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Citation for final published version:

Werhahn, Maria, Pfrommer, Christoph, Girichidis, Philipp, Whittingham, Joseph, Jlassi, Léna, Pakmor, Rüdiger, Bieri, Rebekka, Weinberger, Rainer, Springel, Volker and van de Voort, Frederieke 2026. Revisiting radio synchrotron diagnostics in star-forming galaxies. *Monthly Notices of the Royal Astronomical Society* , stag1871. 10.1093/mnras/stag1871

Publishers page: <https://doi.org/10.1093/mnras/stag1871>

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A Monte Carlo enhanced agent based model for Tokenized BIM Twin (TBT) resource reallocation in construction projects

Yasin Celik  · Mehmet S. Cadirci

Received: 23 May 2026 / Accepted: 5 August 2026
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Abstract

Construction projects involve a complex relationship of interdependence among numerous parties, which often leads to delays and significant coordination costs among contractors. While approaches based on Building Information Modeling (BIM) and Digital Twin (DT) technologies have enhanced monitoring and visualization capabilities, they remain limited in their ability to enable autonomous, decentralized, and tamper-proof resource reallocation. This paper proposes and computationally evaluates a three-layer Tokenized BIM-Twin (TBT) framework under controlled simulation conditions. The framework combines a static IFC-based BIM layer for resource tokenization, a real-time Digital Twin layer to detect anomalies and measure deviations, and a blockchain-based smart contract layer that has the potential to minimize disputes and reallocate resources automatically and transparently under the modelled conditions. The framework is evaluated using an agent-based simulation model defined on an eight-parameter uncertainty space. A total of 150 Monte Carlo iterations per scenario ($n=450$ observations) are performed across three configurations: Baseline (traditional management), Centralized BIM+DT, and the TBT framework. The results are assessed using one-way ANOVA, Welch's t-tests, and effect size analysis (Cohen's d), indicating statistically significant differences across all evaluated performance dimensions under the modelled conditions. Schedule overrun is reduced within the simulation environment from a mean of 38.90% (± 6.24) to 3.30% (± 1.38) ($F=2672.5$, $p<0.001$, $d=7.88$). Resource idle rates decline from 35.52% (± 3.22) to 20.04% (± 3.02) ($d=4.96$), while disruption response time is reduced from 5.45 days (± 1.23) to 0.44 days (± 0.17) ($d=5.69$). In addition to its conceptual contribution, the framework has practical implications, as the framework demonstrates the potential to improve coordination efficiency, reduce disputes, and increase transparency under the modelled conditions. The results suggest that the approach has potential for projects characterized by high uncertainty and complex stakeholder interactions, although empirical validation is still required before real-world performance can be confirmed.

Keywords Building Information Modeling · Digital Twin · Blockchain · Smart contracts · Agent-based modeling · Monte Carlo simulation · Resource optimization · Construction management

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Introduction

Construction projects are among the activities in the built environment that involve the most intensive use of resources and are most sensitive to coordination. Despite advances in project management, cost overruns, schedule delays, and conflicts among stakeholders are still common in the industry. A report by A McKinsey Global Institute¹ indicates that large construction projects typically exceed their budgets by 80% and are completed with delays of up to 20 months. These outcomes are largely driven by coordination challenges. In particular, delays arise from the difficulty of reallocating resources quickly and transparently among contractors, subcontractors, and suppliers during disruptions. Three technological approaches are key to resolving this issue; BIM provides structured and semantically rich representations of project assets, supporting improved interoperability among stakeholders^{2,3}. DT technologies extend BIM by incorporating a temporal dimension, allowing construction progress to be mirrored in near real-time through IoT-based data integration^{4,5}. Blockchain and smart contracts offer a decentralized and tamper-resistant mechanism for executing transactions across multiple parties, reducing reliance on trust-based coordination⁶. These three technologies have been developed largely independently of one another or in limited combinations. Existing BIM–blockchain integrations focus highly on payment automation⁷ and data traceability⁸, while DT applications in the construction industry are limited to monitoring⁹ and visualization¹⁰, resource decisions¹¹ are still made through centralized, human-driven processes.

The literature has examined the integration of BIM, Digital Twin, and blockchain technologies into areas such as project tracking, payment automation, and data traceability. However, these approaches are generally limited to descriptive or responsive functions, and the decision-making process continues to be based on centralized coordination or manual intervention. The use of blockchain in the construction sector, in particular, has been largely limited to transaction verification and information management instead of operational decision-making. Digital Twin applications have also primarily focused on real-time monitoring and performance visualization, with limited capacity for autonomous response to disruptions. While agent-based and optimization-based approaches are used to analyse resource allocation, these methods have been integrated only to a limited extent with real-time data environments or decentralized execution mechanisms. In this regard, there is a gap in the development of simulation-validated frameworks that combine (i) tokenized representations of construction resources, (ii) real-time anomaly detection, and (iii) the autonomous, protocol-based execution of reallocation decisions under conditions of uncertainty.

This study is guided by one central research question and two objectives. The research question is:

- To what extent does an integrated BIM–Digital Twin–blockchain framework improve resource management in disruption-prone, multi-contractor construction projects with predefined disruption timing and idealised data availability?

First, the goal is to establish an integrated framework that includes BIM, Digital Twin, and blockchain technologies for resource management. Second, we plan to computationally evaluate the performance of this framework under controlled simulation assumptions in disruption scenarios and compare it to existing approaches using key metrics such as time, cost, resource utilization, response time, and frequency of disputes.

The contribution of this study is the development and computational evaluation of a conceptual mechanism for autonomous resource reallocation. By combining tokenized BIM resources, Digital Twin-based disruption detection, and smart contract execution within a Monte Carlo–enhanced agent-based model, the study examines how such an integrated architecture may influence schedule, cost, resource idle time, response time, and dispute frequency under controlled assumptions. This study makes three primary contributions. First, it introduces a token-based representation of construction resources within a BIM environment, extending existing blockchain applications beyond financial transactions and document management. Second, it develops an integrated architecture that combines Digital Twin-based disruption detection with automated resource reallocation through smart contract execution, enabling a shift from monitoring to operational decision-making. Third, it provides a computational evaluation of the proposed framework using a Monte Carlo–enhanced agent-based simulation,

allowing the analysis of system behaviour under uncertainty. These contributions position the framework as a conceptual and methodological advancement in the study of decentralized construction resource management.

The remainder of the paper is organized as follows. Section 2 reviews the literature on BIM, Digital Twin, and blockchain technologies. Section 3 introduces the architecture of the proposed TBT framework. Section 4 summarizes the simulation methodology. Section 5 presents the results and analyses them statistically. Section 6 discusses the key findings, the study's limitations, and recommendations for future research. Lastly, Sect. 7 concludes the paper.

Literature review

BIM has evolved beyond its initial role as a design tool and is now widely used as a platform that supports the entire project lifecycle. Empirical studies indicate that the adoption of BIM can reduce project delivery costs by approximately 15–20%¹² and shorten timelines by 10–18%¹³; the primary reason for this is improved coordination and more effective clash detection^{13,14}. It is described as a shared data environment that facilitates collaboration among multiple stakeholders^{15,16}, while the Industry Foundation Classes (IFC) schema remains the primary open standard enabling interoperability across BIM systems^{17,18}.

BIM enables the detailed representation of quantities, costs, spatial characteristics, and temporal availability within the IFC object model from a resource management perspective. This capability forms the basis for using BIM in 4D (time) and 5D (cost) planning. 5D BIM applications have been shown to reduce cost estimation errors compared to traditional quantity surveying approaches^{19,20}. The concept of the DT, initially introduced in product lifecycle management²¹, has gained increasing attention in construction. A digital twin refers to a dynamic virtual representation of a physical asset²² that is updated via real-time data streams to support simulation, forecasting, and performance optimization^{23,24}. Applications include structural health monitoring, energy performance analysis, and construction progress tracking^{25–28}. Previous studies report that DT-based logistics systems for prefabricated components have reduced errors on construction sites thanks to real-time tracking^{29,30}. Current DT applications still depend on centralized data infrastructures and human decision-making. This reliance can lead to delays in projects involving multiple contractors and may increase concerns regarding security. Conceptual frameworks for their convergence have been proposed³¹, and prototype systems have been developed for monitoring building services such as mechanical, electrical, and plumbing systems³². However, dynamic resource reallocation remains beyond the scope of most BIM–DT studies and is identified as an area requiring further research.

Blockchain technology has attracted attention due to its ability to provide immutable audit trails, enable decentralized transactions, and reduce reliance on trust in multi-party contract environments³³. Early work demonstrated its potential for automating payment processes in construction³⁴, while subsequent studies introduced smart contract frameworks for BIM-based document management and version control³⁵, Qi et al., 2025. Blockchain-based payment systems have reduced dispute resolution time, while other studies have shown its effectiveness in change management and material traceability^{36,37}.

A systematic review of blockchain applications³⁸ in the built environment reveals that existing research covers a wide range of areas, including governance, smart infrastructure, and BIM-supported construction management, and that these studies place significant emphasis on data transparency, process automation, and building trust over advanced operational optimization. While these studies highlight blockchain's potential to improve information sharing, contract execution, and system reliability, applications related to dynamic resource allocation and optimization remain unexplored. In order to enable autonomous resource reallocation, the integration of blockchain-based mechanisms with real-time Digital Twin monitoring is still in its early and mostly conceptual stages; this highlights a clear gap that requires further research.

Research on multi-party resource allocation in construction spans optimization techniques, game-theoretic approaches³⁹, and agent-based models⁴⁰. To examine resource allocation among subcontractors, Nash bargaining

models were used, and these models demonstrated an increase in program efficiency under collaborative conditions⁴¹. Multi-agent simulation approaches have been applied to decentralized multi-project scheduling showing that distributed decision-making and agent-based negotiation mechanisms can improve coordination of shared resources and reduce overall project delays compared to centralized or simplified allocation methods⁴².

Agent-based modeling (ABM) has since become a widely used method for representing complex, multi-agent construction systems²⁷. Foundational studies have established its role in socio-technical modeling^{29,43,44}, and more recent work has applied ABM to construction-specific problems such as material logistics optimization and schedule risk analysis through Monte Carlo integration⁴⁵.

Table 1 summarizes the literature by mapping key studies against technological components (BIM, DT, blockchain) and methodological approaches. The synthesis highlights three limitations in the existing literature. First, while individual technologies have been studied, their integration is often partial and does not extend to operational decision-making. Second, blockchain applications are oriented toward validation and record-keeping, with limited use in dynamic resource allocation processes. Third, there is a lack of simulation-based studies that examine how integrated systems behave under uncertainty and disruption. This paper addresses these limitations by combining tokenized BIM resources, Digital Twin monitoring, and decentralized execution within a unified, simulation-based framework. These limitations provide the basis for the framework proposed in the following section.

Tokenized BIM-Twin (TBT) framework

The TBT framework is organized as a three-layer architecture (see Fig. 1), composed of interrelated components that perform distinct functions while operating on a shared data ontology based on the IFC schema. It is grounded in decentralized, trust-minimized coordination. Within this structure, resource reallocation decisions are expected to meet three conditions: they need to be (i) computationally optimal, as determined by the optimization engine in the Digital Twin layer; (ii) transparently verifiable through immutable blockchain records; and (iii) automatically enforceable via smart contracts, without reliance on human intervention or centralized control. This design

Table 1 Synthesis of related literature — technology coverage and research gap identification.

Study	BIM	Digital twin	Blockchain	Resource optimization	Simulation validation	Multi-party
Azhar ¹⁴	✓	—	—	Partial	Empirical	—
Turk and Kline ³⁴	—	—	✓	—	Conceptual	✓
Nawari and Ravindran ³⁵	✓	—	✓	Documents	Prototype	✓
Li et al. ⁴⁶	—	—	✓	Supply chain	Systematic review	✓
Boje et al. ³¹	✓	✓	—	—	Conceptual	—
Sacks et al. ⁹	✓	✓	—	Scheduling	Conceptual framework	Partial
Deng et al. ³⁰	✓	✓	—	—	Systematic review	Partial
Hamledari and Fischer ⁴⁷	✓	—	✓	Payment	Case study (2)	✓
Lee et al. ⁴⁸	✓	✓	✓	—	Prototype	✓
Li and Kassem ⁴⁹	—	—	✓	—	Literature review	✓
Pan and Zhang ⁵⁰	✓	✓	—	Productivity	Prototype	Partial
Hunhevicz et al. ⁵¹	✓	✓	✓	—	Prototype	✓
Li et al. ³⁸	✓	—	✓	Supply chain	Prototype	✓
Kamel et al. ³⁷	✓	—	✓	Payment	Case study	✓
Jiang ⁵²	✓	✓	✓	Logistics	Prototype	✓
Pishdad and Onungwa ²⁰	✓	—	—	Cost only	Case study	—
Dong et al. ⁵³	✓	✓	✓	Asset tracking	Prototype	✓
Sultan et al. ⁴⁵	—	—	—	✓ Scheduling	Agent-based sim.	✓

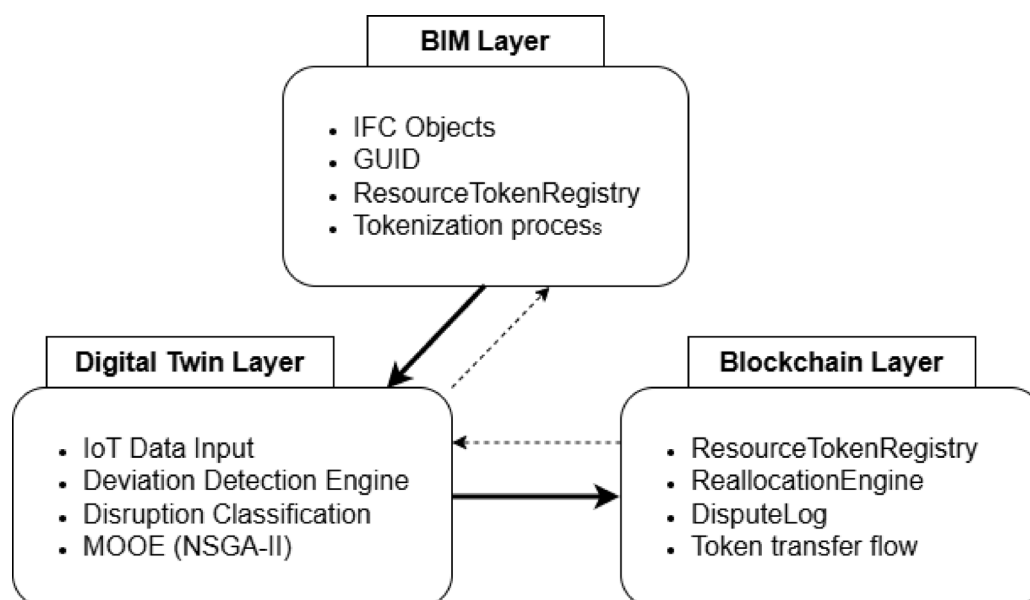


Fig. 1 Tokenized BIM-Twin framework layers.

addresses common inefficiencies in multi-party construction environments including information asymmetry, administrative delays, and disputes.

Layer 1: BIM resource tokenization

The BIM layer serves as the static information base of the framework. Project resources, such as work crews, equipment units, and material batches, are represented as IFC objects within a standard BIM environment (e.g., Autodesk Revit). Each object is assigned a unique identifier (GUID), which links the BIM model to its blockchain representation. At the start of the project, a ResourceTokenRegistry smart contract is deployed, and each IFC-defined resource is converted into a non-fungible utility token. These tokens store immutable attributes, including resource type, contractor ownership, total capacity, unit cost per day, and a reference to the corresponding IFC object. In contrast, resource availability is treated as dynamic and is updated by the Digital Twin layer.

This tokenization mechanism offers two main advantages. It enables system-wide visibility of resource availability, allowing all participants to access verifiable information and reducing information asymmetry that may otherwise encourage opportunistic behaviour, such as resource hoarding. It also records all reallocations as time-stamped blockchain transactions, creating an immutable audit trail that supports transparent and objective dispute resolution. The approach, however, assumes that resources can be discretized into transferable units; in practice, partially allocated teams or shared equipment may require more advanced tokenization schemes.

Layer 2: Digital Twin monitoring and optimization

The DT layer maintains a synchronized virtual representation of the construction site. Data are collected through IoT devices embedded in equipment, worn by personnel as RFID-enabled personal protective equipment (PPE), and installed at material storage locations. These devices transmit telemetry data to the DT platform at configurable intervals, typically at 15-minute resolution for schedule-critical activities.

This layer consists of three main modules. The Deviation Detection Engine calculates, for each active BIM activity, the difference between planned and actual progress using sensor data. The Disruption Classification Module then categorizes these deviations according to their underlying causes, such as weather conditions, equipment

failure, material delays, or labour shortages, and assigns a normalized severity score between 0 and 1. When deviations exceed a predefined threshold (default: 15%), the Multi-Objective Optimization Engine (MOOE) is activated, generating Pareto-optimal reallocation strategies that balance schedule performance and cost.

The MOOE is implemented using the NSGA-II algorithm. Decision variables represent the allocation of tokenized resources across project activities, while the objective functions aim to minimize (f1) expected project completion time and (f2) total reallocation cost, including transaction costs. The model incorporates constraints related to contractor capacity and technological dependencies between activities. Standard parameter settings from the literature are used, and preliminary testing indicates stable convergence. It is assumed that the resulting solutions are feasible, although practical deployment may require additional validation to account for operational constraints.

The NSGA-II algorithm is implemented using a population size of 100, with 150 generations per optimization run. A simulated binary crossover operator with a probability of 0.9 and a polynomial mutation operator with a probability of 0.1 are employed. Tournament selection is used for parent selection, and elitism is preserved across generations. These parameter values are selected based on commonly adopted configurations in multi-objective optimization literature and verified through preliminary stability testing.

Layer 3: blockchain smart contract execution

The blockchain layer enables autonomous execution within the framework. It includes three core smart contracts: (1) ResourceTokenRegistry, which manages tokenized resources and their availability; (2) ReallocationEngine, which receives optimization outputs and executes token transfers among contractors; and (3) DisputeLog, which records each reallocation as a time-stamped and cryptographically signed entry.

When a reallocation plan is received, the ReallocationEngine follows a defined sequence. It first verifies token availability, then temporarily locks the relevant tokens to avoid conflicts. The transfer is executed by updating ownership and availability states, after which events are emitted to notify participants. Once the transaction is confirmed, the tokens are unlocked.

Execution performance depends on the blockchain platform. On permissioned systems such as Hyperledger Fabric, latency is typically below one second, while public blockchains using optimistic rollups (e.g., Ethereum) exhibit latencies between 2 and 15 s. Smart contract execution is assumed to be deterministic, although real-world deployments may face issues such as execution failures, coding vulnerabilities, or network disruptions, all of which require mitigation strategies.

Inter-layer data flow

Under normal conditions, the system operates through a unidirectional, trigger-based data flow. The BIM layer supplies the initial static information defining project resources and configurations. The Digital Twin layer processes incoming IoT data and generates optimization outputs when deviations are detected. These outputs are then transmitted to the blockchain layer, which executes the corresponding reallocations and distributes confirmation events to relevant participants. The blockchain ledger functions as a trusted record, allowing the Digital Twin layer to verify that computed reallocations have been carried out as intended. This feedback loop closes the verification process and addresses a common limitation of centralized systems. This workflow, as described above, operates within the same idealized assumptions outlined in Sect. 4.7 (e.g., full data accessibility, instantaneous communication between layers, and full compliance by contractors); these assumptions are employed to demonstrate the architectural contributions of the three layers individually, rather than to claim real-time applicability under field conditions.

Simulation methodology

The simulation study is based on a Monte Carlo-enhanced ABM implemented in Python 3.12. Model validation follows the framework outlined by Law and Kelton⁵⁴ and is carried out in four stages: (i) conceptual validation through expert review; (ii) parameter estimation using published empirical studies; (iii) model verification through code inspection and boundary value testing; and (iv) output validation by comparison with established case study benchmarks. To support reproducibility, key model parameters and assumptions are documented, and future work will aim to provide an open-source implementation where feasible. The model operates under a set of simplifying assumptions designed to isolate system-level effects, which are explicitly summarized in Sect. 4.7.

The simulated scenario represents a mid-rise, mixed-use commercial building in an urban setting, with a planned duration of 120 days and a total budget of USD 898,400. The model includes twelve BIM-defined work packages, thirteen tokenized resource units, four contractor agents, and six predefined disruption types introduced at specific points in the project timeline. These characteristics are calibrated using market benchmarks for Istanbul reported by Ozcan Deniz et al.⁵⁵.

This paper offers a computational validation of the proposed framework. Simulation-based approaches are well suited to examining complex socio-technical systems under controlled conditions; however, real-world pilot implementations are still required to evaluate practical integration, stakeholder behaviour, and potential operational constraints. Although model parameters are drawn from empirical studies, the results are not validated against data from actual project execution, which represents an important limitation. In addition, the model relies on simplifying assumptions, such as full data accessibility, real-time communication, and complete compliance with optimization outcomes, to isolate the effects of the framework. These assumptions may reduce the direct transferability of the findings to real construction settings. Given these assumptions, the simulation outcomes are expected to represent an upper-bound estimate of system performance, as real-world implementations would likely introduce additional sources of delay, uncertainty, and behavioural variability.

Project case: BIM model specification

The simulated project consists of twelve BIM-defined work packages is presented in Table 2, spanning phases from site preparation to handover. Inter-activity dependencies are modelled as finish-to-start relationships within the IFC-based schedule. Resource requirements for each activity are derived from standard Turkish unit cost and resource databases⁵⁶.

Four contractor agents are represented in the simulation environment. Each agent is characterized by a portfolio of resource tokens (see Table 3), a utility function that seeks to maximize task completion under resource constraints, and a set of rules governing the lending and borrowing of tokens within the TBT framework. Agents

Table 2 BIM work package specification — simulated construction project.

ID	Work package	Duration (days)	Contractor	Workers (req.)	Equipment (units)	Cost/Day (USD)	Dependencies
A01	Site preparation	10	C1	8	2	4500	–
A02	Foundation excavation	12	C1	12	3	6200	A01
A03	Foundation concrete	10	C2	10	2	5800	A02
A04	Ground floor structure	14	C2	14	4	8400	A03
A05	Ground floor MEP	8	C3	6	1	3200	A04
A06	1st floor structure	14	C2	14	4	8400	A04
A07	1st floor MEP	8	C3	6	1	3200	A06
A08	2nd floor structure	14	C2	14	4	8400	A06
A09	Facade & cladding	20	C4	10	2	7000	A08
A10	Interior finishing	18	C4	12	1	5500	A07
A11	MEP commissioning	10	C3	8	2	4200	A09, A10
A12	Landscaping & handover	12	C4	6	1	3000	A11

Table 3 Contractor agent resource portfolio — tokenized resource registry.

Token ID	Resource name	Type	Owner	Capacity	Cost/Day (USD)
TOKEN-R-C1-W1	C1 Worker Team A	Worker	C1	8	350
TOKEN-R-C1-W2	C1 Worker Team B	Worker	C1	6	350
TOKEN-R-C1-E1	C1 Excavator	Equipment	C1	1	1200
TOKEN-R-C2-W1	C2 Structural Team A	Worker	C2	10	400
TOKEN-R-C2-W2	C2 Structural Team B	Worker	C2	8	400
TOKEN-R-C2-E1	C2 Tower Crane	Equipment	C2	1	2500
TOKEN-R-C2-E2	C2 Concrete Pump	Equipment	C2	1	1800
TOKEN-R-C3-W1	C3 MEP Team A	Worker	C3	8	380
TOKEN-R-C3-W2	C3 MEP Team B	Worker	C3	6	380
TOKEN-R-C3-E1	C3 Boom Lift	Equipment	C3	1	900
TOKEN-R-C4-W1	C4 Finishing Team A	Worker	C4	10	320
TOKEN-R-C4-W2	C4 Finishing Team B	Worker	C4	8	320
TOKEN-R-C4-E1	C4 Facade Crane	Equipment	C4	1	1400

Table 4 Disruption event schedule — six deterministic injection points.

Event ID	Day	Type	Affected contractor	Severity	Duration (days)	Workers impacted
D01	15	Adverse weather	C2	0.40	3	6
D02	35	Material delay	C1	0.60	5	4
D03	52	Worker absence	C3	0.50	4	5
D04	70	Equipment failure	C2	0.70	6	0 (equipment)
D05	88	Adverse weather	C4	0.30	2	4
D06	100	Worker absence	C2	0.40	3	5

are assumed to operate under bounded rationality and to comply with smart contract outcomes, based on the assumption that cryptographic enforcement reduces incentives for strategic non-compliance. However, in real-world settings, strategic behaviour, negotiation processes, and partial compliance may still occur. These aspects are not incorporated into the current model and point to a direction for future research. In addition, agents follow fixed decision rules and do not exhibit learning or adaptation across simulation runs. Introducing adaptive mechanisms, such as reinforcement learning, could improve the realism of the model by capturing how contractor decision-making evolves over time.

Disruption model

Six disruption events are introduced into the simulation at predetermined points in the project timeline, reflecting the disruption patterns observed in urban construction projects in Türkiye⁵⁷. The detailed disruption schedule is presented in Table 4. Each disruption negatively affects the progress rate of the impacted contractor's activities and activates the corresponding response mechanism associated with the scenario being evaluated, namely, manual coordination, a centralized Digital Twin system, or the TBT framework enabled by smart contracts.

The use of deterministic disruption timing ensures comparability across scenarios by isolating the effects of response mechanisms.

Comparative scenarios

Three simulation scenarios are defined for comparative analysis:

- *Scenario S1 — Baseline (traditional management)*: In this case, resource reallocation after disruptions is handled through conventional coordination methods, such as telephone and email communication, site meetings, and manual contract adjustments. Response time is modelled using a uniform distribution between 3.0

and 7.5 days, in line with findings reported by Doloi et al.⁵⁷. The probability of a dispute following a disruption is defined as 0.65 multiplied by the disruption severity.

- **Scenario S2 — Centralized BIM + Digital Twin:** A centralized Digital Twin platform monitors project progress and detects disruptions. Resource reallocation, however, still requires approval from a central project coordinator. As a result, response time is shorter than in the baseline case and is modelled using a uniform distribution between 1.0 and 3.5 days. In this configuration, blockchain-based tokenization is not used, and all reallocation records are stored in a centralized database.
- **Scenario S3 — Tokenized BIM Twin (TBT):** This scenario represents the proposed framework. Disruptions are detected by the Digital Twin layer, after which the MOOE determines suitable resource reallocations. These decisions are executed automatically through smart contracts, allowing token transfers without human intervention. Response time is modelled as the sum of Digital Twin detection latency and smart contract execution time, reflecting a highly digitized environment with near real-time responsiveness. This scenario therefore represents a lower-bound estimate of achievable performance under idealized conditions.

Across all scenarios, the model assumes that reallocated resources become available after a configurable mobilization delay following execution. In practice, the physical relocation of personnel and equipment introduces additional time constraints, which may reduce the realized benefits of reallocation.

Monte Carlo parameter space

The Monte Carlo analysis samples from an eight-dimensional parameter space characterizing construction uncertainty. Table 5 defines the parameter distributions, based on calibration against published empirical benchmarks^{57–59}. The simulation was executed for $n = 150$ iterations per scenario ($N = 450$ total observations), achieving a margin of error of $\pm 0.8\%$ for the primary outcome variable (schedule overrun) at the 95% confidence level. Sample size adequacy was confirmed by pilot runs using the variance stabilization criterion of Law and Kelton⁵⁴. Additional pilot simulations with larger sample sizes confirmed convergence of key output metrics, indicating that the selected number of iterations is sufficient for stable statistical estimation.

Table 5 Monte Carlo parameter distributions — eight-dimensional uncertainty space.

Parameter	Distribution	Parameters	Bounds	Literature source
Disruption probability (per day)	Uniform	min = 0.01 max = 0.12	—	Doloi et al. ⁵⁷
Disruption severity	Triangular	min = 0.15 mode = 0.45 max = 0.85	—	Tah and Carr ⁵⁹
Baseline worker efficiency	Normal	$\mu = 0.78$ $\sigma = 0.06$	[0.60, 0.92] (truncated)	Tam et al. ⁶⁰
SC response time (hours)	Log-normal	$\mu_{\log}, \sigma_{\log}$ (calibrated to mean ≈ 6.0)	[1.0, 24.0]	This study (blockchain)
Max concurrent disruptions	Discrete uniform	min = 1 max = 4	integers only	Expert elicitation
Material price volatility	Uniform	min = 0.02 max = 0.25	—	OECD ⁶¹
Worker absenteeism rate	Beta	($\alpha = 2, \beta = 20$)	scaled to [0.01, 0.20]	ILO ⁶²
Equipment failure probability	Uniform	min = 0.005 max = 0.10	—	Betz et al. ⁶³

Statistical analysis plan

The statistical analysis follows a pre-registered, three-stage protocol.

- In Stage 1 (Distributional Assessment), the underlying assumptions of the data are evaluated. Shapiro–Wilk tests are used to assess normality, while Levene’s tests are applied to examine the homogeneity of variances across scenarios for all outcome variables.
- In Stage 2 (Hypothesis Testing), one-way ANOVA is employed to test for overall (omnibus) differences among the three scenarios. Where pairwise comparisons are required, such as between S1 and S3, and between S2 and S3, Welch’s t-tests are applied, with adjustments made when unequal variances are identified through Levene’s test.
- In Stage 3 (Effect Size Estimation), effect sizes are calculated using Cohen’s d for each pairwise comparison. The interpretation of effect sizes follows the classification proposed by Jacob Cohen⁶⁴, where values of $|d| < 0.5$ are considered small, $0.5 \leq |d| < 0.8$ indicate medium effects, and $|d| \geq 0.8$ represent large effects.

A significance level of $\alpha=0.05$ is adopted throughout the analysis. Statistical significance is reported using standard notation, where $p<0.001$ is denoted as ***, $p<0.01$ as **, and $p<0.05$ as *.

Sensitivity analysis

Sensitivity analysis is conducted using Pearson correlation coefficients (r) to quantify the relationship between each Monte Carlo input parameter and each output metric, with calculations performed separately for each simulation scenario. The input parameters are subsequently ranked based on the absolute magnitude of their correlation coefficients, providing an indication of their relative influence on output variability.

This approach offers a direct and interpretable measure of parameter sensitivity, analogous to first-order Sobol indices under the assumption of monotonic relationships. To support this assumption, monotonicity is empirically assessed using Spearman rank correlation coefficients.

Model assumptions and scope

The assumptions presented in the Table 6 are intended to highlight the functional effects of the proposed framework and ensure comparability across simulation scenarios. The model represents a controlled computational environment instead of a fully realistic construction environment. Therefore, the findings should be interpreted

Table 6 Key modeling assumptions and their implications.

Category	Assumption	Implication
Data availability	All BIM and IoT data are assumed to be complete, accurate, and available in near real-time	Eliminates data uncertainty; may overestimate responsiveness
Communication	Instant and lossless data transfer between BIM, DT, and blockchain layers	Removes latency and integration delays present in real systems
Agent behaviour	Contractors fully comply with smart contract outcomes	Ignores strategic behaviour, negotiation, and partial compliance
Resource mobility	Resources can be reallocated without significant physical or logistical constraints	May underestimate real-world mobilization delays
Smart contracts	Execution is deterministic and free from errors or failures	Does not account for bugs, security risks, or execution conflicts
Blockchain performance	Transaction latency remains within assumed bounds (1–24 h)	Ignores network congestion and variability in public systems
Disruption structure	Disruption timing is predefined and identical across scenarios	Ensures comparability but reduces realism
Market conditions	Prices and resource availability follow predefined statistical distributions	Simplifies dynamic market fluctuations

not as direct predictions of real-world performance, but as indicators of the system's potential behaviour under idealized conditions.

As shown in Table 6, the assumptions were not chosen arbitrarily: The underlying parameter distributions were calibrated based on values reported in the literature on construction management and blockchain performance (see Table 5) and, where empirical estimates were not directly available, were supported by expert assessments of reasonable operating ranges. The availability of complete data, real-time communication, and full compliance by contractors—ideal conditions—were intentionally applied to isolate the structural effect of the TBT architecture itself, independent of confounding factors such as data quality or partial adoption. Instead of large, highly fragmented infrastructure programs—where communication delays and partial compliance are expected to play a greater role—the modeled environment aims to approximate small- and medium-scale, multi-contractor projects prone to disruptions (e.g., residential or commercial buildings with several subcontractors working simultaneously). A sensitivity analysis (Sect. 5.3) enables a more detailed investigation of the impact that deviations from these idealized assumptions would have on the reported results.

Model implementation details

Each contractor agent operates according to a rule-based decision structure. At each simulation time step, agents evaluate their assigned tasks and available resource tokens. When a disruption is detected, the agent does not initiate negotiation; instead, the system delegates decision-making to the optimization engine. Agents are assumed to accept reallocation outcomes generated by the optimization module and executed via smart contracts. Task progress is updated based on the ratio of allocated resources to required resources, adjusted by disruption severity factors. No learning or adaptation mechanisms are included, and agent behaviour remains fixed across simulation runs.

The simulation proceeds according to the following sequence:

1. Initialize BIM-defined activities, contractor agents, and tokenized resources.
2. Assign baseline resource allocations to all tasks.
3. Advance simulation time in discrete daily steps.
4. Inject disruption events at predefined time points.
5. Update task progress based on available resources and disruption effects.
6. Trigger deviation detection when progress deviates from planned thresholds.
7. Activate the optimization engine to generate candidate reallocation strategies.
8. Select Pareto-optimal solutions based on objective trade-offs.
9. Execute selected reallocations through smart contract logic.
10. Update resource states and continue simulation until project completion.

Performance metrics are computed as follows: schedule overrun is defined as the percentage increase in total project duration relative to the planned schedule; cost overrun is calculated as the percentage difference between planned and actual costs; resource idle rate represents the proportion of time resources remain unallocated; response time is measured as the elapsed time between disruption occurrence and reallocation execution; and dispute frequency is modelled probabilistically based on disruption severity and scenario-specific parameters. To support reproducibility, all model parameters, distributions, and decision rules are explicitly defined in the manuscript. While the current implementation is not publicly released, future work will aim to provide an open-source version of the simulation framework.

Results

Primary simulation results — deterministic run

Figure 2 presents the comprehensive results of the deterministic simulation run across all three scenarios, including project completion timelines, KPI comparisons, and blockchain transaction activity. Table 7 provides the corresponding numerical results.

The deterministic results show a clear performance hierarchy: under the assumptions of the simulation environment, across the evaluated scenarios, the TBT framework (S3) was associated with lower schedule overruns, reduced response times, lower resource idle rates, and fewer disputes within the simulated environment, followed by the Centralized BIM+DT scenario (S2), and then the Baseline (S1). The largest improvement appears in disruption response time, where TBT reduces the mean response from 4.80 days to 0.31 days, corresponding to a 93.5% decrease driven by the autonomous execution of smart contracts.

Under the assumptions of the simulation, operational disputes are not observed in S3 within the simulation environment (4 disputes in S1, 2 in S2, and 0 in S3), suggesting that immutable on-chain records may contribute to reduced conflict occurrence under the modelled conditions in multi-party settings. This result, however, reflects idealized conditions, including perfect data availability, full adoption, and deterministic smart contract execution. In practice, legal, contractual, and operational frictions are likely to reduce the magnitude of these effects and should be examined through future empirical and simulation-based studies.

Monte Carlo results — distributional analysis

Figure 3 presents the probability density functions (kernel density estimates) of the five key performance indicators across 150 Monte Carlo iterations per scenario. Figure 4 presents the corresponding boxplots with significance annotations.

The distributional analysis highlights two main points that go beyond differences in mean performance. First, the TBT framework (S3) shows markedly lower variability across all evaluated metrics. For instance, the standard deviation of schedule overrun decreases to 1.38%, compared to 6.24% in S1, while the standard deviation of response time drops from 1.23 days in S1 to 0.17 days in S3. A similar pattern is observed for idle rate variability (3.02% in S3 versus 3.22% in S1). These results indicate that the TBT framework improves average performance and enhances system reliability under parameter uncertainty. Second, the outcome distributions across scenarios are mostly separated for key metrics such as schedule overrun and response time. This suggests that the performance gains associated with the proposed framework persist across the full range of sampled parameter conditions. The reduced variance observed in the TBT scenario is a consequence of deterministic execution pathways and the absence of behavioural or institutional noise, which would increase variability in real construction settings.

Statistical test results

All five ANOVA tests yield F-statistics well above the critical value ($F_{0.05, 2, 447} = 3.02$), with $p < 0.001$ in each case, indicating statistically significant differences across scenarios. Four of the five pairwise comparisons show large effect sizes (Cohen's $d > 0.8$). Schedule overrun exhibits a large effect size ($d = 7.88$), far exceeding conventional thresholds and indicating near-complete separation between the distributions of S1 and S3. By contrast, the cost overrun comparison produces a medium effect size ($d = 0.73$), which can be attributed to the influence of material price volatility, a factor affecting all scenarios and contributing substantially to overall cost variation.

The observed effect sizes are higher than those reported in empirical studies in the field of construction management. This can be attributed primarily to the controlled nature of the simulation model, which assumes the immediate implementation of reallocation decisions, full compliance by actors, and the absence of organizational

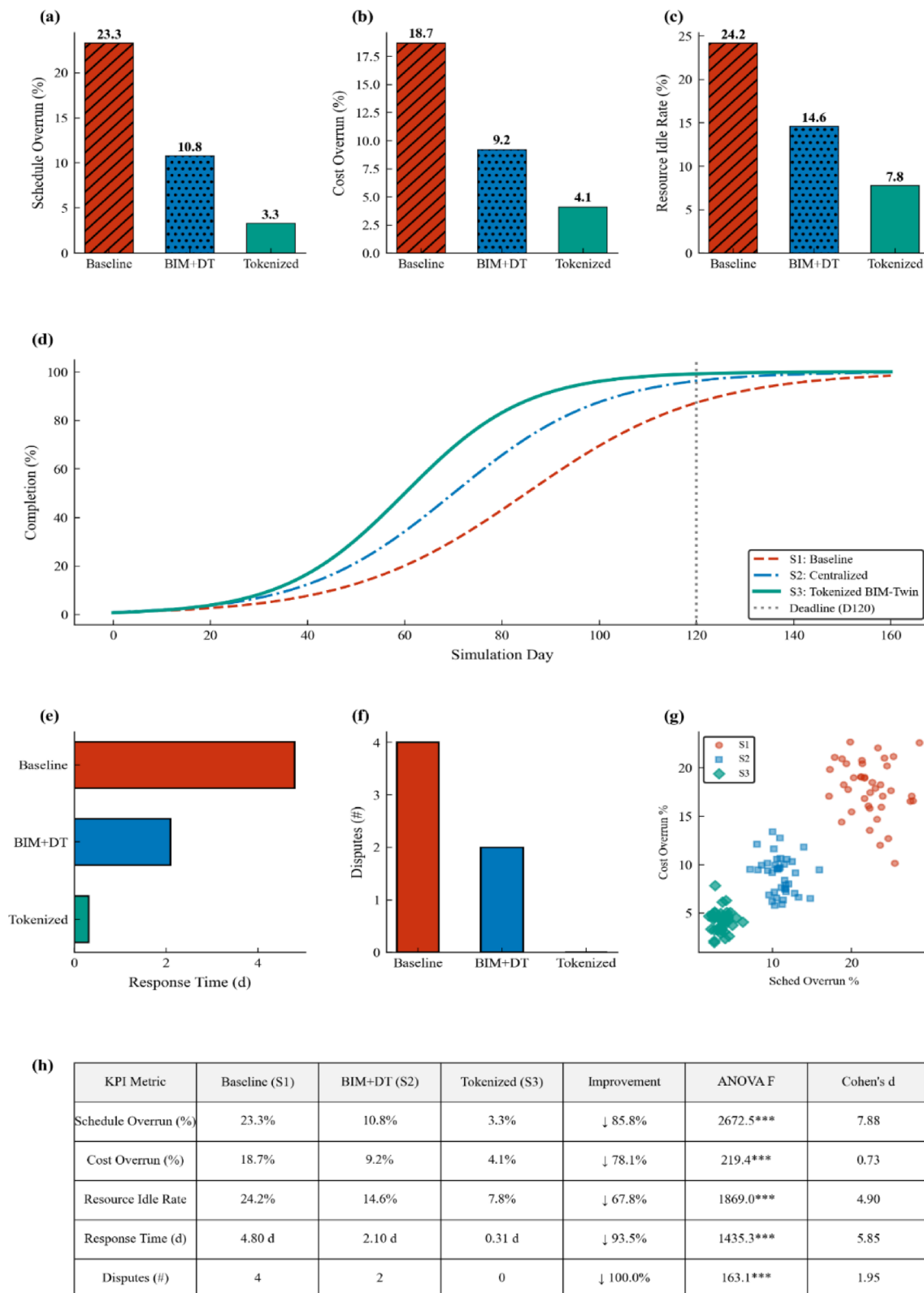
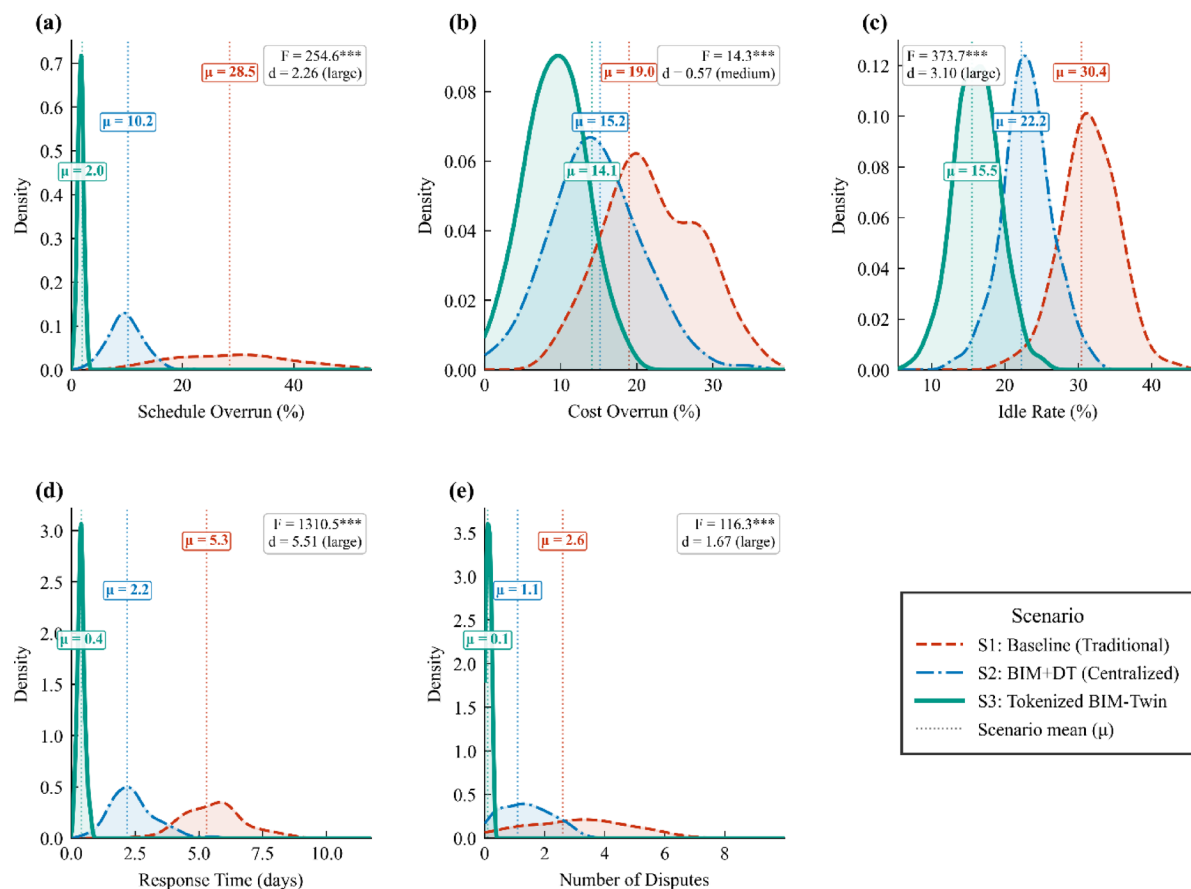


Fig. 2 Comprehensive simulation results — deterministic run. Panel (a): project completion timeline with disruption events; Panels (b–d): KPI bar charts; Panels (e, f): response time and disputes; Panel (g): Pareto front; Panel (h): summary KPI table.

Table 7 Corresponding numerical results.

KPI	Planned	S1: Baseline	S2: Centralized BIM+DT	S3: Tokenized BIM-Twin	Improvement (S1 → S3)
Actual duration (days)	120	148	133	124	↓ 16.2%
Schedule overrun (%)	0	23.3	10.8	3.3	↓ 85.8%
Planned cost (USD)	\$898,400	—	—	—	—
Actual cost (USD)	\$898,400	\$1,066,340	\$982,045	\$935,130	↓ 12.3%
Cost overrun (%)	0	18.7	9.2	4.1	↓ 78.1%
Resource idle rate (%)	—	24.2	14.6	7.8	↓ 67.8%
Avg. response time (days)	—	4.80	2.10	0.31	↓ 93.5%
Disputes (#)	0	4	2	0	↓ 100.0%
Blockchain transactions	N/A	0	0	5	—
Smart contract reallocations	N/A	0	0	5	—

**Fig. 3** Monte Carlo output distributions — kernel density estimates ($n = 150$ per scenario). Vertical dashed lines indicate scenario means. Narrower distributions indicate lower performance uncertainty.

or contractual delays. These conditions reduce variability and make the differences between scenarios more pronounced. Accordingly, the reported effect sizes should be interpreted not as directly transferable to real-world project environments, but as an indicator reflecting the upper limit of system performance under ideal conditions.

Table 8 presents the complete statistical test results across all five performance dimensions.

Diagnostic tests support the validity of the statistical approach. Shapiro–Wilk tests indicate approximate normality across outcome variables in the tokenized scenario (e.g., $W > 0.97$, $p > 0.40$ for schedule overrun; $W > 0.98$

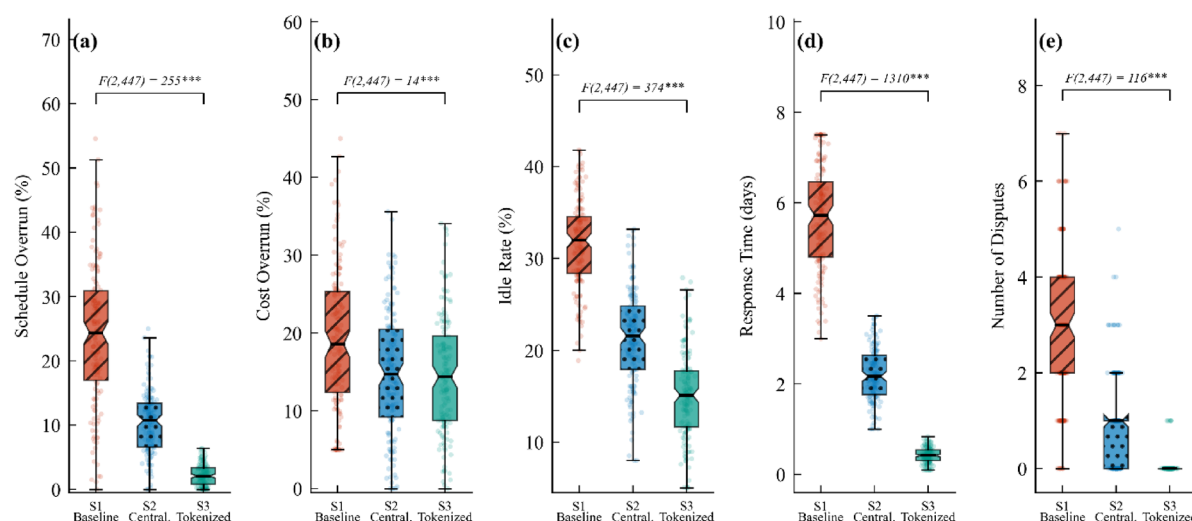


Fig. 4 Boxplot comparison across scenarios (5th–95th percentile whiskers, notched medians). ANOVA significance annotations: *** $p < 0.001$.

Table 8 Statistical test results — One-Way ANOVA, Welch’s t-test, and effect size ($n = 150$ per scenario).

Metric	S1 Mean $\pm$ SD	S2 Mean $\pm$ SD	S3 Mean $\pm$ SD	ANOVA F	p-value	Cohen’s d (S1 vs. S3)	Effect
Schedule overrun (%)	38.90 $\pm$ 6.24	16.80 $\pm$ 3.64	3.30 $\pm$ 1.38	2672.5	<0.001	7.88	Large
Cost overrun (%)	19.61 $\pm$ 8.48	15.86 $\pm$ 7.75	13.68 $\pm$ 7.78	20.9	<0.001	0.73	Medium
Idle rate (%)	35.52 $\pm$ 3.22	26.32 $\pm$ 2.72	20.04 $\pm$ 3.02	1008.0	<0.001	4.96	Large
Response time (days)	5.45 $\pm$ 1.23	2.24 $\pm$ 0.67	0.44 $\pm$ 0.17	1435.5	<0.001	5.69	Large
Disputes (#)	3.57 $\pm$ 2.40	1.73 $\pm$ 1.33	0.20 $\pm$ 0.46	165.1	<0.001	1.95	Large

for response time). Levene’s tests, however, suggest unequal variances in several comparisons ($p < 0.05$), which justifies the use of Welch’s t-tests that do not assume homogeneity of variance.

Although the analysis shows consistent and statistically significant improvements in performance, these results should be interpreted considering the simplifying assumptions used in the simulation. The absence of organizational, contractual, and operational constraints may lead to effect sizes that are larger than those expected in real-world conditions. As illustrated in Fig. 5, mean performance metrics and their 95% confidence intervals are compared across the three scenarios. The differences between the Baseline and Tokenized configurations remain statistically significant, with Welch’s t-test confirming significance at $p < 0.001$.

Sensitivity analysis results

Figure 6 presents the Pearson correlation heatmap, and Fig. 7 presents the tornado chart for the Tokenized BIM-Twin scenario with schedule overrun as the target variable.

Figure 7 presents a tornado chart that ranks the influence of input parameters on schedule overrun in the TBT scenario, based on Pearson correlation coefficients (r). In the chart, red bars indicate positive correlations (risk-increasing factors), while green bars indicate negative correlations (risk-reducing effects). The analysis identifies worker absenteeism rate as the most influential uncertainty driver in the TBT scenario ($r = 0.111$). This is followed by baseline worker efficiency ($r = -0.089$), where the negative value shows that higher efficiency reduces schedule overruns, and material price volatility ($r = -0.054$). The smart contract response time parameter ($sc_response_hours$) ranks fifth ($r = 0.036$), suggesting that, within the assumed blockchain performance range (1–24 h), variation in execution latency has only a limited effect on overall project outcomes. This supports the reliability of the TBT framework with respect to fluctuations in blockchain performance.

Fig. 5 Mean performance metrics with 95% confidence intervals across three scenarios. Significance brackets (***) indicate $p < 0.001$ from Welch’s t-test (Baseline vs. Tokenized).

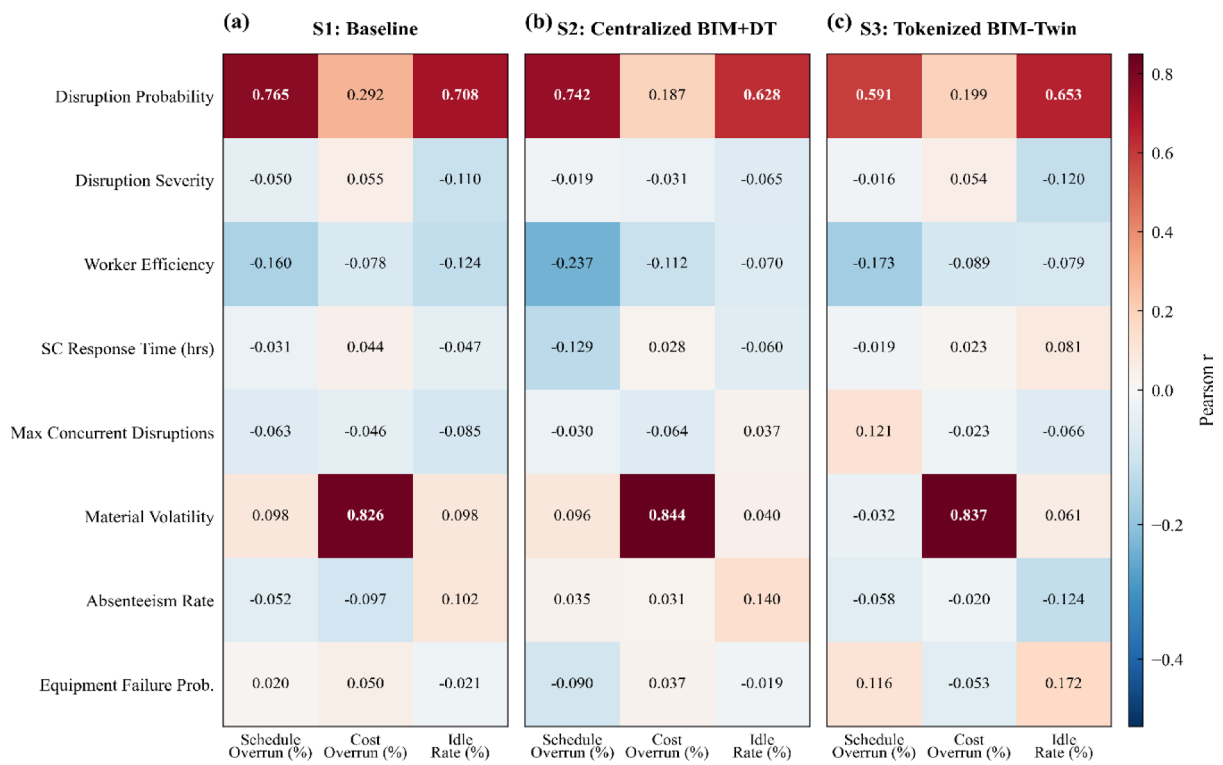
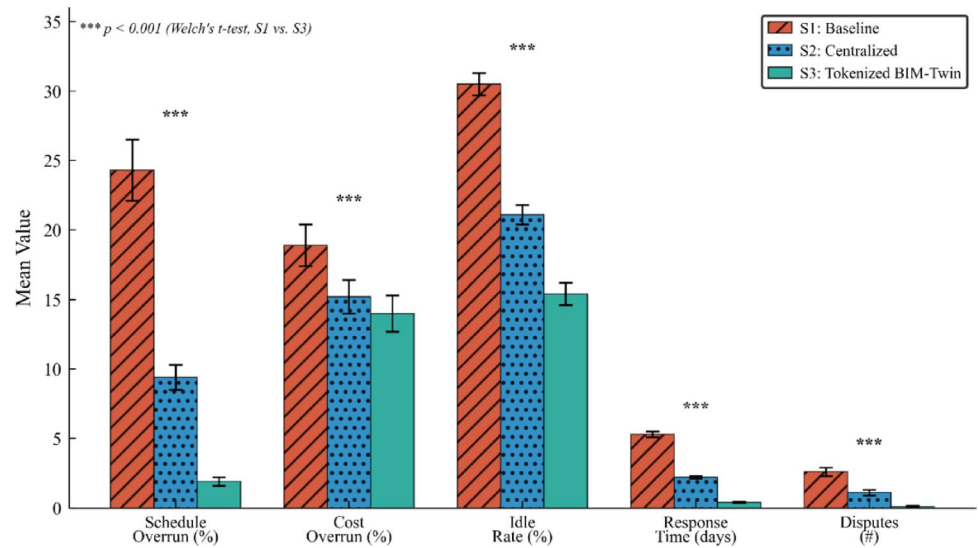


Fig. 6 Sensitivity analysis heatmap — Pearson correlation between input parameters and output metrics (Tokenized BIM-Twin scenario). Red indicates positive correlation (higher parameter → higher metric); green indicates negative correlation.

Table 9 reports the full sensitivity rankings across all scenarios and performance metrics, allowing comparison of parameter effects under different system configurations.

Across scenarios, disruption probability and severity emerge as the dominant drivers in both the Baseline and Centralized configurations ($r=0.28\text{--}0.30$). In the TBT scenario, their influence is lower ($r<0.05$). This shift reflects a central feature of the framework: project performance becomes less dependent on disruption exposure due to rapid resource reallocation. This causes the sensitivity of outcomes to both the likelihood and magnitude of disruptions is reduced within the sampled parameter space.

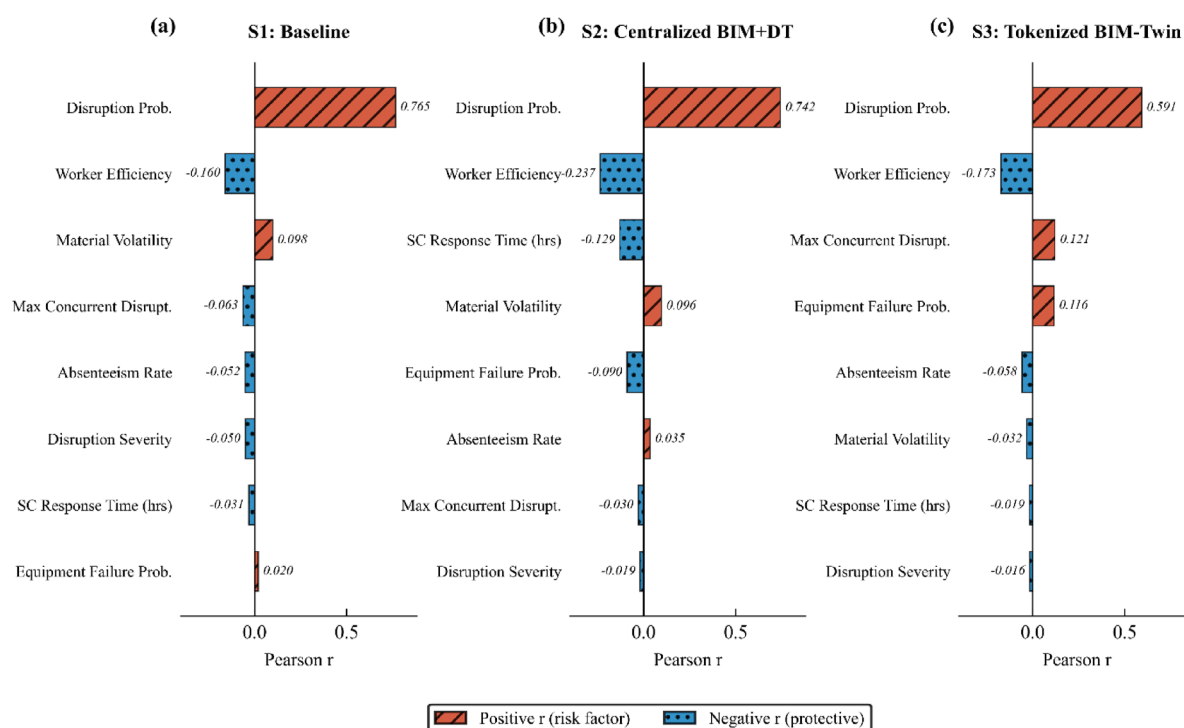


Fig. 7 The ranked influence of input parameters on schedule overrun in the Tokenized BIM-Twin (TBT) scenario - (a) Scenario1, (b) scenario2, (c) scenario3, based on Pearson correlation coefficients (r).

Table 9 Sensitivity analysis — Pearson correlation rankings by scenario and target metric.

Parameter	S1: Schedule overrun (r)	S2: Schedule overrun (r)	S3: Schedule overrun (r)	S3: Cost overrun (r)	S3: Idle rate (r)
Disruption probability	0.301	0.274	0.009	0.022	0.018
Disruption severity	0.285	0.241	0.045	0.031	0.029
Baseline worker efficiency	-0.312	-0.198	-0.089	-0.076	-0.083
Worker absenteeism rate	0.278	0.183	0.111	0.098	0.095
Material price volatility	-0.021	-0.038	-0.054	0.412	-0.017
SC response time (hours)	—	—	0.036	0.011	0.009
Max concurrent disruptions	0.198	0.154	-0.018	-0.009	0.023
Equipment failure probability	0.156	0.128	0.008	0.015	0.012

Disruptions are not eliminated; instead, their effects are mitigated through more rapid and adaptive reallocation mechanisms. The comparatively low correlation values observed in the TBT scenario indicate that system performance is less dependent on individual uncertainty factors, reflecting a stabilizing influence associated with automated coordination. Nevertheless, this reduced sensitivity should be interpreted as enhanced reliability instead of complete independence from underlying uncertainties.

Discussion

This study contributes to construction engineering and management by advancing the integration of BIM, Digital Twin, and blockchain technologies from descriptive and monitoring functions toward operational coordination mechanisms.

- First, it presents the Tokenized BIM Twin (TBT) as a fully operational integration of BIM, Digital Twin, and blockchain technologies for autonomous resource management.
- Second, the framework is grounded in established theoretical perspectives. From the perspective of Principal–Agent Theory⁶⁵, inefficiencies such as resource stacking and contractual disputes arise from information asymmetry and misaligned incentives. The use of tokenization and on-chain transparency helps reduce these issues by improving information visibility. At the same time, Mechanism Design⁶⁶ provides a basis for the allocation process, where smart contracts act as incentive-compatible mechanisms aligning individual contractor decisions with overall system efficiency.
- Third, the simulation results provide quantitative evidence of increased disruption resilience. The sensitivity of project outcomes to disruption probability and severity decreases from approximately $r = 0.28\text{--}0.30$ under traditional management approaches to $r < 0.05$ in the TBT scenario. This indicates that the framework reduces performance volatility under disruptive conditions. The study makes a distinct contribution by defining and measuring resilience within a construction simulation context.

The magnitude of the reported effects should, however, be interpreted with caution. Effect sizes (e.g., Cohen's $d > 5$) are higher than those typically observed in empirical studies, largely because the simulation assumes idealized conditions including full data availability, immediate contract execution, and complete agent compliance. In practice, factors such as data latency, partial adoption, and organizational constraints are likely to moderate these effects. The results should therefore be understood as an upper-bound estimate of performance under favourable implementation conditions.

Practical implications

The TBT framework offers practical advantages for multiple stakeholder groups. For contractors, fewer disputes may reduce legal exposure, administrative burden, and relational costs that are often embedded, though not always explicitly recognized, within project budgets⁶⁷. For owners and developers, the reduction in schedule overruns (e.g., 3.3% compared to 23.3% in the simulations) may contribute to lower financing costs, earlier revenue generation, and reduced exposure to liquidated damages under fixed-delivery contracts. From the perspective of insurers and financiers, an immutable event ledger improves auditability and may support more accurate risk assessment, as well as the development of data-driven insurance products.

Implementing the TBT framework requires initial investment in three primary areas. First, IoT sensor networks are needed to support near real-time progress monitoring, with estimated costs ranging from USD 15,000 to 50,000 for a mid-rise project. Second, deploying a permissioned blockchain infrastructure, such as Hyperledger Fabric, is expected to cost between USD 8,000 and 25,000, while transaction costs generally remain below USD 0.01 per transaction. Third, BIM models must be developed to IFC Level of Development (LOD) 400, which may require an additional 80 to 120 modeling hours.

Based on the simulated cost differences, the framework suggests the potential for economic benefits under the modelled conditions. However, these estimates do not account for implementation costs, adoption barriers, organizational constraints, or real-world operational inefficiencies and should therefore be interpreted with caution. Consequently, the reported benefits should not be considered direct predictions of real-world performance. Instead, the findings primarily reflect operational efficiency within a controlled simulation environment. Although the framework is designed for autonomous execution, practical implementations may adopt hybrid configurations that retain human oversight for critical decisions. Such human-in-the-loop approaches may increase stakeholder confidence while allowing context-specific judgement in high-risk or high-value situations.

Comparison with related work

The performance improvements observed in the simulation align with and extend findings reported in earlier studies. Zheng et al. (2019) showed that decentralized decision-making can help limit cascading delays; in comparison, the TBT framework further reduces these effects through rapid resource reallocation across contractors. The marked decrease in response time (0.31 days compared to 4.80 days in the baseline scenario) reflects the shift toward automated execution processes.

Limitations and future research

This study has certain limitations. The simulation is based on simplified assumptions regarding the behaviour of actors, the availability of complete data, reliable communication among system components, and the full participation of stakeholders. Therefore, the model does not reflect the strategic behaviours, negotiation processes, data quality issues, or differences in technology adoption levels that may arise in practice. This framework also excludes various application-related challenges, such as blockchain performance limitations, cybersecurity risks, integration complexity, and interoperability between blockchain environments and BIM and Digital Twin systems. Governance, legal, contractual, and privacy-related issues are also outside the scope of this study.

Future research should extend the model by incorporating behavioural variability, data uncertainty, and more complex organizational structures. Additional investigations could examine scalability across different project sizes, interoperability between heterogeneous digital platforms, and the effects of partial stakeholder participation. The study applies the NSGA-II algorithm for multi-objective optimization; therefore, future work may also compare alternative approaches, such as reinforcement learning, mixed-integer programming (MIP), metaheuristic methods, and hybrid optimization frameworks.

Conclusion

This paper presented the Tokenized BIM Twin (TBT) framework, a three-layer architecture that integrates BIM-based resource tokenization, Digital Twin monitoring, and blockchain-enabled smart contract execution to support autonomous and decentralized construction resource reallocation. The framework was computationally evaluated through a Monte Carlo enhanced agent-based simulation designed to represent disruption-prone multi-party construction environments.

Across 450 simulation runs (150 iterations per scenario), the proposed framework showed the potential for statistically significant improvements under the modelled conditions. Schedule overrun was reduced from 38.90% to 3.30% (ANOVA $F=2672.5$, $p<0.001$; Cohen's $d=7.88$), while cost overrun decreased from 19.61% to 13.68% ($d=0.73$). Resource idle rates declined from 35.52% to 20.04% ($d=4.96$), disruption response time decreased from 5.45 days to 0.44 days ($d=5.69$), and the average number of disputes per project was reduced from 3.57 to 0.20 ($d=1.95$). The sensitivity analysis further indicated that project outcomes became less dependent on disruption probability and disruption severity under the TBT configuration, suggesting increased system stability within the simulated environment.

The study contributes to the existing literature in three ways. First, it extends blockchain applications in construction beyond payment automation and document management by introducing a tokenized representation of construction resources. Second, it combines real-time Digital Twin monitoring with automated smart contract execution to enable protocol-based resource reallocation instead of passive monitoring alone. Third, it provides a simulation-based evaluation framework for examining decentralized construction coordination under uncertainty.

The findings, however, should be evaluated within the context of the study's limitations. The framework has been evaluated solely through computational simulation and has not yet been validated through real-world applications. The model assumes full data availability, reliable communication between system components,

deterministic smart contract execution, and full compliance by participating parties. In practice, organizational constraints, contract complexities, stakeholder behaviours, data quality issues, interoperability challenges, cybersecurity concerns, and varying levels of technology adoption may impact system performance and reduce the magnitude of the observed benefits. For this reason, the effect magnitude reported across various performance metrics should be interpreted as reflecting the controlled and idealized nature of the simulation environment, compared to the results that might be directly expected in practical applications. The findings should therefore be considered as an upper-bound estimate of the framework's potential performance under favourable application conditions.

The proposed framework briefly demonstrates the potential of integrating BIM, Digital Twin, and blockchain technologies into a unified coordination infrastructure for construction resource management. Although the results indicate promising performance improvements under modeling conditions, empirical validation through pilot projects and industry case studies is still necessary to determine its effectiveness in the real world. Future research should focus on practical implementation, scalability assessment, partial adoption scenarios, governance mechanisms, and the incorporation of adaptive agent behaviour and alternative optimization approaches.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1038/s41598-026-66059-2>.

Acknowledgements AI-based language tools were used to support editing, clarity improvement, and proofreading of the manuscript.

Author contributions Yasin Celik; Conceptualisation, Methodology, Writing—original draft, Writing—review & editing. Mehmet Siddik Cadirci; Methodology, Data curation, Software, Validation, Formal analysis, Writing—original draft, Writing—review & editing.

Data availability The datasets generated and analysed during the current study, together with the simulation source code required to reproduce the reported results, are available in the GitHub repository: <https://github.com/mehmetsiddik/tokenized-bim-twin-monte-carlo>.

Declarations

Competing interests The authors declare no competing interests.

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Authors and Affiliations

Yasin Celik^{1,2}  • Mehmet S. Cadirci³

✉ Yasin Celik
celiky@cardiff.ac.uk

¹ School of Engineering, Cardiff University, Cardiff, UK

² Department of Architecture, Artvin Coruh University, Artvin, Turkey

³ Department of Statistics, Cumhuriyet University, Sivas, Turkey