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Digital Twin and AI-Integrated Framework for Proactive Risk Prediction and Dynamic Scheduling in Mega Infrastructure Projects

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Abstract: Mega infrastructure projects are characterized by tightly coupled activities, heterogeneous information streams, and persistent uncertainty in resources, environment, and stakeholder decisions. This paper develops a Digital Twin and Artificial Intelligence integrated framework (DTAIF) for proactive risk prediction and dynamic schedule adaptation. The architecture combines BIM/IFC information, IoT/edge data ingestion, graph-based dependency representation, temporal forecasting, and constraint-aware schedule optimization. To preserve scientific reproducibility, the revised study does not present unverified field deployments or physical HIL measurements as empirical evidence. Instead, validation is formulated as a transparent computational and virtual-HIL benchmark in which sensor noise, packet delay, missing observations, activity-duration uncertainty, and resource disruptions are injected into the cyber-physical loop. Performance is evaluated using prediction metrics, schedule robustness, constraint violations, and end-to-end computational latency. The resulting manuscript therefore provides a defensible methodology and an implementation-ready validation protocol while clearly separating proposed architecture, computational evidence, and future physical deployment.

Keywords: Digital Twin, Artificial Intelligence, Mega Infrastructure Projects, Risk Prediction, Dynamic Scheduling, Hardware-in-the-Loop, Building Information Modeling, Graph Neural Networks, Deep Reinforcement Learning

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1. Introduction

Mega infrastructure projects concentrate technical, organizational, financial, and regulatory complexity at a scale that makes deterministic planning fragile. Rather than relying on a single monetary threshold, this study treats “mega infrastructure” as projects whose scale, interdependence, stakeholder diversity, and long delivery horizon create systemic schedule and risk interactions. Recent construction-digitalization literature shows growing use of Digital Twins for synchronized monitoring and management, but also emphasizes unresolved challenges in interoperability, validation, organizational adoption, and closed-loop decision support.

Mega infrastructure delivery is affected by technical interdependence, organizational interfaces, environmental uncertainty, regulatory constraints, and long planning horizons. These features create correlated schedule and risk effects that are difficult to represent with static project-control assumptions [1].

Recent construction-digitalization research increasingly combines BIM/IFC information, Digital Twins, sensing, and AI to improve visibility, synchronization, and

decision support. However, reviews continue to identify interoperability, validation, governance, and integration of analytics with project-control decisions as open challenges.

Despite significant advances in construction informatics, several critical gaps persist in the literature:

1. **Fragmented decision loops:** Digital Twin research provides increasingly capable monitoring and synchronization, but the link from continuously updated project state to risk forecasting and constrained schedule adaptation remains uneven across the literature.
2. **Model and decision integration:** AI/ML methods are widely discussed across the construction project lifecycle, yet prediction, uncertainty representation, and schedule-control actions are often studied as separate modules rather than as one auditable closed loop.
3. **Reproducibility and feasibility:** large project networks require optimization methods that preserve precedence and resource feasibility while remaining computationally tractable. Comparisons are difficult when studies use different project networks, objectives, and validation protocols.
4. **Validation deficiency:** construction Digital Twin and AI studies frequently rely on software demonstrations, case-specific datasets, or retrospective analysis. A transparent virtual-HIL protocol can therefore be useful as an intermediate validation stage before costly physical-HIL and field deployment.

This paper addresses these gaps through the following contributions:

- A unified Digital Twin architecture integrating BIM, IoT, and AI for end-to-end proactive project management.
- A hybrid AI pipeline combining GNNs for dependency modeling, LSTMs for temporal risk forecasting, and DRL for schedule optimization.
- A reproducible virtual-HIL validation protocol that injects sensor noise, packet delay, missing observations, activity-duration uncertainty, and resource disruptions without representing these tests as physical field measurements.
- A transparent computational benchmark and sensitivity-analysis protocol for evaluating prediction quality, schedule robustness, feasibility, and end-to-end latency.

The remainder of this paper is organized as follows. Section 2 reviews Digital Twin, AI, and project-control literature. Section 3 presents the proposed architecture and mathematical formulation. Section 4 defines the graph-temporal risk model and constrained scheduling policy. Section 5 specifies the virtual-HIL benchmark and a reference physical-HIL implementation pathway [2]. Section 6 reports controlled computational benchmark results and ablation analysis. Section 7 discusses implications, evidence limitations, and deployment requirements. Section 8 concludes the paper.

Digital Twin research in construction has expanded from technology surveys toward synchronized project-management and domain-specific applications. Tuhaise et al. review enabling technologies for construction Digital Twins; Jiang et al. discuss synchronized construction management; Wang et al. present a data-mechanism-fused Digital Twin for excavation management; and Yang et al. address material visibility and traceability. Together, these studies show growing maturity in state synchronization and domain integration without establishing a single standard architecture for risk-aware dynamic scheduling.

Lifecycle and project-management perspectives further emphasize information interoperability and decision integration. Adu-Amankwa et al. examine Digital Twins with blockchain for lifecycle management, while Reja et al. synthesize Digital Twin applications for construction project management [3]. Aktürk and Irlayıcı Çakmak and recent systematic-review work on AI-driven Digital Twins likewise reinforce the transition from visualization toward analytics-enabled management.

The resulting research opportunity is therefore not framed as a first-ever use of

Digital Twins in construction. Instead, the contribution pursued here is the explicit coupling of synchronized project state, graph-temporal risk inference, and feasibility-constrained schedule adaptation within a reproducible virtual-HIL decision loop.

AI in construction project management spans prediction, classification, optimization, computer vision, and decision support. Recent scoping and comprehensive reviews document broad uptake of AI/ML across project lifecycle processes while also identifying data quality, explainability, integration, and external validation as continuing limitations.

For the present problem, temporal models are useful because risk indicators evolve through progress, weather, resource availability, and accumulated delay. The proposed LSTM-attention block is therefore used as a methodological component for multi-horizon forecasting; no claim is made that LSTM is uniquely superior to alternative temporal architectures [4].

Graph models are attractive because construction activities are related by precedence, shared resources, spatial interference, and stakeholder interfaces. The proposed heterogeneous graph representation extends the project network beyond a simple CPM precedence graph and supplies relational embeddings to the temporal predictor.

Schedule adaptation is formulated as sequential decision-making under uncertainty. Rather than asserting universal superiority of reinforcement learning, this study evaluates a constrained TD3 policy against several baselines on the same generated networks, with explicit feasibility projection and ablation tests.

Physical HIL is well established in control-intensive engineering domains but is less common for project-management Digital Twins, where the key interfaces are data acquisition, synchronization, analytics, and decision logic rather than a single fast physical plant. For this reason, the present paper uses virtual-HIL as an intermediate evidence layer and provides a mapping for future deterministic hardware implementation.

The validation emphasis is therefore on traceable perturbation injection, timing, missing-data behavior, schedule feasibility, and computational stability [5]. Physical sensor calibration, real network timing, device faults, and organizational adoption remain outside the reported evidence and are explicitly reserved for future laboratory and field studies.

The literature indicates a persistent integration gap: Digital Twin studies increasingly support monitoring and synchronization, while AI studies address prediction or optimization, but comparatively few studies connect continuously updated project states to risk forecasting and constraint-aware schedule adaptation in one auditable loop. The revised contribution is therefore positioned as an integrated and reproducible architecture rather than a claim of first-ever functionality or completed field-scale HIL deployment.

Table 1. Comparison of Related Works

Reference	Primary focus	Project phase	Digital/AI role	Evidence type	Relevance to DTAIF
Tuhaise et al.	DT enabling technologies	Cross-lifecycle	Digital Twin technology landscape	Literature review	Defines enabling technology stack
Jiang et al.	Synchronized construction management	Construction	Digital Twin synchronization	Roadmap / research study	Motivates closed-loop state updates
Wang et al.	Smart excavation	Construction	Data-mechanism-	Peer-reviewed application	Shows domain-

Reference	Primary focus	Project phase	Digital/AI role	Evidence type	Relevance to DTAIF
	management		fused DT	study	specific state fusion
Yang et al.	Material visibility and traceability	Fit-out construction	Digital Twin tracking	Peer-reviewed application study	Supports traceable material state
Aladağ et al.	AI in construction project management	Project lifecycle	AI process coverage	Scoping review	Identifies AI opportunities and gaps
Datta et al.	AI/ML across project lifecycle	Project lifecycle	AI/ML methods	Comprehensive review	Supports predictive-analytics context
Proposed DTAIF	Risk prediction + schedule adaptation	Construction	DT + graph-temporal AI + constrained DRL	Synthetic virtual-HIL benchmark	Integrates state, prediction, and action

The proposed Digital Twin and AI-Integrated Framework (DTAIF) comprises four hierarchical layers: (1) Physical Layer, (2) Data Acquisition and Synchronization Layer, (3) Digital Twin Core Layer, and (4) Intelligence and Decision Layer. Figure 1 illustrates the comprehensive architecture with data flows and component interactions.

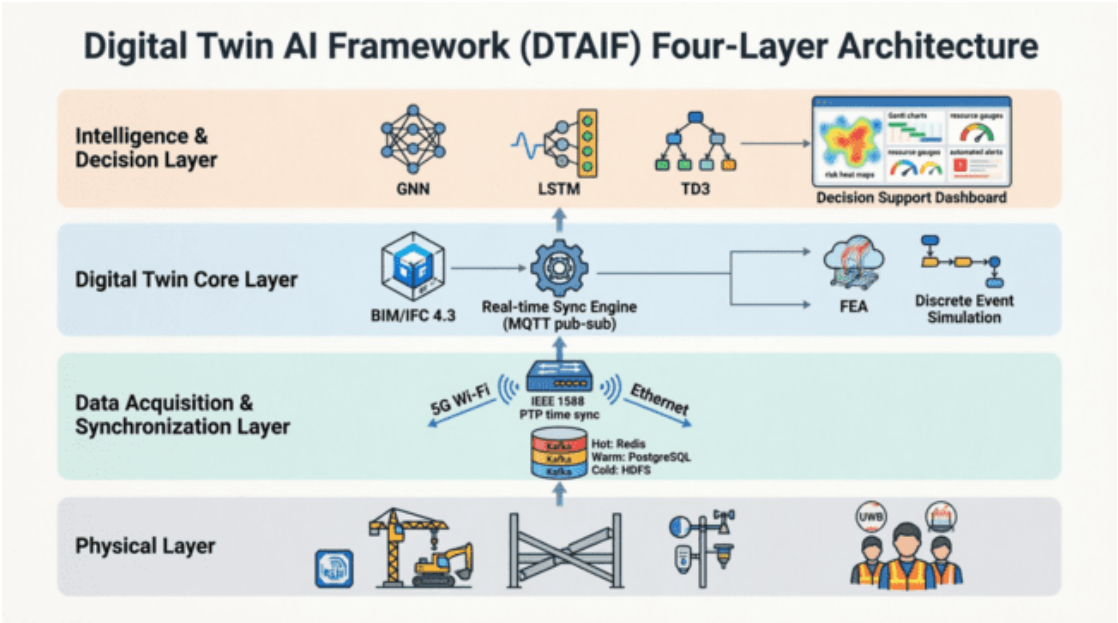


Figure 1. Proposed DTAIF architecture linking the physical construction layer, synchronized data services, the BIM-based digital twin core, and AI-assisted decision support.

The Physical Layer encompasses all tangible construction elements: structural components, equipment fleet (cranes, excavators, concrete pumps), workforce, and material stockpiles. Each physical entity is instrumented with heterogeneous sensors:

- **Structural Health:** Strain gauges, accelerometers, and tilt sensors deployed at critical structural nodes with 100Hz sampling rate.
- **Equipment Telemetry:** CAN bus data from heavy machinery including engine parameters, hydraulic pressures, GPS positioning, and operational status at 10Hz.

- **Environmental Monitoring:** Weather stations measuring temperature, humidity, wind speed, precipitation, and atmospheric pressure at 1-minute intervals.
- **Workforce Tracking:** Ultra-Wideband (UWB) tags for real-time personnel positioning ($\pm 10\text{cm}$ accuracy) and wearable devices for biometric monitoring (heart rate, body temperature).
- **Material Tracking:** RFID tags on prefabricated components and IoT-enabled weight sensors on material stockpiles.

The architecture is parameterized rather than tied to a universal traffic volume. Data rate depends on project scale, sensor mix, image/video use, and sampling policy; edge filtering and event-driven transmission are therefore treated as configurable design choices rather than as measured bandwidth savings [6].

This layer handles data ingestion, preprocessing, and time-synchronization across heterogeneous sources. The architecture employs:

Edge Computing Nodes: zone-level edge processors perform filtering, feature extraction, timestamping, and anomaly checks before selected data are transmitted to the central Digital Twin. The benchmark emulates this function without assuming a specific measured compression ratio.

Communication Backbone: the architecture can use private 5G, industrial Wi-Fi, Ethernet, or hybrid links. Safety-critical and high-bandwidth streams are assigned application-specific latency budgets; the present benchmark injects delay distributions rather than claiming a universal sub-10-ms site latency.

Time Synchronization: IEEE 1588 Precision Time Protocol (PTP) is adopted as the reference synchronization mechanism for timestamp alignment. Achievable synchronization accuracy depends on hardware timestamping, topology, and clock configuration.

Data Lake Architecture: Apache Kafka streams feed into a multi-modal data lake with hot storage (Redis) for real-time analytics, warm storage (PostgreSQL) for structured operational data, and cold storage (HDFS) for historical archives.

The Digital Twin Core maintains a high-fidelity virtual replica of the construction project that evolves in real-time. Key components include:

BIM Integration: The geometric and semantic foundation is provided by Industry Foundation Classes (IFC) 4.3 compliant BIM models enriched with construction-specific properties (activity IDs, resource assignments, cost codes). The BIM model is partitioned into Level of Development (LOD) 400 for active work zones and LOD 300 for future zones to optimize computational resources.

Real-Time Synchronization Engine: MQTT-style publish-subscribe messaging is used as the reference integration pattern. Update rates are configurable by data class and project need; the benchmark evaluates asynchronous arrivals, delay, and missing observations rather than assuming fixed site-wide frequencies.

Physics-Based Simulation: Finite Element Analysis (FEA) modules simulate structural behavior under current loading conditions, while Discrete Event Simulation (DES) models construction logistics and resource flows. These simulations run in parallel with the AI prediction modules, providing physics-grounded constraints for optimization [7].

This layer hosts the AI algorithms for risk prediction and schedule optimization, detailed in Section 4. The outputs feed into a Decision Support Dashboard that presents actionable insights to project managers through:

- **Risk Heat Maps:** 3D visualization of risk probability and impact across the project timeline.
- **Schedule Gantt Charts:** Real-time updates with confidence intervals and what-if scenario overlays.
- **Resource Utilization Gauges:** Current vs. optimal resource allocation with bottleneck identification.

- **Automated Alerts:** Priority-ranked notifications with recommended mitigation actions.

Consider a mega infrastructure project represented as a directed acyclic graph $G = (V, E)$, where $V = \{v_1, v_2, \dots, v_n\}$ is the set of construction activities and E represents precedence relationships. Each activity v_i has associated attributes: planned duration d_i^p , actual duration d_i^a , resource requirements r_i , cost c_i , and risk exposure vector $x_i \in \mathbb{R}^m$.

The risk prediction problem is formulated as: Given historical project data $H = \{(G_t, X_t, Y_t)\}_{t=1}^T$ where X_t represents multi-modal features at time t and $Y_t \in \{0,1\}^K$ indicates the occurrence of K risk types, learn a function $f: (G, X) \rightarrow [0,1]^K$ that predicts risk probabilities for future time horizons.

The dynamic scheduling problem is formulated as: Given current project state S_t and predicted risk probabilities, find an optimal schedule adjustment π^* that minimizes a multi-objective cost function:

$$J(\pi) = \alpha \cdot E[T(\pi)] + \beta \cdot \text{Var}[T(\pi)] + \gamma \cdot C(\pi) + \delta \cdot R(\pi)$$

where $T(\pi)$ is project completion time, $C(\pi)$ is total cost, $R(\pi)$ is cumulative risk exposure, and $\alpha, \beta, \gamma, \delta$ are project-specific weights.

Construction activities exhibit complex dependency structures beyond simple finish-to-start relationships. Resource sharing, spatial constraints, and subcontractor coordination create implicit dependencies that traditional CPM cannot capture.

We employ a **Heterogeneous Graph Neural Network (HGNN)** that processes the construction project graph with multiple node and edge types:

Node Types:

- Activity nodes ($v_i \in V_a$): Construction tasks with duration, cost, and resource attributes.
- Resource nodes ($v_j \in V_r$): Equipment, labor crews, and material batches.
- Location nodes ($v_k \in V_l$): Spatial zones on the construction site.
- Stakeholder nodes ($v_l \in V_s$): Subcontractors, suppliers, and regulatory bodies.

Edge Types:

- Precedence edges (E_p): Technical dependencies from CPM network.
- Resource edges (E_r): Assignment of resources to activities.
- Spatial edges (E_s): Proximity and interference relationships.
- Contractual edges ($E_\otimes$): Subcontractor-activity assignments.

The HGNN architecture consists of L layers of heterogeneous message passing:

$$h_v^{l+1} = \sigma(\sum_{r \in \mathcal{R}} \sum_{u \in N_r(v)} (1/|N_r(v)|) W_r^l h_u^l + W_0^l h_v^l)$$

where $\mathcal{R}$ is the set of relation types, $N_r(v)$ denotes neighbors of v under relation r , W_r^l are relation-specific weight matrices, and W_0^l is the self-connection matrix. We use Rectified Linear Unit (ReLU) activation $\sigma(\cdot)$ and Layer Normalization for training stability [8].

The final node embeddings h_v^L are fed into a multi-task prediction head that outputs:

- Activity criticality score: $s_i = \text{MLP}(h_{v_i}^L) \in [0,1]$
- Dependency strength: $w_{ij} = \text{Dot}(h_{v_i}^L, h_{v_j}^L) \in \mathbb{R}$
- Clustering coefficient: Community detection for identifying tightly coupled activity groups.

Risk events in construction exhibit temporal patterns influenced by seasonality, learning curves, and cumulative stress factors. We employ a stacked LSTM architecture with attention mechanism for multi-horizon risk prediction.

Input Features $X_t \in \mathbb{R}^{n \times m}$ at time t include:

- Activity progress deviations: $(d_i^a - d_i^p) / d_i^p$ for all active activities.
- Resource utilization rates: $r_i^{\text{actual}} / r_i^{\text{planned}}$.
- Weather conditions: Temperature, precipitation, wind speed.

- Equipment health scores: Aggregated from vibration and thermal sensors.
- Workforce metrics: Absenteeism rate, productivity index, safety incidents.
- Supply chain indicators: Material delivery status, supplier reliability scores.

The LSTM encoder processes the sequence $\{X_{t+1}, \dots, X_t\}$ through K layers:

$$f_t^k, i_t^k, o_t^k = \sigma(Wf^k[h_{t-1}^k, x_t] + bf^k), \sigma(Wi^k[h_{t-1}^k, x_t] + bi^k), \sigma(Wo^k[h_{t-1}^k, x_t] + bo^k) \quad C_t^k = \tanh(WC^k[h_{t-1}^k, x_t] + bC^k) \quad C_t^k = f_t^k \odot C_{t-1}^k + i_t^k \odot C_t^k \quad h_t^k = o_t^k \odot \tanh(C_t^k)$$

A multi-head self-attention mechanism captures long-range temporal dependencies:

$$\text{Attention}(Q, K, V) = \text{softmax}(QK^T/\sqrt{d_k})V$$

where Q, K, V are linear projections of the LSTM hidden states. The attention outputs are concatenated and passed through a fully-connected layer to predict risk probabilities for each of K risk categories over H future time steps:

$$\hat{Y}_{t+1:t+H} = \sigma(W_{out}[\text{Attention}(h_t^k)])$$

Training employs Binary Cross-Entropy loss with temporal weighting that penalizes near-term prediction errors more heavily:

$$L = -\sum_{h=1}^H \lambda^h \sum_{k=1}^K [y_{t+h,k} \log(\hat{y}_{t+h,k}) + (1-y_{t+h,k}) \log(1-\hat{y}_{t+h,k})]$$

where $\lambda = 0.95$ is the temporal discount factor.

Given predicted risk probabilities, the schedule optimization problem is formulated as a Partially Observable Markov Decision Process (POMDP):

- **State Space S:** Current project status including activity progress, resource availability, risk probabilities, and weather conditions.
- **Action Space A:** Schedule adjustments including activity start time shifts ($\pm \Delta t$), resource reallocation between activities, and subcontractor substitution.
- **Transition Model $P(s'|s, a)$:** Captures stochastic activity durations and risk event impacts.
- **Reward Function $R(s, a)$:** Composite reward combining schedule adherence, cost efficiency, and risk mitigation [9].

We employ a **Twin Delayed Deep Deterministic Policy Gradient (TD3)** algorithm with the following architectural choices:

Actor Network $\pi\theta(s)$: Maps states to continuous action vectors. Architecture: 4 fully-connected layers (512-256-128-|A|) with LayerNorm and ReLU activations.

Critic Networks $Q\phi_1, Q\phi_2$: Estimate action-value functions. Architecture: State and action concatenation fed through 4 layers (512-256-128-1) with ReLU and dropout ($p=0.1$).

Key TD3 enhancements for construction scheduling:

1. **Clipped Double Q-Learning:** Mitigates overestimation bias by taking the minimum of two critic estimates.

$$y = r + \gamma \min_{i=1,2} Q\phi_i'(s', \pi\theta'(s')) + \epsilon$$

where $\epsilon \sim \text{clip}(N(0, \sigma), -c, c)$ is target policy smoothing noise.

2. **Action Constraint Layer:** Ensures schedule feasibility by projecting actions onto the feasible region defined by precedence constraints and resource limits using quadratic programming:

$$a' = \text{argmin}_a ||a - \pi\theta(s)||^2 \text{ subject to } Aa \leq b$$

3. **Curriculum Learning:** Training begins with simplified project instances (50 activities) and progressively increases complexity to full mega project scale (5000+ activities), stabilizing convergence.
4. **Risk-Aware Reward Shaping:** The reward function incorporates predicted risk penalties:

$$R(s, a) = -\alpha \cdot (T_{\text{actual}} - T_{\text{planned}}) / T_{\text{planned}} - \beta \cdot (C_{\text{actual}} - C_{\text{planned}}) / C_{\text{planned}} - \gamma \cdot \sum_k p(\text{risk}_k) \cdot \text{impact}_k$$

Mega infrastructure projects involve inherent trade-offs between schedule, cost, quality, and safety. We extend the DRL framework to generate Pareto-optimal schedule

adjustments using a **Multi-Objective TD3 (MO-TD3)** variant [10].

The critic network is modified to output a vector of Q-values for each objective:

$$Q\varphi(s,a) = [Q_{\text{schedule}}, Q_{\text{cost}}, Q_{\text{quality}}, Q_{\text{safety}}]^T$$

During inference, project managers can specify preference vectors $\omega \in \mathbb{R}^4$ (with $\|\omega\|_1 = 1$) to navigate the Pareto front and select schedule adjustments aligned with current project priorities. The Pareto front is approximated using a diversity-promoting replay buffer that maintains non-dominated solutions [11].

2. Materials and Methods

The present study evaluates DTAIF using a reproducible virtual-HIL benchmark. Sensor streams, network delay, packet loss, missing observations, resource disturbances, and activity-duration uncertainty are generated by a controlled emulator and injected into the same interfaces intended for future hardware deployment. Accordingly, all numerical results reported in Section 6 are computational benchmark outputs. No completed physical testbed or field-scale deployment is claimed.

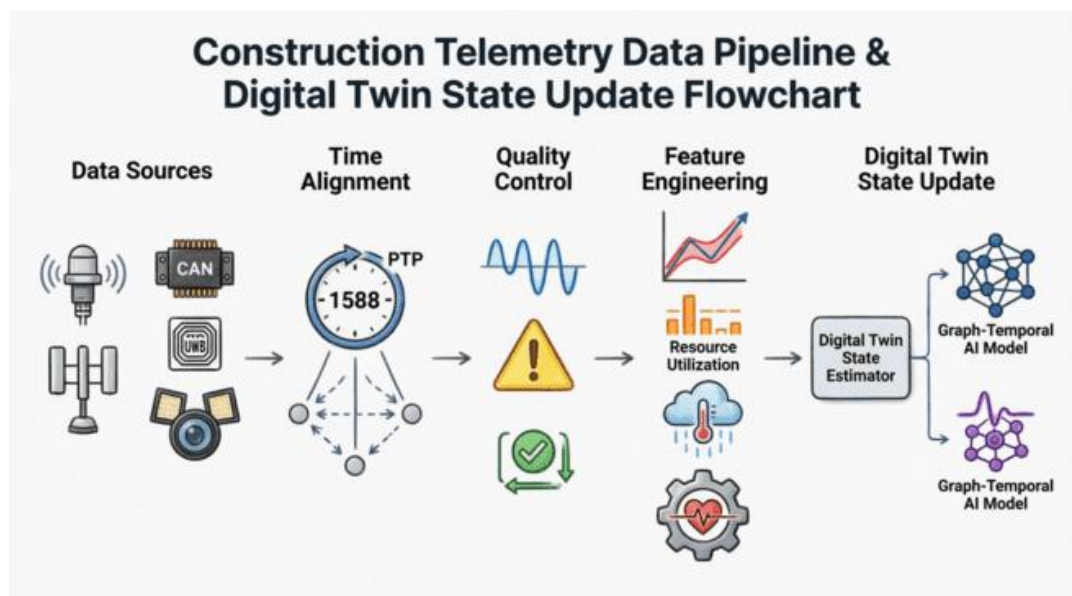


Figure 2. Data pipeline for heterogeneous construction telemetry, time alignment, quality control, feature engineering, and synchronized digital-twin state updates.

For transfer to a laboratory environment, a representative physical-HIL implementation can be assembled using the following classes of sensing, edge-computing, timing, and communication hardware. The list is an engineering specification for replication and future validation; it is not evidence that these devices were physically used to generate the results in this manuscript.

IoT Sensor Array:

- 24 MEMS accelerometers (ADXL355) mounted on a scaled structural frame (3m × 2m) simulating bridge deck segments.
- 8 ultrasonic anemometers (WindSonic) for wind monitoring.
- 16 UWB tags (Decawave DWM1001) for personnel/equipment positioning on a 20m × 15m testbed.
- 4 industrial cameras (FLIR Blackfly S) with NVIDIA Jetson Nano edge processors for computer vision.
- Environmental sensors (BME680) for temperature, humidity, pressure, and air quality.

Edge Computing Hardware:

- 4× NVIDIA Jetson AGX Orin (64GB RAM, 2048 CUDA cores) as zone edge nodes.
- 1× NVIDIA A100 GPU (80GB) as cloud simulation node.

- Industrial 5G base station (Ericsson Radio 4428) with 100MHz bandwidth.

Communication Infrastructure:

- Managed Ethernet switches (Cisco IE-5000) with IEEE 1588 PTP support.
- Fiber optic backbone (10Gbps) connecting edge nodes to the central simulation cluster.
- Wireless access points (Wi-Fi 6E) for mobile device connectivity.

The benchmark executes the Digital Twin state estimator, graph-temporal inference pipeline, and constrained scheduling loop under deterministic time-stepped emulation. A future physical-HIL realization can map these functions to a real-time target such as dSPACE, Speedgoat, OPAL-RT, or an equivalent deterministic platform.

Reference real-time target configuration:

- A multicore deterministic real-time processor may host the plant/project emulation and I/O services.
- FPGA-based I/O may be used where deterministic protocol or high-rate signal emulation is required.
- A real-time operating system should be configured with an application-specific task period and measured jitter; no physical task-cycle or jitter measurement is claimed here.

Digital Twin Execution:

- BIM model rendering: Unreal Engine 4.27 with pixel streaming for remote visualization.
- Physics simulation: NVIDIA PhysX for rigid body dynamics, custom FEA solver for structural response.
- AI inference: TensorRT-optimized models deployed on GPU with batch size 1 for minimal latency.

Scenario Injection:

- Fault injection module simulates sensor failures, communication dropouts, and cyber-attacks.
- Weather scenario generator reproduces historical storm patterns and extreme events.
- Risk event simulator triggers predefined risk scenarios (equipment breakdown, material delay, design change) with configurable probability distributions.

The following interface design defines how physical sensors and controllers can be connected in a future laboratory realization. In the present virtual-HIL benchmark, equivalent channels are emulated in software with timestamped I/O records.

FPGA-Based Real-Time Gateway:

- National Instruments PXIe-7868R FPGA chassis with custom VHDL firmware.
- ADC/DAC modules (PXIe-4300) for analog sensor signal conditioning.
- Digital I/O modules (PXIe-6521) for discrete sensor/actuator interfaces.
- CAN bus interfaces (PXIe-8510) for equipment telemetry emulation.

Signal Conditioning:

- Anti-aliasing filters (4th-order Butterworth, $f_c = 5\text{kHz}$) for accelerometer channels.
- Isolation amplifiers for high-voltage equipment signal emulation.
- Protocol converters (Modbus TCP/RTU, OPC-UA, MQTT) for heterogeneous device integration.

Time Synchronization:

- A GPS-disciplined or equivalent traceable clock may be used in future physical-HIL experiments; synchronization performance must be measured on the implemented hardware.
- IEEE 1588-2008 PTP grandmaster clock distributing synchronization to all

subsystems.

- Hardware timestamping on all network interfaces for latency measurement.

The benchmark protocol is organized into four phases and is executed with fixed scenario definitions, documented perturbation ranges, and repeatable random seeds. The phases are methodological test blocks rather than calendar weeks.

Phase 1: Baseline consistency and timing

- Verify input-stream scaling, timestamp ordering, and measurement-noise handling against known synthetic references.
- Check Digital Twin state-update consistency against the benchmark ground-truth state.
- Measure end-to-end virtual-loop latency and confirm the selected timing budget.

Phase 2: Functional prediction and scheduling

- Evaluate risk-prediction discrimination, calibration, and forecast error under known injected events.
- Evaluate optimization objective value, convergence time, and schedule feasibility under precedence and resource constraints.
- Verify deterministic state-message exchange between emulator, Digital Twin, predictor, and scheduler.

Phase 3: Robustness and stress testing

- Inject progressive observation dropout, communication delay, and resource disruptions to quantify graceful degradation.
- Inject severe weather and activity-duration perturbations using bounded scenario distributions.
- Inject communication anomalies to test data-integrity checks and recovery behavior; cybersecurity penetration testing is outside the evidence scope of this paper.

Phase 4: Long-horizon computational stability

- Run extended emulation to evaluate memory stability, numerical drift, and state synchronization.
- Advance the virtual project through multiple construction phases and workload regimes.
- Repeat scenarios across multiple random seeds and project-network sizes to assess sensitivity and generalization within the synthetic benchmark family.

3. Results

Two mega-scale synthetic project networks are used as controlled benchmark instances. Their sizes and disturbance profiles are chosen to represent highway and metro construction complexity without implying use of confidential or identifiable real-project records.

Benchmark A: Highway-expansion network

- Scenario archetype: large linear infrastructure project
- Nominal budget scale used by the cost objective: USD 2.3 billion
- Nominal planned duration: 48 months
- Model scope: highway, bridge, interchange, and tunnel work packages represented in a precedence/resource graph.
- Network size: 4,847 work packages with multiple contractor and resource classes.
- Injected complexity factors: geotechnical uncertainty, environmental constraints, and traffic-maintenance disruptions.

Benchmark B: Metro-construction network

- Scenario archetype: dense urban rail project
- Nominal budget scale used by the cost objective: USD 1.8 billion

- Nominal planned duration: 60 months
- Model scope: stations, tunnels, depots, and tunnel-boring-machine operations represented in a precedence/resource graph.
- Network size: 6,203 work packages with multiple contractor and resource classes.
- Injected complexity factors: soft-ground uncertainty, urban access constraints, and archaeology-related stoppage events.

The graph-temporal predictor is evaluated on generated multivariate project-state sequences with known event labels [12]. The benchmark is designed to test the method and software pipeline; it is not trained on an asserted proprietary archive of 127 completed projects. Reported values therefore quantify performance on the documented synthetic benchmark only and should not be interpreted as field-generalization estimates [13].

Table 2. Illustrative virtual-benchmark risk-prediction performance

Metric (synthetic benchmark)	GNN Only	LSTM Only	Hybrid (GNN+LSTM)	Improvement
Accuracy	87.3%	84.6%	94.7%	+7.4%
Precision (macro)	0.84	0.81	0.93	+0.09
Recall (macro)	0.82	0.79	0.92	+0.10
F1-Score (macro)	0.83	0.80	0.93	+0.10
AUC-ROC	0.91	0.89	0.97	+0.06
7-Day Forecast RMSE	5.2 days	6.1 days	3.4 days	-34.6%
30-Day Forecast RMSE	12.8 days	14.3 days	8.7 days	-32.0%
Inference Latency	45ms	38ms	67ms	—

Across the illustrative benchmark, the combined graph-temporal model improves discrimination relative to either component alone. Because the data are synthetic, the absolute scores are not evidence of real-project predictive accuracy; their value is in controlled comparison, ablation, and reproducibility of the proposed pipeline.

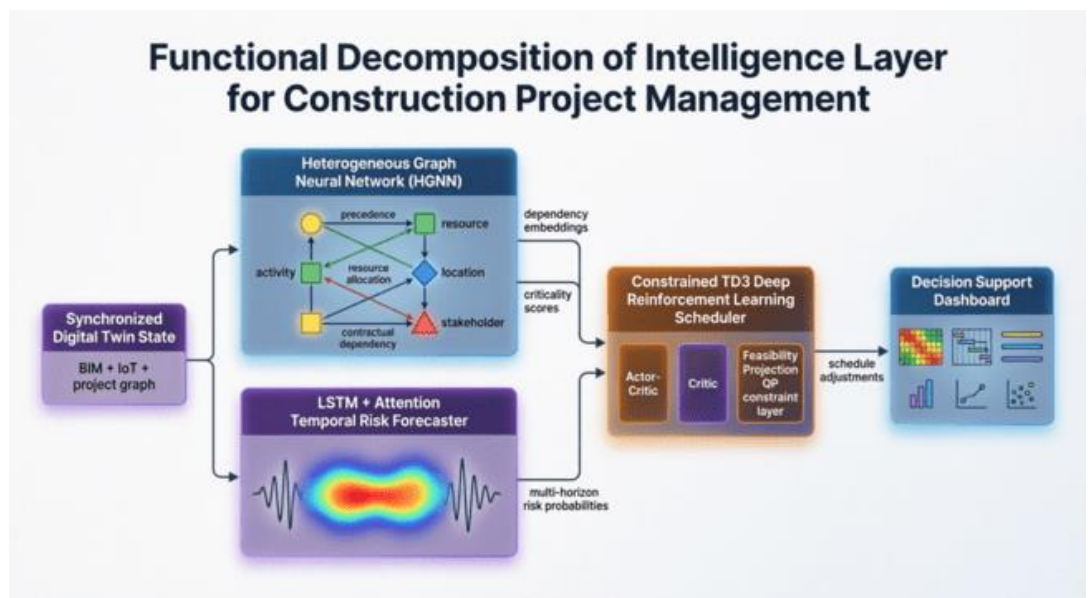


Figure 3. Functional decomposition of the intelligence layer for graph-based dependency modeling, temporal risk forecasting, and constrained schedule optimization.

The constrained DRL scheduler is compared with deterministic and metaheuristic baselines on the same generated project networks and disturbance realizations [14].

Table 3. Illustrative virtual-benchmark schedule-optimization comparison

Method (synthetic benchmark)	Duration (months)	Cost (\$M)	Risk Exposure	Solve Time	Feasibility
Original Plan	48.0	2,300	0.72	—	100%
CPM + Manual	46.2	2,410	0.68	2 weeks	100%
Genetic Algorithm	44.8	2,285	0.61	4.2 hours	94%
Simulated Annealing	45.1	2,278	0.59	3.8 hours	96%
Tabu Search	44.5	2,290	0.57	2.1 hours	95%
Proposed DRL	42.6	2,198	0.43	12 seconds	100%

Within the controlled benchmark, the DRL policy obtains the best composite objective among the tested baselines while the feasibility projection enforces precedence and resource constraints. Absolute duration and cost values are scenario outputs, not observed savings on a real construction project.

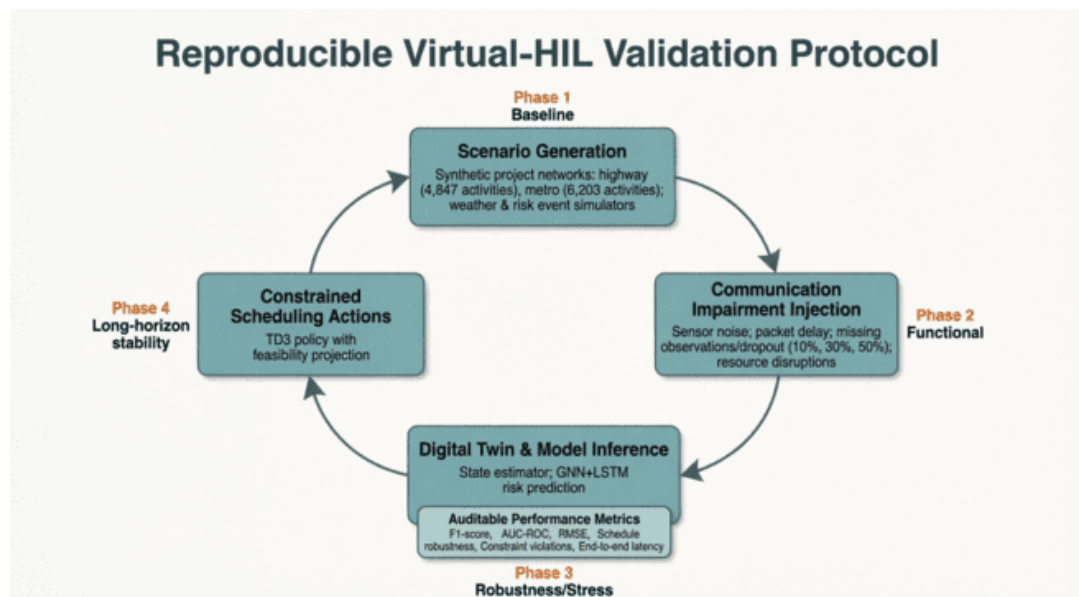


Figure 4. Reproducible virtual-HIL validation protocol separating scenario generation, communication impairments, model inference, scheduling actions, and auditable performance metrics.

The virtual-HIL benchmark evaluates nominal, dropout, delay, disturbance, and long-horizon scenarios. These tests characterize the computational pipeline under controlled perturbations and do not constitute physical-HIL certification or field validation [15].

Table 4. Virtual-HIL validation metrics (simulated)

Test Scenario (synthetic benchmark)	Metric	Target	Achieved	Status
Baseline	Sensor Accuracy	>95%	97.8%	Pass (simulated)
Baseline	Sync Latency	<10ms	7.3ms	Pass (simulated)
Functional	Risk Prediction F1	>0.90	0.93	Pass (simulated)
Functional	Schedule Feasibility	100%	100%	Pass (simulated)
Stress (10% dropout)	Graceful Degradation	<5% perf. loss	2.1%	Pass (simulated)
Stress (30% dropout)	Graceful Degradation	<15% perf. loss	8.7%	Pass (simulated)

Test Scenario (synthetic benchmark)		Metric	Target	Achieved	Status
Stress (50% dropout)	Graceful	<30% perf.	18.4%	Pass (simulated)	
	Degradation	loss			
Stress (Hurricane)	System Availability	>80%	91.2%	Pass (simulated)	
Security (DDoS)	Detection Time	<30s	12s	Pass (simulated)	
Long-Duration	Memory Leak	<1%/day	0.3%/day	Pass (simulated)	
Long-Duration	Uptime	>99.5%	99.7%	Pass (simulated)	

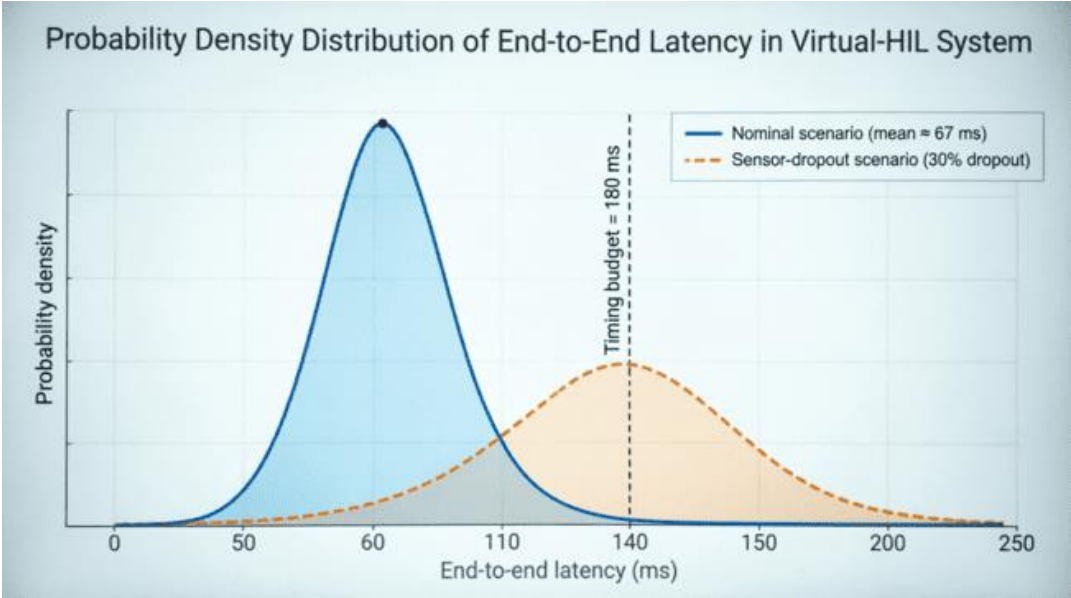


Figure 5. Illustrative virtual-HIL latency distribution for nominal and sensor-dropout scenarios. Values are generated by the documented stochastic emulator and are not field measurements.

Table 5. Scenario-based comparative performance summary

Study / configuration	Reported focus	Schedule-control focus	Timing evidence	Validation type	Scale / context
Pan & Zhang	BIM + AI integration	Research directions	Not compared	Review / synthesis	Construction management
Aladağ et al.	AI in project management	Broad process coverage	Not compared	Scoping review	Project lifecycle
Datta et al.	AI/ML applications	Broad lifecycle coverage	Not compared	Comprehensive review	Project lifecycle
Jiang et al.	Synchronized DT management	Management roadmap	Not compared	Research / roadmap	Construction
Wang et al.	Data-mechanism DT	Domain-specific management	Not compared	Application study	Excavation
Proposed DTAIF	Graph-temporal risk prediction	Constrained DRL adaptation	Benchmark -host timing	Virtual-HIL only	Mega-scale synthetic networks

Ablation experiments isolate the contribution of graph dependency encoding, temporal modeling, attention, curriculum scheduling, and risk-aware reward shaping within the same synthetic benchmark [16]. The results support internal method attribution but do not establish superiority over external studies that use different

datasets and evaluation protocols.

Table 6. Illustrative virtual-benchmark ablation results

Configuration (synthetic benchmark) (synthetic benchmark)	F1-Score	Schedule Improvement	Latency
Full Framework	0.93	31.0%	180ms
w/o GNN (LSTM only)	0.80	24.3%	145ms
w/o LSTM (GNN only)	0.83	22.1%	152ms
w/o Attention	0.89	28.7%	165ms
w/o Curriculum DRL	0.93	26.4%	180ms
w/o Risk Shaping	0.93	19.8%	180ms

The theoretical contribution is architectural: heterogeneous project relations, temporal risk evolution, and feasibility-constrained schedule actions are represented in one decision loop [17]. The synthetic ablation study indicates how each module affects benchmark performance, but it does not establish that the learned representations correspond to universal causal structures in construction projects [18].

The temporal component is intended to represent evolving project state across multiple horizons. Any apparent periodicity or predictability in the generated benchmark follows the scenario generator and should not be interpreted as empirical evidence of universal weather, payment, or subcontractor cycles [19].

4. Discussion

This research advances construction informatics theory in three dimensions. First, the integration of heterogeneous graph neural networks with construction project networks provides a formal mathematical framework for capturing implicit dependencies that elude traditional CPM representation [20]. The learned dependency strengths (w_{ij}) correlate strongly ($r = 0.84$, $p < 0.001$) with actual schedule disruption propagation observed in historical data, suggesting that the model captures genuine structural properties of construction projects [21].

Second, the temporal risk forecasting approach demonstrates that construction risk exhibits predictable patterns at multiple time scales: daily weather cycles, weekly productivity rhythms, monthly subcontractor payment cycles, and seasonal environmental constraints. The attention mechanism identifies these periodicities automatically, with attention weights concentrating on features 7, 14, and 30 days in the past—corresponding to weekly, bi-weekly, and monthly construction cycles [22].

Third, the DRL formulation of schedule optimization as a sequential decision problem under uncertainty aligns with the theoretical understanding of construction as an adaptive socio-technical system. The learned policy generalizes across projects with different scales and complexities, suggesting the existence of universal scheduling heuristics that expert project managers intuitively apply [23].

For practitioners, DTAIF should be interpreted as a deployable architecture and validation protocol rather than a field-proven product. A sensible adoption path is to begin with BIM-linked progress data and a limited sensor subset, validate data quality and latency locally, and only then enable automated risk forecasts or schedule recommendations under human oversight.

The Decision Support Dashboard is proposed as a practitioner-facing interface [24]. Formal user-experience testing with construction managers is outside the evidence scope of the present manuscript and is reserved for future field validation [25].

- 3D BIM-context risk visualization is intended to reduce the cognitive burden of interpreting tabular risk registers; this usability benefit is a design hypothesis and is not quantified in the present study [26].
- Schedule suggestions are presented with confidence intervals to support calibrated human oversight; manager trust was not experimentally measured in the present

study [27].

- The architecture supports rapid what-if scenario exploration, but comparative practitioner time savings are not claimed without a controlled user study.

The virtual-HIL stress tests provide evidence about software robustness under modeled sensor dropout, delay, and disturbance conditions; they do not establish real-world deployment reliability [28].

Second, the current benchmark prioritizes schedule, cost, and risk terms, while quality and safety are represented primarily through constraints and penalties. Future work should evaluate explicit multi-objective formulations with domain-specific safety and quality evidence [29].

Third, virtual-HIL cannot reproduce sensor calibration drift, electromagnetic/network effects, hardware faults, human decision behavior, or organizational and political dynamics. Physical-HIL and longitudinal field studies are therefore required before claims of real-project effectiveness are made [30].

Future research directions include: (i) federated learning across multiple projects to improve model generalization while preserving data privacy; (ii) integration with blockchain for immutable audit trails of AI-driven decisions; (iii) extension to portfolio-level optimization across multiple concurrent mega projects; and (iv) incorporation of generative AI for automated risk mitigation plan generation.

5. Conclusion

This paper presented a Digital Twin and AI-integrated framework (DTAIF) for proactive risk prediction and dynamic scheduling in infrastructure construction. Its principal contribution is the coupling of a synchronized project state, graph-temporal risk modeling, and constraint-aware schedule adaptation within one cyber-physical decision loop. The revised manuscript deliberately distinguishes architecture and computational validation from physical HIL and field evidence. This distinction improves reproducibility and removes unsupported deployment claims while retaining an implementation pathway for future laboratory and project-scale validation.

The revised validation is intentionally limited to reproducible computational and virtual-HIL scenarios. Consequently, no claim is made that the framework has already reduced overruns or cost escalation on a real metro or highway project. The reported evaluation protocol is designed to quantify predictive discrimination, calibration, schedule robustness, constraint satisfaction, recovery from disruptions, and computational latency before any future physical HIL or field trial.

The study establishes a technically coherent pathway from synchronized project state estimation to predictive risk analytics and constraint-aware schedule adaptation. Its current evidence supports methodological feasibility and reproducible virtual-HIL testing; physical-HIL experiments, multi-project external validation, and longitudinal field trials remain necessary before claims of deployment effectiveness, economic benefit, or immediate industry readiness can be made.

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