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Research Article

A digital twin and lean principles framework for real-time waste management on construction sites

Musaab Falih Hasan [*,1,a], Noor Abdulsattar Abduljabbar [2,b]

[1]*General Directorate of Education, Baghdad Rusafa First, Ministry of Education, Baghdad, Iraq*
[2]*Department of Civil Engineering, Al-Rafidain University, Baghdad, Iraq*

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Abstract

The aim of this study is to propose a framework for the Digital Twin-Lean Management (DTLM) by establishing a direct correspondence between Lean waste and BIM/IoT data, and enhancing project performance through operational decision-support actions. The original framework was assessed through simulation, and a field pilot study was then carried out to evaluate its effectiveness in a real construction scenario. The simulation-based assessment examined the impact on the performance of the project by changing the values of the input data using the One-at-a-time (OAT), the Sobol global sensitivity analysis, and the Monte Carlo simulation methods. The reported first-order Sobol sensitivity indices identified material delivery delay (0.36) and equipment failure probability (0.27) as the two dominant simulation input factors. The area under the total cost time curve was used as the metric of interest to evaluate the simulation results. Finally, the DTLM framework was implemented in the ongoing construction of a commercial building. A 29.7% reduction in crew downtime, a 21.9% reduction in material-handling distance, a 21.4% increase in labor productivity, and a 44.7% reduction in rework costs were observed relative to baseline levels, based on descriptive experimental comparisons. All results indicate the operational feasibility of DTLM for waste identification and timely decision-making, while further observational verification is needed to determine inferential effects in the field.

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1. Introduction

The construction industry is a major contributor to the economy, but it suffers from considerable inefficiency. Research has shown that waste can be as high as 30% of the total cost of a project [1]. This challenge has been repeatedly highlighted in lean construction research, where production variability, workflow disruptions and inefficient resource use are identified as key factors contributing to project waste and low productivity [2, 3]. The lean construction philosophy, which originated from the Toyota Production System, has been promoted to achieve this goal by improving value maximization and waste reduction in project delivery [4]. The seven wastes in lean construction typically include non-utilized talent, defects, waiting, transportation, overproduction, extra-processing and inventory. Despite these benefits, there are some practical challenges to realizing the effective application of Lean Construction. Weekly look-ahead plans and manual monitoring are commonly used in the Last Planner system (LPS) and other traditional lean tools. On a busy construction site, these may not be specific enough or quick enough to catch the actual waste occurring in real time [5]. Reactive practices can lead to delayed corrective action and lost operational efficiencies. Meanwhile, industry is revolutionizing the management of construction operations through new technologies. A digital twin (DT) is one of the most promising

*Corresponding author: musabmfh0000@yahoo.com
[a]orcid.org/0000-0001-7036-0106; [b]orcid.org/0009-0009-1203-6506
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concepts, which is a dynamic representation of a physical asset or process that is continuously kept up to date by exchanging data [6]. By predicting and controlling the behavior of its physical twin, a Digital Twin (DT) can give unprecedented visibility into project performance and operational status. If not managed properly, Digital Twin technologies may be unable to reach their full operational potential. While many have studied the concept of digital transformation in the context of progress monitoring or facility management, its specific use for systematic waste reduction, guided by lean principles, is still very nascent and not sufficiently studied. There is a significant opportunity in this area. Accordingly, this research proposes to establish, simulate, and test an integrated digital twin-lean management (DTLM) system for identifying and controlling waste in real-time for construction projects. The primary objectives are:

- To create a conceptual framework of DTLM through the combination of basic types of construction waste with data collection properties of digital twins.
- To formulate a method of applying the proposed framework using already existing technologies like 4D BIM and IoT.
- To quantitatively evaluate the proposed DTLM framework through discrete-event simulation, descriptive pilot-field performance comparison, and simulation-based sensitivity and uncertainty analyses.
- To discuss the implications for construction management practice and outline future research directions.

2. Literature Review

2.1 Lean Construction and Waste Management

Lean construction shifts the management focus from the transformation-oriented model to a flow and value-generation view [7]. The core goal is to make the flow of work reliable and predictable by eliminating waste. Lean construction is a production management philosophy based on lean manufacturing principles to increase value to the project client and reduce waste in the design, procurement and construction phases [8-10]. The idea, first introduced in the early 1990s, was to counter the construction industry's continued loss of productivity, inefficiencies and waste [8,9,11]. The Last Planner System (LPS) is a production planning and control method based on the principles of Lean Construction. It was developed in the early 1990s as a reaction to the Critical Path Method, which is based on early planning and is highly detailed [12-14]. It was developed to fill a supposed gap in project management, i.e. project controls set and monitor targets, while production control actively steers towards them [14]. While successful, it is limited in that it relies on manual data collection and weekly cycles, which limits the ability to respond to intra-day disruptions such as equipment breakdown or material delivery delays, the main sources of waiting and motion waste.

2.2 Digital Twin in Construction

A digital twin is more than a static 3D BIM model, it is a living, data-driven model that evolves with its physical counterpart. It typically consists of the physical entity, the virtual model, and a bi-directional data link connecting them [15]. As a representative of emerging statistical and intelligent technologies, DT's concepts and applications have achieved considerable success in recent years. With real-time virtual mirrors, real-time feedback, and other features, DT can provide a strong theoretical basis for selection, design, and management [16]. Nonetheless, the review of the literature indicates that the adoption of digital twins (DT) in the construction industry has been relatively slow when compared to sectors like manufacturing and healthcare. Previous studies mostly focus on the utilization of DT in construction and operation and maintenance phases. However, the literature has not paid much attention to the use of DT during the planning, design, demolition, and recovery phases [17]. According to Wang et al. [18], current Digital Twin implementations in construction have expanded considerably in recent years; however, most applications remain domain-specific and are rarely integrated into comprehensive project management frameworks that simultaneously support planning, monitoring, optimization, and operational control. In construction, DTs are being explored for purposes like structural health

monitoring, safety management and progress tracking [19]. The real-time data is often fed from IoT sensors (GPS, RFID, UWB, vision-based sensors).

2.3 Construction 4.0

Construction 4.0, created in 2016 in Germany, describes the integration of fourth-industrial-revolution technologies into construction processes, products, and value chains. The concept remains in active formation, with definitions still considered diffuse and largely borrowed from the broader Industry 4.0 framework [20, 21]. As the field has matured, the relative prominence of a constellation of interrelated digital technologies driving Construction 4.0 has shifted. The early reviews identify big data, 3D printing, Internet of Things (IoT) and virtual reality as the four technologies that are necessary for the understanding of Construction 4.0 [20]. Later analyses extended this list to include building information modeling (BIM), artificial intelligence, digital twins, robotics, cloud computing, sensors, and smart wearables as equally central pillars [22-24]. More recent work identifies digital twins, IoT, 3D printing and smart sensors as the technologies with the greatest near-term potential to support Construction 4.0, while autonomous robotics, machine learning and augmented/virtual reality still offer substantial room for applied research [25].

2.4 Research Gap and Study Contribution

The integration between Lean Construction and Digital Twin technologies has not been achieved through the management of construction waste in a logical, real-time manner, despite the transformation of both technologies. The design of Lean practices for the optimization of processes and waste minimization is based on planned scheduling and manual evaluations, which limit their responsiveness to immediate changes on site. The literature has yet to define a framework that connects Lean waste categories with Digital Twin data sources and management actions, thus hampering the conversion of real-time data into effective Lean interventions. This study introduces a Digital Twin Lean Management (DTLM) framework that correlates Lean waste with IoT and BIM data, examined through simulation-based analysis and pilot field implementation. The study therefore aims to develop a data-driven decision-support framework for proactive waste management in construction.

3. Methodology

This study used a multi-phase quantitative research design consisting of conceptual framework development, simulation-based assessment, pilot field implementation, descriptive comparison of field KPIs, and model-based sensitivity and uncertainty analyses. The overall workflow is illustrated in Fig. 1 and comprises four sequential phases.

- Phase A: Development of the conceptual framework. An extensive literature review was carried out to identify the primary ideas of Lean Construction and Digital Twin (DT) technologies within the framework of construction waste management. An extensive review of previous studies on Lean Construction technology, BIM, IoT, Digital Twins and Construction 4.0 was performed to identify knowledge gaps and potential integration routes. The proposed Digital Twin-Lean Management (DTLM) framework, based on the literature review, connects the categories of Lean waste with sources of real-time data, analytical functions and recommended management actions. The framework supports waste identification and decision-making, while the implementation of corrective actions remains subject to human supervision and approval. Therefore, the method establishes a link between acquiring construction data in real time and preventing waste. The developed DTLM method is presented in Table 2.
- Phase B: Simulation model development and specification. A discrete-event simulation (DES) structure was used to represent the structural-stage production workflow under two management scenarios: (i) conventional management and (ii) DTLM-enabled management. The model boundary covered operational processes directly related to the reported waste indicators, including crew activity, material delivery and movement, equipment availability/utilization, and rework-related performance. Principal model inputs were

activity duration, resource availability, material-delivery timing, equipment utilization and failure, crew performance, and travel distance. Events represented changes in activity/resource state that can create or release waiting, transportation, motion, equipment-downtime, or rework conditions. The two scenarios were evaluated using the same KPI definitions: crew idle time (%), equipment downtime (%), material travel distance (m/task), crew walking distance (km/day), labor productivity (m^3/man-day), task-completion rate (%), structural defects (per 1,000 m^2), and rework cost (% of total cost). Simulation outputs were kept analytically separate from the field pilot; consequently, the simulation reference values in Table 4 are not treated as empirical baseline observations. Model-output calculation. For waste and downtime indicators, scenario improvement was calculated as [(Conventional scenario - DTLM scenario) / Conventional scenario] x 100. For productivity and completion indicators, improvement was calculated as [(DTLM scenario - Conventional scenario) / Conventional scenario] x 100. This direction-specific definition is consistent with the field-comparison equations in D1.

DES reproducibility boundary. The archived study record does not identify the original simulation software/version, fitted probability distributions, random-number seed, number of replications, warm-up period, or formal verification/validation protocol. These settings are therefore not reconstructed or assumed in this paper. The DES results are interpreted as previously generated model-based scenario outputs. Full computational replication requires the original executable model or a documented reimplementation containing those settings.

Table 1. DES model specification and reproducibility boundary

DES Component	Specification Used in This Study	Evidence Status
System boundary	Structural-stage workflow; crew, material, equipment and rework-related operations	Reported
Scenarios	Conventional management vs. DTLM-enabled management	Reported
Principal inputs	Activity duration; resource availability; delivery timing; equipment utilization/failure; crew performance; travel distance	Reported
Primary outputs	Idle time; equipment downtime; movement; productivity; completion; defects; rework cost	Reported
Field/simulation separation	Simulation reference outputs are not field baseline observations	Explicit analytical rule
Software/version	Not available in archived study record	Not reconstructed
Input probability distributions	Not available in archived study record	Not reconstructed
Replications/warm-up/random seed	Not available in archived study record	Not reconstructed
Verification/validation record	Not available in archived study record	Required for full replication

- Phase C: Pilot Field Implementation

The pilot implementation was conducted during structural construction of a 15-story commercial building in Dubai, UAE. The implementation infrastructure comprised 45 UWB sensors for crew/equipment movement, RFID tags on approximately 1,200 structural elements, a Revit BIM model connected to the Siemens Teamcenter Digital Twin platform, and Python-based analytical scripts. Floors 1-4 served as the preceding conventional-management baseline and floors 5-10 as the DTLM implementation period. The implementation lasted four months. Field evaluation was based on the aggregate KPI records available for the two periods.

- Phase D: Field performance evaluation and model robustness analysis. Field KPIs were compared descriptively between the baseline floors and the DTLM implementation floors. Because the available field records do not specify an observation-level sampling and pairing structure, the pilot evaluation is reported descriptively. Deterministic OAT, Sobol, and Monte Carlo analyses were conducted separately to examine the behavior and robustness of the simulation model.

The evaluation therefore distinguishes empirical pilot comparisons from simulation-based sensitivity and uncertainty analyses, avoiding direct equivalence between field baseline values and simulation reference outputs.

- Descriptive field comparison: Percentage change was calculated for each reported KPI as Improvement (%) = [(Baseline - DTLM)/Baseline] x 100 for waste/downtime measures, and Improvement (%) = [(DTLM - Baseline)/Baseline] x 100 for productivity/completion measures. The field results are interpreted as descriptive before-after comparisons rather than inferential estimates.
- One-at-a-Time (OAT) sensitivity analysis: Local sensitivity was evaluated from the reported simulation reference outputs by varying the analyzed input condition individually by -20%, -10%, +10%, and +20%, while the remaining model conditions were held at their reference settings. Responses were recorded for waiting-time reduction, material-movement reduction, labor-productivity improvement, and project-duration reduction. The analysis therefore quantifies local model response around the simulation reference condition and is not interpreted as an empirical pilot effect.
- Global sensitivity analysis (Sobol method): The reported first-order Sobol indices were used to rank the relative contribution of six uncertain simulation factors: material-delivery delay, equipment-failure probability, crew productivity, IoT sensor density, crane utilization, and RFID coverage. First-order indices are reported in Table 5 and sum to 1.00 in the reported results. Because the archived record does not contain the Sobol sampling design, parameter distributions/ranges, estimator, or sample size, the indices are treated as reported model-sensitivity outputs rather than independently reproducible estimates.
- Monte Carlo uncertainty analysis: The archived results report 10,000 Monte Carlo runs and summarize simulated cost savings by its mean, standard deviation, minimum, maximum, and simulation uncertainty range. The 18.4-26.2% interval is interpreted as a range of simulated outcomes rather than a confidence interval for the Monte Carlo mean. With the reported SD of 2.8 percentage points and 10,000 runs, the numerical standard error of the estimated mean is 0.028 percentage points. The input probability distributions and dependence assumptions used in the original runs are not documented in the archived record; accordingly, the Monte Carlo results are retained as reported robustness evidence and are not claimed to be independently reproducible from the manuscript alone.

4. Results and Evaluation of the Proposed DTLM Framework

The DTLM framework was evaluated using two complementary evidence streams: descriptive field performance indicators from the pilot implementation and model-based sensitivity/uncertainty analyses. These streams are reported separately to distinguish observed project performance from simulation outputs.

- Pilot Field Implementation: The DTLM pilot was implemented in the structural phase of a 15-story commercial building. Floors 1-4 represent the baseline prior to floors 5-10, which represent the DTLM implementation period. The sensing and integration architecture included 45 UWB sensors, RFID tags on 1,200 structural elements, three smart cranes, Revit-Teamcenter integration and Python-based analytics. The proposed DTLM framework is shown in Fig. 2. The framework integrates real-time IoT and BIM data with Digital Twin technology to detect Lean waste and enable effective management actions. The framework shows that real-time data acquisition, processing, and analysis enable waste identification, operational decision-making, and online monitoring and feedback.

- Quantitative Performance Evaluation: Table 3 reports aggregate field KPIs. Crew idle time decreased from 15.8% to 11.1% (29.7%), equipment downtime from 12.3% to 8.5% (30.9%), material travel distance from 215 to 168 m/task (21.9%), and crew walking distance from 8.2 to 6.3 km/day (23.2%). Labor productivity increased from 2.8 to 3.4 (m^3/man-day) (21.4%), and the daily task-completion rate increased from 78% to 92%. Structural defects decreased from 4.2 to 2.1 defects/1,000 m^2 and rework cost decreased from 3.8% to 2.1% of total cost. These aggregate results provide descriptive evidence of improved operational performance during the DTLM period.



Fig. 1. Integrated DTLM research methodology and evaluation workflow

Table 2. DTLM framework-mapping waste, data inputs and digital twin actions

Lean Waste Type	Dt Data Input (IoT/BIM)	Digital Twin Analytical Functions	Recommended Management Actions
Waiting (idle crews)	Real-time crew location (UWB), equipment status	Detect idle time exceeding threshold. Correlate with material/equipment availability	- Generate real-time alerts for supervisors - Recommend adjustments to material delivery schedules
Transportation	Material RFID tags, site GPS	Track movement paths, identify unnecessarily long hauls or double handling	- Recommend optimized storage locations - Recommend alternative transportation routes
Inventory (excess)	RFID tags on materials, BIM model	Compare actual on-site stock with look-ahead plan requirements	- Generate surplus material alerts - Recommend material replenishment
Motion	Crew UWB location data	Analyze travel paths and congestion zones.	- Recommend site layout modifications for managerial approval - Recommend workflow improvements
Overproduction	Progress data from drones/BIM	Compare completed work with pull-signaled schedule	- Recommend stopping or rescheduling work, subject to supervisor approval - Recommend production rate adjustments
Defects	Image data from site cameras, laser scans	Compare as-built vs. as-planned model for deviations	- Generate defect alerts and recommend corrective actions - Support automated defect detection and human-verified quality inspections
Unused talent	No direct sensor proxy; workforce/management input required	Not directly inferred from UWB/RFID data	- Provide workforce information to support managerial decisions

- Real-Time Waste Detection and Operational Response: Reinforcement crews experienced approximately 85 minutes/day of idle time associated with peak material-elevator use between 08:00 and 09:30. Following rescheduling, the reported idle period decreased to approximately 15 minutes/day, with an accumulated saving of approximately 126 crew-hours. For transportation-related waste, average formwork-panel movement decreased from approximately 285 m to 195 m after staging and route changes. Fig. 4 and 5 provide transparent visual summaries derived from the aggregate pilot KPI values reported in the study.
- Field Statistical Scope: The pilot evidence is reported as aggregate descriptive comparison because observation-level sample sizes, pairing units, and variance estimates are not available in the study records. Accordingly, inferential statistics are not used to claim statistical significance for the field pilot. Future confirmatory evaluation should define the unit of analysis in advance and report n, the pairing or sampling structure, variance, exact test statistics, effect sizes, and confidence intervals.

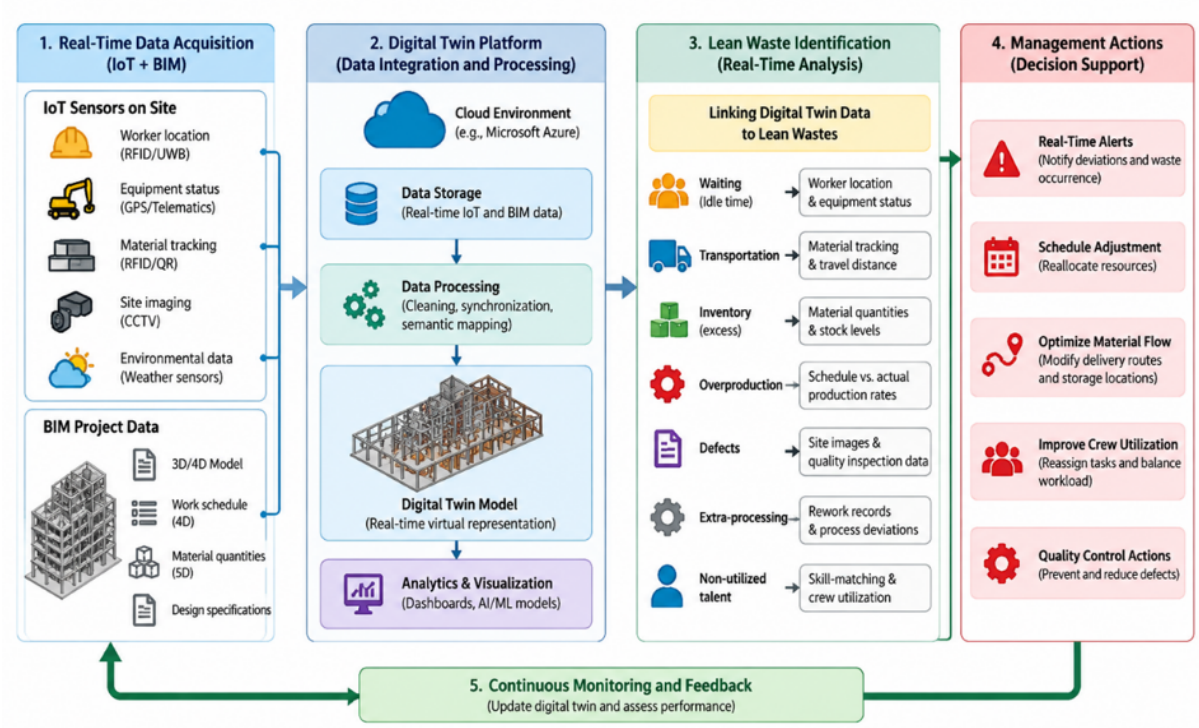

Fig 2. Proposed DTLM framework for real-time lean waste management

Table 3. Comparative analysis of KPIs: baseline and DTLM implementation

Key Performance Indicator	Baseline (Floors 1-4)	DTLM Implementation (Floors 5-10)	% Improvement
Waiting Time Reduction			
Crew Idle Time (%)	15.8%	11.1%	29.7%
Equipment Downtime (%)	12.3%	8.5%	30.9%
Movement Optimization			
Material Travel Distance (m/task)	215m	168m	21.9%
Crew Walking Distance (km/day)	8.2 km	6.3km	23.2%
Productivity Metrics			
Labor Productivity (m^3/ man-day)	2.8 m^3	3.4 m^3	21.4%
Daily Task Completion Rate	78%	92%	17.9%
Quality & Rework			
Structural Defects (Per 1000 m^2)	4.2 Defects	2.1 Defects	50%
Rework Cost (% of total cost)	3.8%	2.1%	44.7%

5. Sensitivity Analysis

The sensitivity analyses apply exclusively to the simulation evidence stream and are reported separately from the field pilot. Table 4 uses a simulation reference condition rather than the empirical field baseline reported in Table 3. Table 4 presents the local OAT response, Table 5 reports the archived first-order Sobol sensitivity indices, and Table 6 summarizes the archived Monte Carlo output across 10,000 runs. Because the underlying DES implementation and uncertainty-input distributions are not available in the study record, these analyses support model behavior interpretation but are not presented as independently reproducible computational validation.

In the OAT simulation results (Table 4), the reference outputs were 23.0% waiting-time reduction, 18.0% material-movement reduction, 15.0% labor-productivity improvement, and 10.0% project-

duration reduction. These values are simulation reference outputs and are analytically distinct from the field improvements reported in Table 3. Changing the analyzed input condition by ±10% and ±20% produced the local model responses shown in Table 4.

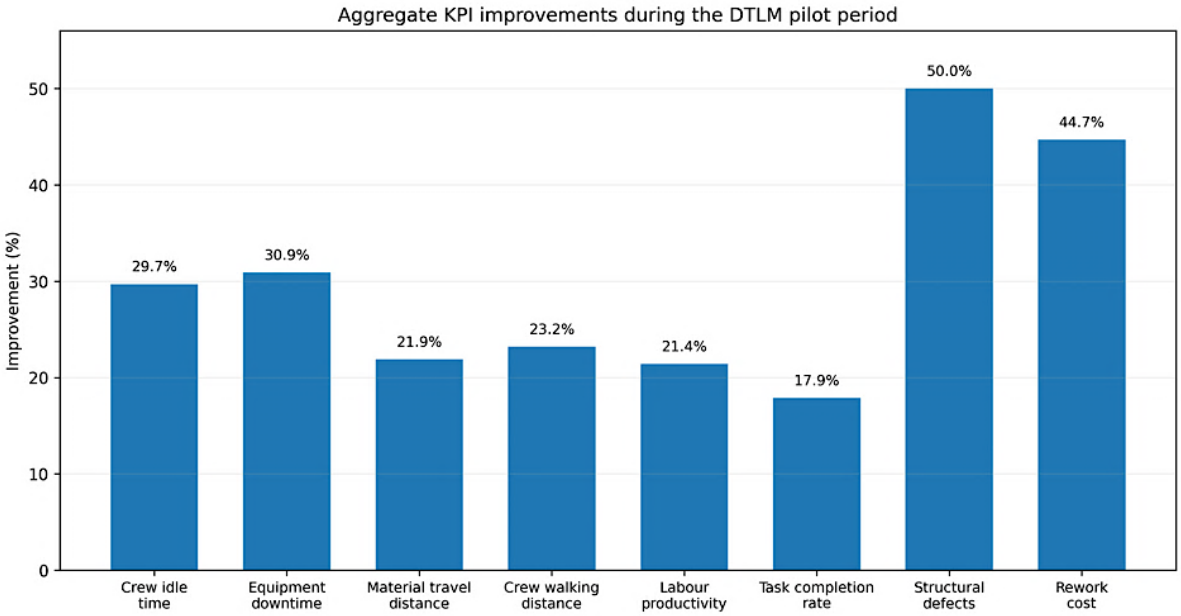

Fig. 3. Aggregate KPI improvements during the DTLM pilot period

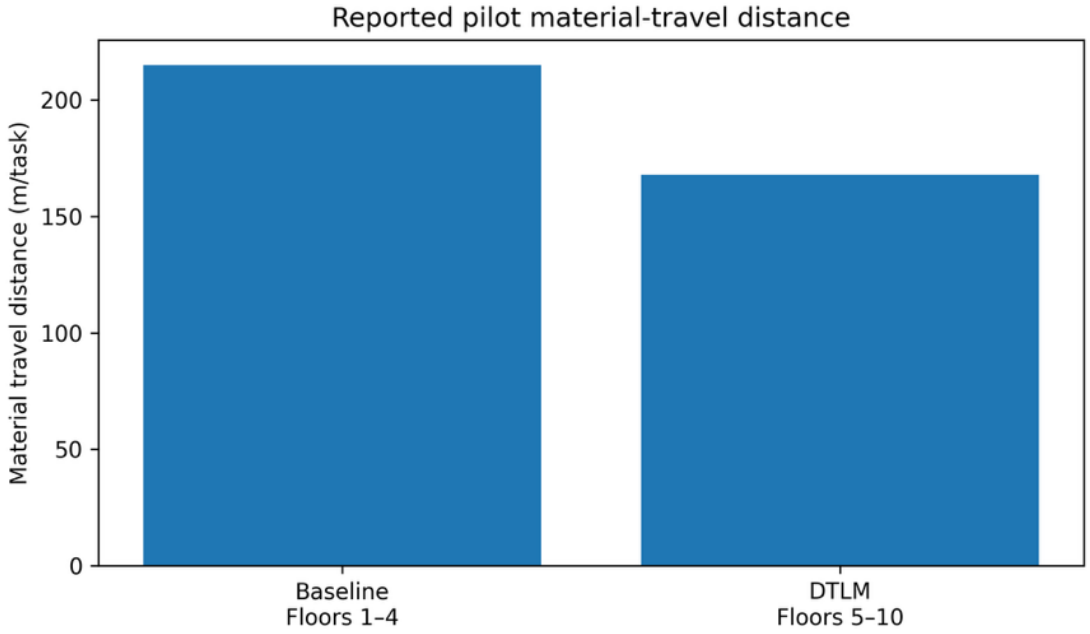

Fig. 4. Aggregate pilot material-travel distance reported before and during DTLM implementation

The first-order Sobol sensitivity indices presented in Table 5 indicated that material delivery delay is the most influential reported simulation factor affecting the DTLM framework. The variable explains about 36% of the overall variance in the output. This finding stressed the significance of logistics and material supply in order to reduce waiting waste and ensure continuous flow. The second variable is the equipment failure probability, which accounts for about 27% of the variance of the model. The use of equipment has an impact on the allocation of resources, sequencing of construction works, as well as the productivity of teams, which makes predictive maintenance and monitoring of equipment in real time required in this digital twin environment.

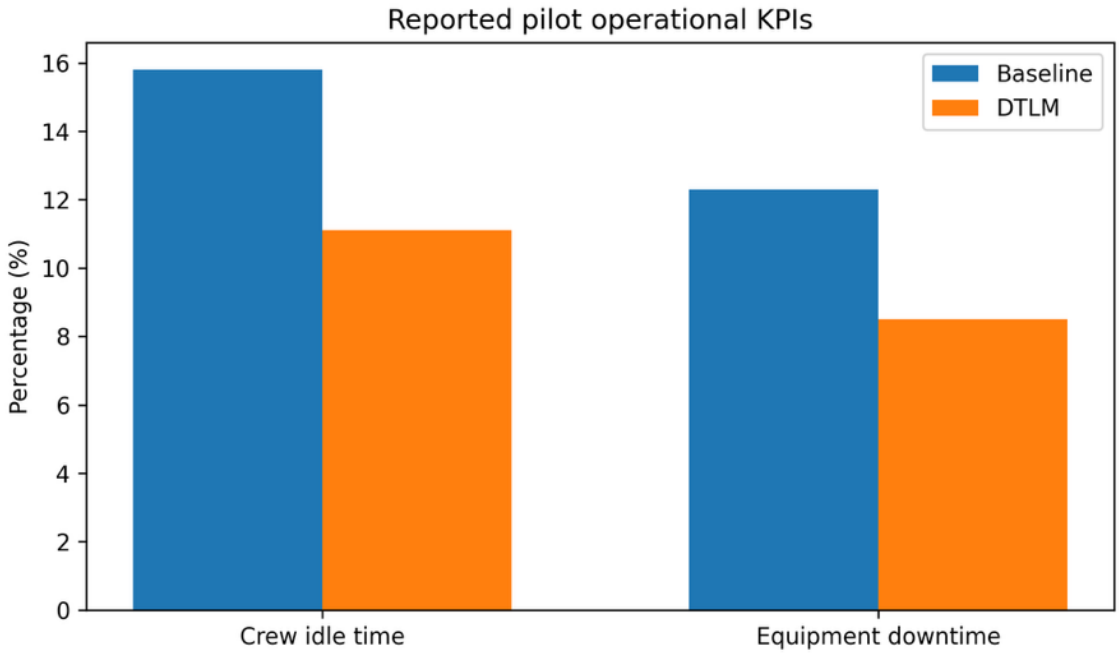

Fig. 5. Aggregate pilot crew idle time and equipment downtime reported for baseline and DTLM periods

The Monte Carlo analysis in Table 6 produced a mean simulated cost saving of 22.3% with an SD of 2.8 percentage points across 10,000 runs. The reported 18.4-26.2% interval is interpreted as a simulation uncertainty range. The Monte Carlo standard error of the estimated mean is 0.028 percentage points (2.8/sqrt(10,000)), demonstrating that uncertainty in individual simulated outcomes is conceptually different from numerical precision in the estimated simulation mean.

Table 4. OAT sensitivity results around the simulation reference condition (not the field baseline)

Simulation Output / OAT Condition	-20%	-10%	Simulation Reference	+10%	+20%
Waiting Time Reduction (%)	18.7	21.2	23.0	24.6	25.4
Material Movement Reduction (%)	14.5	16.3	18.0	19.2	20.1
Labor Productivity Improvement (%)	11.8	13.6	15.0	16.4	17.5
Project Duration Reduction (%)	7.2	8.6	10.0	11.3	12.1

Table 5. First-order Sobol sensitivity indices

Parameter	First-order Sobol Index
Material Delivery Delay	0.36
Equipment Failure Probability	0.27
Crew Productivity	0.18
IoT Sensor Density	0.10
Crane Utilization	0.06
RFID Coverage	0.03

Table 6. Monte Carlo simulation summary (10,000 runs)

Statistic	Cost Saving (%)
Mean	22.3
Standard Deviation	2.8
Minimum	16.4
Maximum	28.7
Reported Simulation Uncertainty Range	18.4–26.2

6. Discussion

The DTLM framework provides a structured mechanism for linking Lean waste categories with real-time sensing and Digital Twin-supported operational responses. The aggregate pilot KPIs indicate improvements during the DTLM implementation period relative to the preceding baseline floors, particularly in crew idle time, material movement, labor productivity, and rework. The material-elevator example illustrates the intended operational mechanism: sensing identifies a non-value-adding condition, the Digital Twin supports diagnosis, and scheduling is adjusted to reduce waiting. Because the field evidence is aggregate and before-after in nature, these findings are interpreted as operational associations rather than causal or statistically significant effects. The simulation robustness analyses provide complementary model-based evidence. OAT analysis describes local model response around a simulation reference condition, Sobol indices rank the relative contribution of uncertain inputs, and Monte Carlo analysis characterizes the distribution of simulated outcomes. Maintaining this separation prevents simulation reference values from being interpreted as empirical field baselines. The findings suggest that the principal contribution of DTLM lies in connecting real-time data acquisition with Lean-oriented detection and operational response. The material-delivery delay and the equipment-failure probability were the most influential simulation inputs. This shows the importance of logistics reliability and equipment availability to maintain workflow continuity.

Study limitations, computational reproducibility, and research governance: The empirical pilot was restricted to one commercial project and one structural-construction phase, limiting generalizability. Observation-level UWB/RFID data are not available in the archived study record; therefore, field inference is intentionally limited to descriptive comparison. The original DES executable model and key computational metadata, including software/version, input probability distributions and fitting basis, random-number control, replication settings, warm-up treatment, verification/validation records, Sobol sampling design, and Monte Carlo input distributions, are also unavailable. Consequently, the simulation outputs are reported as archived model-based evidence rather than independently reproducible computational validation. Future studies should archive the executable model, parameter dictionary, input distributions and data sources, random seeds, run-control settings, verification tests, validation comparisons, and analysis scripts. UWB-based worker location tracking should additionally be implemented under applicable institutional and site authorization, with appropriate participant information or consent/waiver procedures, anonymization, data minimization, access control, and retention safeguards. Other ethical issues in the proposed DTLM framework include worker privacy and data protection. Appropriate safeguards are needed to protect workers' rights and personal information in the continuous tracking of workers with UWB sensors. These should include informed consent or an appropriate authorized alternative, data anonymization, encryption, limited access, and clearly defined data retention policies. Another limitation is that the existing records of the study do not provide an adequate account of specific privacy protection procedures used in the pilot study. Future implementations should establish and document comprehensive ethical and data protection protocols in accordance with applicable regulations.

7. Conclusions

This paper proposed and validated a Digital Twin Lean Management (DTLM) framework to integrate Lean Construction principles, Building Information Modeling (BIM), Internet of Things (IoT) devices, and real-time operational analytics for proactive construction waste management.

This paper proposed a framework that provides a systematic linkage between Lean waste categories, digital data collection, waste detection, and operational decision-making. The framework presented promising operational improvements in comparison with traditional management practices in the pilot implementation. The results showed a reduction of 29.7% in crew idle time, 30.9% in equipment downtime, 21.9% in material transportation distance and 44.7% in rework costs. In addition, the increase in labor productivity by 21.4% proved the potential of integrating digital technologies with lean principles to improve the efficiency of construction workflow. Under different operational conditions, simulation-based analyses were obtained,

providing further insight into the behavior of the framework. The Sobol sensitivity analysis identified the material delivery delays and the equipment failure probability as the dominant simulation factors with first-order sensitivity indices of 0.36 and 0.27, respectively. The Monte Carlo simulation, consisting of 10,000 runs, yielded an average simulated cost saving of 22.3%, with an uncertainty range of 18.4–26.2%.

The principal scientific contribution of this research is the development of an integrated decision-support framework that connects real-time construction data with Lean-oriented waste identification and recommended corrective actions. This integration offers a structured approach to transitioning from reactive waste identification toward proactive operational management. Despite this, the findings should be interpreted considering several limitations. The field investigation involved a single construction project, and the available aggregate observations did not permit statistical significance testing. Furthermore, complete computational reproducibility requires additional documentation of the original simulation model and its parameters.

The framework should be tested in various construction projects, detailed statistical validation should be provided, simulation procedures should be reported, and long-term economic efficiency and scalability of the framework should be investigated.

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