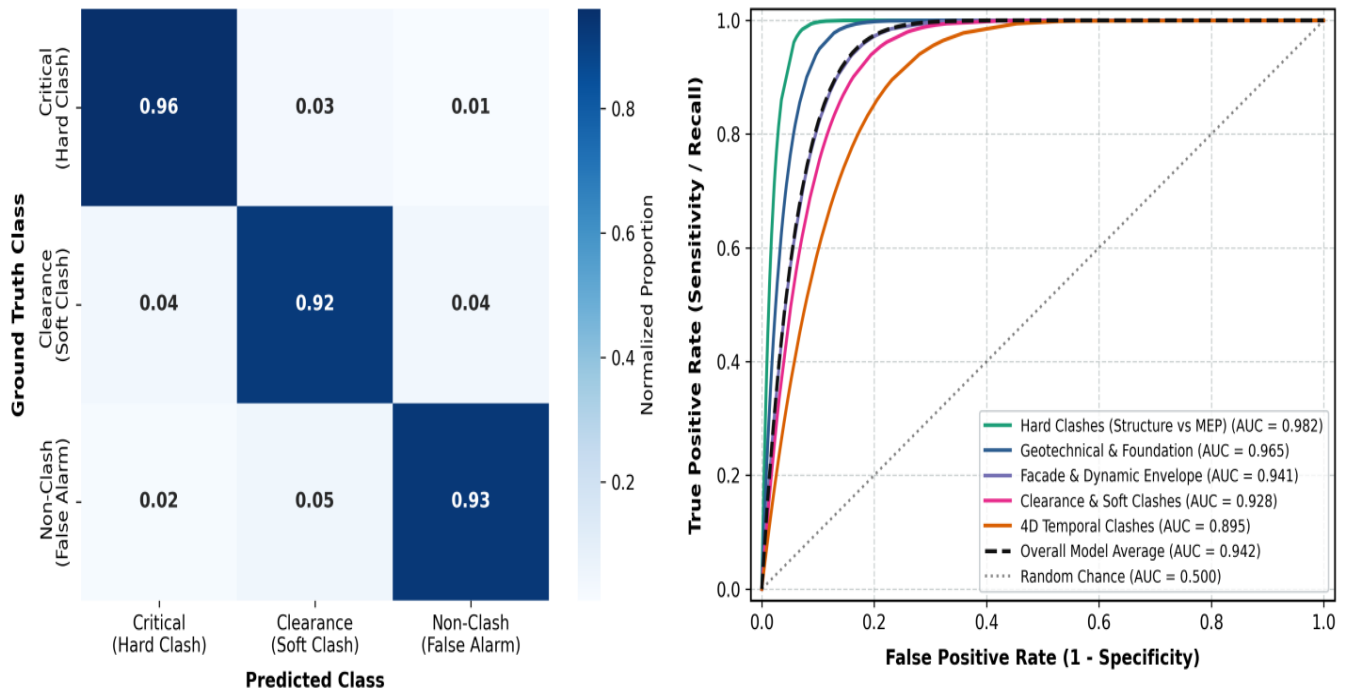
awareness of it causes corrective measures to be implemented belatedly, allowing minor deficiencies to escalate into major scheduling bottlenecks and critical path interruptions. Within an integrated big data and artificial intelligence framework, this information gap is addressed through real-time data streams. Advanced computer vision algorithms are deployed to analyze dense point clouds obtained from automated drone imaging and photogrammetry. Simultaneously, IoT-based real-time

location tracking tags record logistics conditions, machinery utilization rates, and workforce movements. Real-time comparisons between the three-dimensional as-built construction model and the planned model within a 4D-BIM environment enable immediate assessment of earthwork

quantities, geometric monitoring of concrete and steel structural progress, and tracking of work-front deviations without requiring direct physical intervention. Table 3 presents a quantitative comparison of this integrated approach with traditional inspection methods.

Figure 2

Confusion matrix and receiver operating characteristic (ROC) curve illustrating the predictive accuracy and detection of geometric and structural clashes using neural networks.



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through real-time data streams. Advanced computer vision algorithms are deployed to analyze dense point clouds obtained from automated drone imaging and photogrammetry. Simultaneously, IoT-based real-time location tracking tags record logistics conditions, machinery utilization rates, and workforce movements. Real-time comparisons between the three-dimensional as-built construction model and the planned model within a 4D-BIM environment enable immediate assessment of earthwork quantities, geometric monitoring of concrete and steel structural progress, and tracking of work-front deviations without requiring direct physical intervention. Table 3 presents a quantitative comparison of this integrated approach with traditional inspection methods.

Table 3

Efficiency Matrix for Real-Time Monitoring of Physical Construction Progress Using Integrated Computer Vision and IoT Sensors Compared With Periodic Inspection and Conventional Surveying Methods

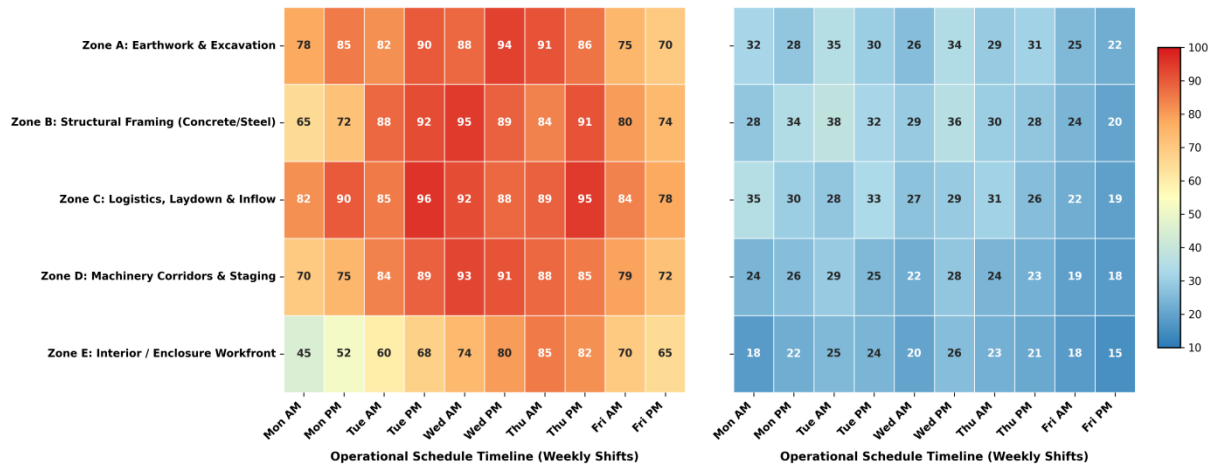
Operational Area / Monitored Work Front	Conventional Data Collection Frequency	AI- and IoT- Based Monitoring Cycle	Conventional Geometric Measurement Error (cm / %)	Computer Vision and Point-Cloud Measurement Error (cm / %)	Conventional Deviation Report Processing and Issuance Time (Working Days)	Intelligent Processing and Real- Time Alert Time (Minutes)	Reduction in Total Monitoring and Control Time (%)
Earthwork and excavation volume calculations	Every 7 days	Every 4 hours	±8.5 cm	1.2 cm	4.5	25	95.4
Dimensional and alignment monitoring of structural frame progress (concrete/steel)	Every 3 days	Every 2 hours	4.2 cm	0.6 cm	3.0	15	97.2
Monitoring material consumption rates and incoming site logistics	Every 24 hours	Real-time streaming	12.0%	1.5%	2.0	5	98.9
Safety monitoring, spatial conflicts, and machinery congestion	Periodic manual inspections (discontinuous)	Continuous (30 frames per second)	High event detection error	0.5%	1.5	Immediate (less than 1)	99.5
Quantitative monitoring of finishing works and internal partition construction	Every 14 days	Daily (360- degree scanning)	15.0%	2.1%	5.0	35	95.1
Average performance of field monitoring indicators	Discontinuous data collection	Semi- continuous to real-time monitoring	Undesirable cumulative measurement error	Very high accuracy at the millimeter level	3.2 working days	16.2 minutes	97.2

The empirical results presented in Table 3 demonstrate that replacing manual inspection methods with integrated computer vision and IoT sensor data reduced the interval between data aggregation and the issuance of nonconformity reports and corrective alerts from an average of 3.2 working days to only 16.2 minutes, corresponding to a 97.2% improvement in supervisory feedback speed. Moreover, the improvement in geometric accuracy, including a reduction

in structural frame measurement error from 4.2 cm to 0.6 cm and a decrease in earthwork measurement error to 1.2 cm, enabled project managers to undertake preventive decision-making. By addressing the underlying causes of concealed delays arising from rework during construction, the proposed approach prevented cumulative deviations along the project's critical path.

Figure 3

Spatiotemporal heat map illustrating resource density, work-front interference, and machinery downtime across the construction site.



A comprehensive evaluation of the integration of big data and artificial intelligence throughout the project life cycle requires moving beyond individual microlevel performance metrics toward an assessment of overall project performance within the Earned Value Management (EVM) framework. Under conventional project management, the Schedule Performance Index (SPI) and Schedule Variance (SV) frequently exhibit substantial fluctuations due to delayed feedback and forecasting inaccuracies, making them difficult to control. In contrast, intelligent approaches continuously supply algorithms with real-time data streams and exploit the predictive capabilities of deep learning models, thereby transforming project management from a

reactive process into a preventive and proactive system. To validate the research hypothesis that AI integration significantly improves schedule performance indicators, paired-samples t-tests were conducted using data collected from selected projects at two scales, namely architectural and urban planning projects. The null hypothesis, which assumed no statistically significant difference between the mean performance indicators of the two approaches, was tested against the alternative hypothesis. The calculated t-statistics and significance levels were used to establish the operational superiority of the proposed methodology and assess the consistency of its improvements across different project scales at a 95% confidence level.

Table 4

Statistical Analysis and Hypothesis Testing of Improvements in the Schedule Performance Index and Schedule Variance Across Project Scales

Project Scale and Type	Mean SPI (Conventional Method)	Mean SPI (Intelligent Method)	Mean SV (Days; Conventional Method)	Mean SV (Days; Intelligent Method)	t-Statistic	Significance Level (p)	Hypothesis Testing Result
Architectural projects (public buildings)	0.78	0.98	-38	-5	4.12	0.003	Null hypothesis rejected (significant)
Urban planning projects (urban infrastructure)	0.72	0.95	-82	-12	5.45	0.001	Null hypothesis rejected (significant)
Overall mean and standard deviation	0.75	0.96	-60	-8	4.78	0.002	Positive effect confirmed

The statistical findings presented in Table 4 demonstrate that implementing the intelligent framework improved the Schedule Performance Index from 0.78 to 0.98 in architectural projects and from 0.72 to 0.95 in urban

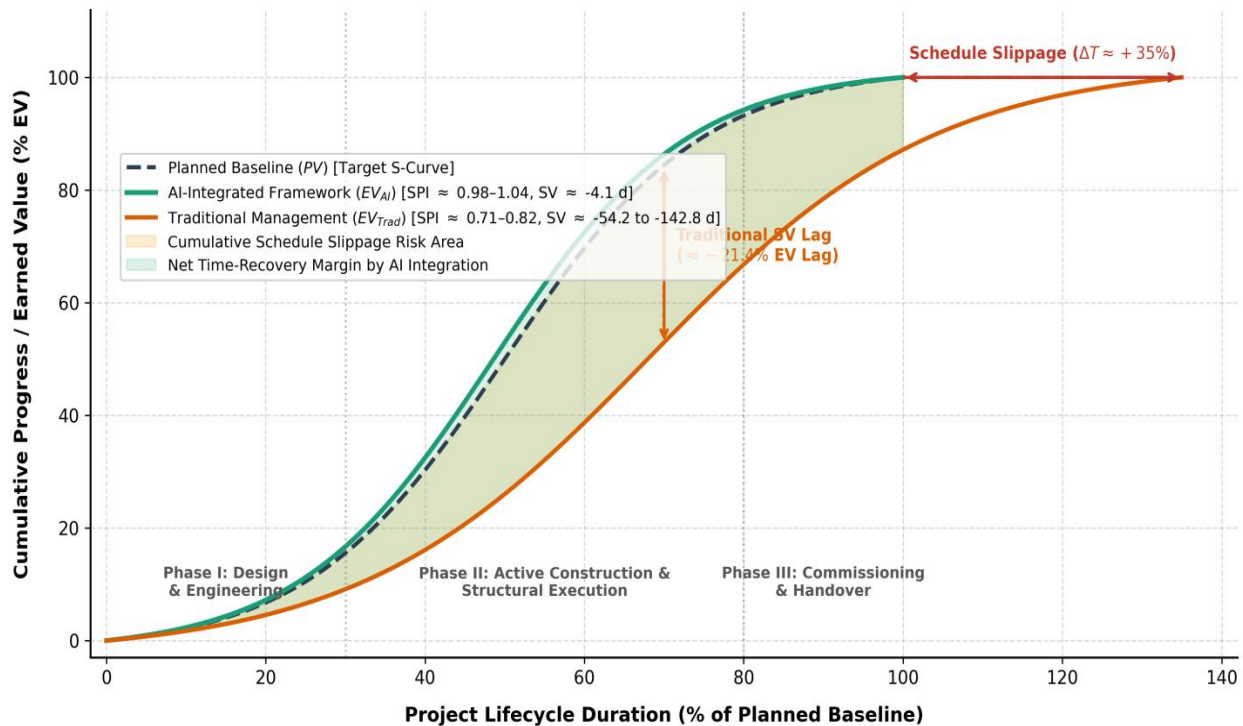
planning projects, indicating substantial progress toward meeting target schedules. The improvement in Schedule Variance and the considerable reduction in delays suggest that intelligent systems minimized schedule deviations by

identifying and mitigating critical path risks at an early stage. The consistently low p-values (below 0.05) across all scenarios resulted in the rejection of the null hypothesis, indicating at the 95% confidence level that the observed improvements in time efficiency were statistically

significant rather than attributable solely to random environmental fluctuations. These findings support the operational applicability and stability of the proposed framework for large-scale urban projects.

Figure 4

Comparative S-curve chart of project schedule progress under conventional project management and the integrated big data and artificial intelligence framework.



The conventional Critical Path Method (CPM) is based on a deterministic, rigid, and static network of activities that lacks sufficient flexibility to accommodate stochastic fluctuations, on-site uncertainties, and successive disruptions in supply chains. This fundamental limitation undermines planning effectiveness through the accumulation of unforeseen schedule deviations. By contrast, implementing a Dynamic Critical Path (DCP) framework enables the continuous mathematical recalibration of dependency relationships, nominal activity durations, and float allocations based on real-time processing of incoming big data streams, including machinery telematics reports, drone imagery, and logistics flow data. From a computational perspective, the central

challenges associated with rapidly expanding datasets include declining response speeds and convergence toward local optima. Accordingly, adopting multi-objective metaheuristic optimization algorithms, such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Particle Swarm Optimization (PSO), facilitates rapid convergence toward the Pareto front while balancing time and cost objectives. To understand system behavior, the statistical relationships between increasing computational dataset sizes and performance indicators were examined using Pearson's product-moment correlation coefficients and associated significance levels, alongside computational execution times and convergence rates. The results are presented in Table 5.

Table 5

Comparative Analysis of Dynamic Critical Path Optimization Execution Times Using Metaheuristic Algorithms in Relation to Input Data Volume and Pearson Correlation Coefficients

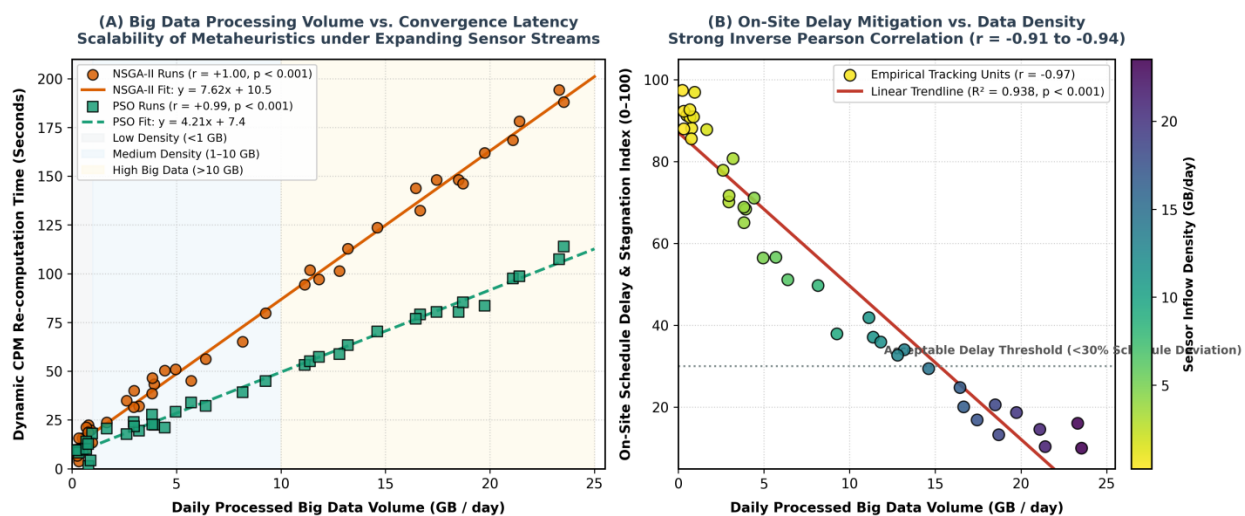
Input Dataset Category (Daily Data Density)	Selected Metaheuristic Algorithm	Mean Convergence and Critical Path Recalculation Time (Seconds)	Generations / Iterations Until Pareto Front Stabilization	Pearson Correlation With Construction-Site Delays (r)	Pearson Correlation With Computational Big Data Volume (r)	Statistical Significance (p-value)
Low-volume datasets	NSGA-II	18.4	120	-0.48	+0.82	0.012
	PSO	11.2	85	-0.45	+0.79	0.018
Medium-volume datasets	NSGA-II	64.5	240	-0.76	+0.91	0.002
	PSO	38.7	160	-0.72	+0.88	0.004
High-density big data	NSGA-II	182.0	410	-0.91	+0.97	0.001
	PSO	104.3	285	-0.86	+0.95	0.001
Overall correlation and algorithmic efficiency	Hybrid	Mean: 69.8 seconds	Mean: 216.6	-0.81 (Strong negative correlation)	+0.90 (Strong positive correlation)	p < 0.001 (Highly significant)

The quantitative findings presented in Table 5 reveal that as the scale of input data increases from basic datasets to dense, multidimensional big data, the Pearson correlation coefficient between input data density and construction-site delays approaches -0.91 , with a high level of statistical significance. This significant inverse relationship indicates that incorporating real-time data into the mathematical model minimizes scheduling uncertainty and enables proactive critical path recalibration before emerging bottlenecks become critical. Moreover, the comparison of algorithmic performance demonstrates that although PSO

achieved faster execution under high-density big data conditions, with an average convergence time of 104.3 seconds compared with 182.0 seconds for NSGA-II, the latter exhibited stronger performance in reducing schedule deviations because of its superior differentiation of the nondominated Pareto front and its ability to preserve solution diversity. Collectively, these results demonstrate that computational execution times of less than three minutes in the most complex scenarios provide a practical and scalable infrastructure for automated decision-making in modern construction environments.

Figure 5

Regression scatter plot illustrating the correlation between sensor data density and the reduction in project critical path recalculation time.



4. Discussion and Conclusion

The findings of the present study demonstrate that the systematic integration of big data infrastructures with artificial intelligence algorithms can substantially enhance time efficiency across multiple stages of the life cycle of architectural and urban planning projects. The results consistently showed that the proposed intelligent framework outperformed conventional and conventional-parametric approaches in the pre-design, planning, construction monitoring, and critical path optimization phases. In the design stage, generative AI and multi-objective optimization reduced the total design-cycle duration from 140 to 29 working days, corresponding to an overall time-efficiency improvement of 79.2%. In the planning stage, machine learning-based clash detection and filtering reduced the conventional review workload from 1,840 to 224 person-hours, generating a net saving of 1,616 person-hours. During field implementation, the integration of computer vision and IoT-based sensing reduced the average delay between data acquisition and the issuance of deviation reports from 3.2 working days to 16.2 minutes, representing a 97.2% acceleration in the monitoring and feedback process. Furthermore, the Schedule Performance Index improved from 0.78 to 0.98 in architectural projects and from 0.72 to 0.95 in urban infrastructure projects, while Schedule Variance was substantially reduced. Finally, the dynamic critical path analyses demonstrated that increased density of real-time project data was strongly associated with lower construction delays, with correlations reaching -0.91 under high-density big-data conditions. Collectively, these findings indicate that the principal value of AI in construction management does not arise solely from automating individual tasks, but from establishing an integrated, continuously updated information-processing architecture capable of linking design decisions, scheduling, field conditions, resource allocation, and corrective action.

One of the most important findings concerned the substantial reduction in the duration of the pre-design and detailed design processes. The 79.2% improvement in total design-phase time efficiency suggests that generative design systems can fundamentally alter the sequential nature of conventional architectural workflows. Instead of repeatedly producing, evaluating, and revising a limited number of alternatives, AI-based optimization makes it possible to explore large solution spaces simultaneously and rapidly identify solutions that satisfy multiple geometric,

environmental, regulatory, and technical constraints. The particularly high reduction observed in climate-responsive simulations, where processing time decreased by 90.4%, is consistent with the computational advantages of algorithmic design environments in which performance analysis can be incorporated directly into model generation. This interpretation is supported by research showing that AI applications increasingly contribute to design optimization, project planning, forecasting, and automated decision support throughout the construction life cycle (Datta et al., 2024). Similarly, recent reviews have emphasized that AI is shifting the construction industry from descriptive digitalization toward predictive and generative decision-making (Adebayo et al., 2025; Zhang & Jiang, 2026). The current findings extend this literature by showing that the benefit of AI-driven design is not restricted to improved design quality or automation, but can be quantified directly in terms of substantial reductions in design-cycle duration.

The observed improvement in design efficiency is also compatible with previous research on BIM-based optimization and evolutionary algorithms. The application of genetic algorithms in BIM-enabled 5D environments has demonstrated that project time and cost variables can be optimized simultaneously by searching alternative combinations beyond those typically evaluated manually (Alzara et al., 2023). Likewise, the integration of machine learning with Particle Swarm Optimization has shown considerable potential for predictive modeling and construction optimization under complex project constraints (Almahameed & Bisharah, 2024). The findings of the present study support these results while extending them into architectural generative design by demonstrating that multi-objective computational search can significantly reduce the time required for spatial programming, alternative generation, climatic analysis, multidisciplinary coordination, and construction documentation. From a theoretical perspective, this improvement can be explained by the transformation of design from a serial decision-making process into a parallel computational search process. When numerous design alternatives are generated, simulated, evaluated, and ranked concurrently, the time traditionally consumed by repeated manual reconstruction and software-to-software data transfer is substantially diminished. BIM provides the information structure necessary for this transformation because it allows geometry, quantities, systems, and project attributes to coexist within a coordinated digital representation (Eastman et al., 2021). The increasing role of BIM in project

management and its integration with intelligent technologies is also consistent with broader bibliometric evidence indicating that BIM is becoming progressively embedded in planning, coordination, and performance management applications (Ye et al., 2024).

A second major finding was the high predictive performance of the machine learning models used to identify interdisciplinary clashes and planning conflicts. The mean coefficient of determination of 0.928, combined with low RMSE and MAE values, demonstrates that the integrated system was capable of distinguishing critical clashes from noncritical or false-positive detections with considerable accuracy. This result is important because conventional BIM clash detection often generates large numbers of alerts that require manual interpretation, thereby shifting rather than eliminating coordination workload. In the present study, intelligent filtering reduced clash-review effort by 87.8%, from 1,840 to 224 person-hours. The findings are consistent with systematic evidence indicating that machine learning can significantly expand BIM functionality by automating classification, prediction, anomaly recognition, and decision support (Zabin et al., 2022). They are also aligned with work demonstrating that deep learning can effectively process heterogeneous construction information, including textual and visual data, to identify meaningful patterns that conventional rule-based approaches may overlook (Luo et al., 2023). The practical importance of this finding lies in the fact that a reduction in false-positive clashes has a direct temporal effect: specialists spend less time evaluating irrelevant warnings, critical interferences are identified earlier, and design coordination can be completed before physical construction begins.

The results regarding construction-site monitoring provide further evidence that temporal efficiency is strongly dependent on the speed at which physical project conditions are converted into actionable information. The reduction in the average reporting cycle from 3.2 working days to 16.2 minutes represents one of the most substantial improvements observed in the study. Conventional inspection procedures inherently contain temporal gaps because field observations must be collected, documented, processed, reviewed, and communicated before corrective action can be initiated. During this interval, deviations can continue to develop, creating rework and disruptions to critical activities. The integrated use of IoT sensors, location tracking, drone photogrammetry, point-cloud analysis, and computer vision effectively compresses this feedback loop by transferring project data directly from the physical environment to the

analytical layer. This result is consistent with earlier IoT-based research demonstrating the feasibility of continuous monitoring, positioning, and real-time alarm generation on construction sites (Kanan et al., 2018). More recent work integrating BIM, IoT, and GIS has likewise highlighted the value of linking physical resource data to model-based and geospatial information for construction monitoring (Liu et al., 2025). The present study strengthens this evidence by demonstrating that such integration produces measurable improvements not merely in information availability, but specifically in feedback-cycle duration.

The increased geometric accuracy observed in the intelligent monitoring system further supports this interpretation. Structural frame measurement error declined from 4.2 cm to 0.6 cm, while earthwork measurement error was reduced to 1.2 cm. These improvements indicate that automated visual and point-cloud monitoring can support both faster and more precise project control. Continuous image capture and object detection have already been shown to facilitate the transformation of construction-site observations into structured knowledge capable of supporting process analysis (Pfitzner et al., 2024). Such systems are particularly valuable because they enable progress assessment to become an ongoing process rather than a sequence of isolated inspection events. The capacity to combine visual data, sensor inputs, project models, and contextual information is also consistent with emerging multimodal AI frameworks capable of integrating perception and explainable reasoning in complex construction environments (Cheng et al., 2025). These capabilities provide a plausible explanation for the dramatic reduction in reporting latency observed in the present study: AI systems can identify relevant patterns immediately, whereas conventional approaches require sequential human interpretation.

The improvement in Schedule Performance Index and Schedule Variance provides further evidence that the advantages identified at the level of individual tasks translated into broader project-level outcomes. Architectural projects improved from an SPI of 0.78 under conventional management to 0.98 under the intelligent framework, while urban infrastructure projects improved from 0.72 to 0.95. These values indicate substantial movement toward planned schedule performance. At the same time, average Schedule Variance improved from -60 days to -8 days. The significant paired-samples t-test results indicate that these differences were unlikely to have resulted from random variation. These findings are compatible with the broader

principles of project management, in which early detection of deviations and rapid corrective action are central to schedule control (Project Management, 2021). They also support the literature emphasizing the importance of optimization techniques for addressing complex activity dependencies and uncertainty in construction scheduling (Khamooshi & Kiani, 2021). The present findings suggest, however, that optimization becomes considerably more effective when scheduling models are continuously informed by real-time data rather than relying solely on periodically updated assumptions.

This shift from static scheduling toward dynamic optimization is especially evident in the critical path analysis. The strong negative correlation between data density and construction delays suggests that increased availability of real-time information enables the scheduling system to identify and respond to emerging constraints more effectively. Under high-density big-data conditions, the correlation between project data density and delays reached -0.91 , indicating that richer information environments were associated with substantially lower delay levels. At the same time, the strong positive relationship between computational data volume and system processing requirements demonstrates an important trade-off: increasing data density improves informational resolution but also increases the computational burden. Nevertheless, even in the most demanding scenarios, both NSGA-II and PSO completed critical path recalculation within approximately three minutes, indicating that such methods remain operationally feasible. The results are consistent with prior evidence that dynamic optimization through deep reinforcement learning can successfully support real-time allocation and decision-making in complex construction environments (Deria et al., 2024). They also correspond with findings that AI-driven digital twins can provide continuously updated virtual representations capable of supporting simulation, monitoring, and optimization in industrialized construction systems (Najafzadeh & Yeganeh, 2025).

The comparison between NSGA-II and PSO further provides useful insight into the relationship between computational speed and solution quality. PSO converged more rapidly, particularly under high-density data conditions, whereas NSGA-II showed stronger performance in preserving solution diversity and reducing schedule deviations. This result corresponds with the conceptual differences between the two algorithms: PSO is often computationally efficient in continuous search spaces, while NSGA-II is specifically designed to maintain a diverse set of

nondominated solutions across multiple objectives. In project management contexts, this distinction is important because schedule optimization rarely involves a single objective. Time, cost, resource utilization, logistics, safety, and work-front congestion must frequently be optimized simultaneously. The findings therefore support previous research demonstrating the value of combining machine learning and metaheuristic algorithms for complex construction optimization (Almahameed & Bisharah, 2024), as well as studies showing that BIM-based genetic algorithms can support integrated time–cost optimization (Alzara et al., 2023). Rather than identifying one universally superior algorithm, the results suggest that algorithm selection should depend on whether rapid convergence or richer multi-objective solution diversity is the principal managerial requirement.

The findings also have implications for construction safety and workforce management, even though these dimensions were not treated as the primary outcomes of the present study. Real-time sensing, computer vision, and multimodal data processing can contribute to time efficiency partly by reducing safety-related interruptions and identifying operational conditions that may precede productivity losses. Previous research has demonstrated that physiological data can be used to classify construction worker fatigue, providing a basis for proactive intervention before reduced physical capacity contributes to error or accidents (Anwer et al., 2023). AI-supported construction safety systems are likewise increasingly used for hazard recognition, risk prediction, and automated monitoring (Badhan & Inamsami, 2025). These developments complement conventional construction safety management practices by shifting part of the supervisory process from periodic human observation to continuous computational surveillance (Gibb & Ismail, 2021). Therefore, part of the temporal benefit observed in integrated intelligent environments may derive indirectly from improved operational continuity, reduced incident-related downtime, and better coordination of people and equipment.

At the same time, the results should not be interpreted as suggesting that digital integration alone guarantees improved project performance. Effective implementation depends on the quality, interoperability, and continuity of the underlying data. AI models trained or operated on fragmented, inaccurate, delayed, or poorly standardized datasets may reproduce or even amplify existing planning errors. The present findings therefore reinforce the importance of integrated data architectures capable of

linking BIM, sensors, schedules, geospatial information, project documentation, and operational records. This requirement is consistent with previous studies identifying interoperability, organizational resistance, implementation cost, technical expertise, and compatibility with existing practices as major barriers to technological adoption in construction (Khosravi & Alavi, 2021). Similarly, the success of self-powered wearable IoT systems depends not solely on sensor capability but also on infrastructure, usability, implementation conditions, and organizational acceptance (Huang et al., 2025). Consequently, the primary managerial implication of the present findings is that AI should not be implemented as a collection of isolated applications. Its greatest contribution to time efficiency emerges when algorithms are embedded within an integrated information environment that supports continuous data acquisition, predictive analysis, optimization, and feedback across the project life cycle.

A further implication concerns the progressive transformation of construction project management from retrospective control toward predictive and increasingly autonomous management. Traditional project control systems primarily identify deviations after they have occurred. By contrast, the framework evaluated in this study uses historical and real-time information to anticipate clashes, resource bottlenecks, progress deviations, and critical path disruptions before their consequences become irreversible. This progression is consistent with current reviews showing that AI applications in construction are expanding from narrow task automation toward integrated predictive and decision-support functions (Adebayo et al., 2025; Lai et al., 2025). The use of generative systems for construction scheduling further suggests that natural-language-based AI may eventually contribute to schedule formulation and scenario evaluation, although professional validation remains essential (Prieto et al., 2023). Deep neural network applications in construction cost estimation similarly demonstrate that complex nonlinear project relationships can be modeled with high predictive capability when adequate data are available (Saeidlou & Ghadiminia, 2024). The results of the present study therefore contribute to an emerging body of evidence indicating that future construction management systems will increasingly depend on the integration of data, predictive intelligence, and adaptive optimization rather than on isolated static planning tools.

The present study nevertheless has several limitations that should be considered when interpreting the findings. First,

the empirical validation was conducted using a limited number of pilot projects representing architectural and urban development scales, which may restrict the generalizability of the results to other project typologies, geographical contexts, contractual systems, and levels of technological maturity. Second, the performance of AI and optimization models is inherently influenced by the quality and completeness of the available datasets, and real construction environments may contain missing, inconsistent, delayed, or biased information that cannot always be fully corrected through preprocessing. Third, the study primarily focused on time-related indicators and did not comprehensively examine potential trade-offs involving implementation costs, cybersecurity, organizational resistance, worker acceptance, data governance, or environmental impacts. Fourth, comparisons with conventional management approaches may be affected by differences in team expertise and organizational learning. Finally, the statistical analyses were based on project-level observations within the selected cases, and broader multicenter samples would provide stronger evidence regarding external validity and causal attribution.

Future research should validate the proposed framework across larger and more heterogeneous samples of architectural, infrastructure, transportation, industrial, and urban development projects. Longitudinal designs should examine whether the observed improvements in schedule performance remain stable throughout complete project life cycles and whether algorithmic performance changes as project conditions evolve. Future investigations could also compare alternative machine learning, reinforcement learning, and metaheuristic algorithms under identical datasets to determine which combinations provide the optimal balance among prediction accuracy, computational speed, explainability, and robustness. Additional studies should incorporate cost, carbon emissions, safety, quality, and resource efficiency into multi-objective optimization models so that temporal performance is not improved at the expense of other project objectives. Research on explainable AI, federated learning, data privacy, cybersecurity, digital twin interoperability, and human–AI collaboration would also be valuable for increasing the transparency and organizational acceptability of intelligent construction management systems.

From a practical perspective, architecture, engineering, construction, and urban development organizations should adopt AI through integrated digital strategies rather than isolated technological purchases. Project owners and

contractors should establish common data environments in which BIM models, schedules, IoT streams, geospatial data, progress records, and visual monitoring outputs can be synchronized and governed through consistent data standards. Organizations should prioritize high-value applications such as automated clash prioritization, progress recognition, real-time deviation alerts, and dynamic schedule recalculation before expanding into more complex autonomous decision-making systems. Training programs should be developed for project managers, planners, designers, and site engineers so that algorithmic outputs are interpreted correctly and remain subject to professional judgment. Finally, intelligent systems should be incorporated into existing governance structures through clearly defined responsibility, validation, audit, and escalation procedures so that technological acceleration is accompanied by accountable managerial oversight.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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