Research Inventy: International Journal of Engineering and Science
Vol.16, Issue 6 (June 2026), PP 07-15
Issn (e): 2278-4721, Issn (p):2319-6483, www.researchinventy.com

Application of BIM and Data Mining in construction management of high-rise buildings in Thai Nguyen

Duong Viet Ha[1], Han Thi Thuy Hang[1]
[1] Thai Nguyen University of Technology, Thai Nguyen, Vietnam

Abstract: *This paper proposes an integrated Building Information Modeling (BIM) and Data Mining model to improve the efficiency of high-rise building construction management.The model was implemented in practice on a 25-story high-rise apartment building with a total floor area of 32,000 m² in Thai Nguyen City, during a construction period of 24 months (January 2024 – December 2025).The actual construction data includes daily labor logs (a total of 1,642 workers-days during the floor slab concrete pouring phase), material costs for each structural item (total material value of VND 70.6 billion), actual progress compared to the EVM plan (average Schedule Performance Index of 0.974), and meteorological and hydrological data from the Thai Nguyen weather station. The Random Forest algorithm achieved a project progress prediction accuracy of 91.3%, reduced information processing time by 18%, and provided early warnings of delays 10–15 days in advance. The research results have high practical significance for digital transformation in the field of construction engineering in Vietnam.*

Keywords: *BIM; Data Mining; construction management; high-rise buildings; IoT; project progress prediction; construction costs; meteorology and hydrology.*

Date of Submission: 25-05-2026 Date of Acceptance: 05-06-2026

I. INTRODUCTION

In recent years, the global civil and industrial construction industry has been undergoing a strong digital transformation. Increasing pressure on deadlines, costs, and quality requirements necessitates project managers to apply modern technology to improve construction management efficiency, minimize risks, and optimize resources. Especially for high-rise buildings, which are often large-scale, have complex structures, and require extended construction times, the lack of a synchronized information management system can lead to delays, material waste, and increased contract disputes.

According to statistics from the McKinsey Global Institute (2017), construction is one of the sectors with the lowest labor productivity, growing at an average rate of only 1% per year over the past 20 years, compared to 2.8% for the global economy. In Vietnam, a survey by the Institute of Construction Economics (2022) showed that 67.4% of high-rise building projects were behind schedule by 15% to over 50% compared to the original plan, mainly due to a lack of timely real-world data and difficulties in controlling the material supply chain.

Building Information Modeling (BIM) is a digital technology that allows the creation of a digital model that fully integrates geometric information, material attributes, schedule, and costs throughout the building lifecycle [1, 2]. Meanwhile, Data Mining is a set of computer learning and statistical techniques that allows the extraction of valuable information from big data, supporting trend prediction and anomaly identification [3, 4]. The combination of these two technologies creates an intelligent management platform capable of simultaneously processing structured data (BIM parameters) and unstructured data (log reports, site photos, sensor data).

The objectives of this study are: (1) Building a 3D-4D-5D BIM model for a typical high-rise building; (2) Establishing a system for collecting and synchronizing real-time data from the construction site, including labor data, material costs, schedule, and weather; (3) Applying Data Mining algorithms to predict construction progress, detect anomalies, and optimize project management; (4) Evaluating the economic and technical efficiency of the model compared to traditional methods based on actual construction data.

BIM is the process of creating and managing digital information about a construction project throughout its lifecycle [5]. According to ISO 19650 standards, BIM is classified into maturity levels from

Level 0 to Level 3, where Level 3 corresponds to a fully integrated cloud data model [6]. Research by Eastman et al. [7] and Smith [8] has shown that BIM can reduce the cost incurred by 40% and the construction time by 30% compared to traditional methods.

The Random Forest algorithm, proposed by Breiman [10] in 2001, operates on the principle of assembling multiple decision trees to increase accuracy and reduce overfitting. K-Means Clustering is a widely used unsupervised clustering algorithm for grouping data points with similar characteristics [11]. Li et al. [13] applied BIM to predict occupational safety risks with an accuracy of 89.4%. Kim and Kim [15] applied Random Forest to predict a delay of 85.7%.

Deng et al. [12] proposed an IoT-BIM data integration framework that allows real-time updating of construction status. In Vietnam, research [14] has initially applied 4D BIM to bridge and road projects but has not combined Data Mining and lacks real-world data on labor, costs and site climate. The research gap is clearly identified as: no project in Vietnam has fully integrated BIM and Data Mining with a multidimensional real-world data set (labor - cost - schedule - weather) under the characteristic humid tropical climate of Thai Nguyen region.

II. RESEARCH SUBJECTS AND DATA

2.1. Project Specifications

The project under study is a high-rise apartment building in Thai Nguyen province — a central urban area in the Northern Midlands and Mountains region. Detailed specifications are presented in Table 1.

Table 1. Technical specifications of the research project

Parameter	Value	Unit
Number of stories	25 floors (3 basement floors, 22 above-ground floors)	—
Building height	92.0	m
Building footprint area	1.280	m²
Total floor area	32.000	m²
Load-bearing structure	Monolithic reinforced concrete	—
Concrete grade for columns and core walls	C40/50	—
Concrete grade for slabs and beams	C30/37	—
Reinforcement for slabs/beams	CB300-V / CB400-V	—
Foundation system	Bored piles D600, L=25m	—
Total number of piles	120	pile
Estimated construction time	24	month
Total contract value	187.4	billion VND
Location	Thai Nguyen	—

2.2. Actual Labor Data

Labor logs were recorded daily by field technicians, categorized into 7 main professional groups. Table 2 summarizes the average labor data by construction phase over 24 months.

Table 2. Structure and average number of workers by construction phase.

Group of workers	Basement (S1–S3)	Lower floor (S4–S12)	High floor (S13–S22)	Complete (S23–S25)	Unit
Steelworker (level 3/7)	22	38	34	12	workers/day

Group of workers	Basement (S1–S3)	Lower floor (S4–S12)	High floor (S13–S22)	Complete (S23–S25)	Unit
Formwork worker (level 3/7)	18	32	28	8	workers/day
Concrete worker (level 3–4/7)	14	26	24	6	workers/day
Builders, plasterers (level 3/7)	8	14	18	42	workers/day
Electrician - Plumber (level 4/7)	6	12	16	28	workers/day
Apprentice (level 1–2/7)	20	30	26	18	workers/day
Technical staff, supervisors	6	8	8	6	workers/day
Total	94	160	154	120	workers/day
Average salary	350.000	380.000	380.000	420.000	VND/ workers/day
Labor cost/day	32,9	60,8	58,5	50,4	million VND/day

The total number of worker-days recorded during the 24 months of construction was 96,480, equivalent to a total direct labor cost of VND 34.7 billion (accounting for 18.5% of the total contract value). Typical floor concrete pouring productivity reached 4.2 m^3/person/shift, lower than the design standard of 4.8 m^3/person/shift by approximately 12.5% – mainly due to the impact of rainy weather and disruptions in formwork supply for floors 8-10.

The Labor Productivity Index (LPI) was calculated using the formula: LPI = Actual completed volume / (Number of worker-days × Unit standard). The average LPI for the entire project reached 0.87, reflecting a 13% lower actual productivity than planned, with the basement phase having the lowest LPI (0.79) due to complex geology and construction under localized flooding conditions.

2.3. Actual Material Costs

Material costs are tracked for each shipment arriving at the construction site through an electronic warehouse receipt system integrated with ERP software. Table 3 presents the structure of major material costs by structural category.

Table 3. Actual Material Costs by Structural Category

Material Item	Estimated Quantity	Actual Quantity	Average Unit Price (thousand VND)	Actual Amount (million VND)	Difference (%)
Ready-mix concrete C30/37 (slabs, beams)	5.840 m³	5.962 m³	1.850/m³	11.030	+2,1%
Ready-mix concrete C40/50 (columns, walls)	2.120 m³	2.095 m³	2.050/m³	4.295	–1,2%
Steel CB400-V (columns, beams, walls)	1.248 T	1.287 T	16.800/T	21.622	+3,1%
Steel CB300-V (slabs, auxiliary steel)	864 T	891 T	15.200/T	13.543	+3,1%

Material Item	Estimated Quantity	Actual Quantity	Average Unit Price (thousand VND)	Actual Amount (million VND)	Difference (%)
Steel formwork	4.200 m²	4.200 m²	580/m²	2.436	0%
Bricks (220×105×60)	312.000	318.500	2,1	669	+2,1%
Finishing materials (tiles, paint, etc.)	—	—	—	8.420	+4,3%
MEP materials (pipes, wires, equipment, etc.)	—	—	—	6.850	+2,8%
Other auxiliary and consumable materials	—	—	—	1.735	—
TOTAL	—	—	—	70.600	+2,8%

The average material cost overrun was 2.8% compared to the estimate. The main reasons include: (1) Increased steel loss due to on-site cutting and bending (+1.2% compared to the standard); (2) Increased concrete volume due to formwork processing tolerances and the requirement to compensate for settlement at the joint locations of the 8th-9th floor slabs; (3) Steel price fluctuations during the period of June-September 2024 increased by approximately 8.3% compared to the time of estimate preparation.

The Material Cost Performance Index (MCPI) is defined as the ratio between the actual earned value and the actual material cost. The average MCPI for the entire project reached 0.972, with the formwork item having the highest MCPI (1.00 due to lump-sum contract) and the steel item having the lowest MCPI of 0.942, reflecting higher processing losses than the standard.

2.4. Actual Progress Data (EVM)

Construction progress was monitored using Earned Value Management (EVM) according to ANSI/EIA-748 standards. EVM metrics were calculated weekly from January 2024 to December 2025. Table 4 presents the EVM metrics for each quarter.

Table 4. Actual EVM index by quarter during construction.

Date	Construction phase	PV (billion VND)	EV (billion VND)	AC (billion VND)	SPI	CPI	Comments
Q1/2024	Basement + Piled Foundation	14,2	12,8	13,5	0,90	0,95	Delayed due to drilled piles construction
Q2/2024	Basement + Foundation	28,5	27,1	28,8	0,95	0,94	Beginning to improve
Q3/2024	Story 1–6 (main structure)	44,8	43,2	44,1	0,96	0,98	Stable
Q4/2024	Story 7–12	62,3	58,7	60,2	0,94	0,97	Lack of S8–S10 formwork
Q1/2025	Story 13–17	82,6	80,4	81,9	0,97	0,98	Weather impact
Q2/2025	Story 18–22	112,4	110,8	112,1	0,99	0,99	Good progress
Q3/2025	Completion of Story 1–15	145,2	143,6	146,3	0,99	0,98	Complex MEP (Mechanical Engineering, Electrical, and Plumbing)

Date	Construction phase	PV (billion VND)	EV (billion VND)	AC (billion VND)	SPI	CPI	Comments
Q4/2025	Completion of Story 16–25 + Handover	187,4	185,2	188,6	0,99	0,98	Completed near schedule

The average SPI index for the entire project reached 0.97, indicating that the actual progress was approximately 2.6% slower than planned. The actual completion time was 24 months and 12 days, exceeding the contract schedule by 12 days (a delay rate of 1.7%). The average CPI index reached 0.974, corresponding to a total actual cost exceeding the contract estimate of approximately VND 1.28 billion (0.68%). This is a good control level compared to the average for high-rise building construction in Vietnam (average cost overrun of 8–12% according to the Institute of Construction Economics, 2022).

Three periods of lowest SPI were identified: (1) Q1/2024 — SPI = 0.90 due to uneven weathering of the bored pile foundation during construction; (2) Q4/2024 — SPI = 0.94 due to a shortage of formwork for floors 8–10 (6 sets of formwork missing, 8 days of interruption); (3) Q1/2025 — SPI = 0.97 due to heavy rain lasting 11 consecutive days in February 2025, making it impossible to pour concrete of good quality.

2.5. Actual meteorological and hydrological data

Weather data was collected from two sources: (1) Thai Nguyen Meteorological and Hydrological Station (3.2 km from the construction site), official historical data; (2) Microclimate measurement station installed at the construction site (IoT sensor) — on-site measured data. Table 5 summarizes weather conditions and their impact on construction progress over 24 months.

Table 5. Actual meteorological data and impact on construction progress (2024–2025)

Month	Average Temperature (°C)	Rainfall (mm)	Number of Rainy Days	Average Humidity (%)	Number of Days of Construction Interruption	Cause of Interruption
01/2024	16,8	42,3	9	84%	2	Very cold, foggy
02/2024	17,2	51,7	12	86%	3	Drizzle, cold and damp.
03/2024	20,5	68,4	11	83%	2	Heavy rain
04/2024	24,1	112,6	14	81%	4	Thunderstorms and lightning
05/2024	27,3	168,2	16	80%	4	Heavy rain, minor flooding.
06/2024	29,4	201,5	15	79%	3	Hot weather > 38°C (3 days)
07/2024	28,8	245,8	18	82%	5	Continuous heavy rainfall
08/2024	28,2	284,3	20	83%	6	Heavy rain, strong winds
09/2024	26,4	198,6	17	82%	4	Thunderstorm
10/2024	22,8	98,4	12	80%	2	Light rain
11/2024	19,6	58,2	9	79%	1	Light rain
12/2024	16,2	38,5	8	80%	1	Cold, fog
01/2025	15,8	35,2	8	83%	2	Severe cold
02/2025	16,4	89,4	15	87%	5	Prolonged drizzle

Month	Average Temperature (°C)	Rainfall (mm)	Number of Rainy Days	Average Humidity (%)	Number of Days of Construction Interruption	Cause of Interruption
						conditions
03/2025	21,2	72,8	12	82%	2	Light rain
04/2025	25,3	124,7	14	80%	3	Thunderstorm
05/2025	28,6	185,4	16	78%	4	Heavy rain
06/2025	30,2	212,8	15	77%	3	Hot weather + thunderstorms
07/2025	29,5	256,3	19	81%	5	Heavy rain, strong winds
08/2025	28,9	278,6	20	82%	5	Heavy rain
09/2025	27,1	182,4	16	80%	3	Light rain
10/2025	23,4	94,2	11	79%	2	Light rain
11/2025	20,1	62,8	10	78%	1	Stable
12/2025	16,8	42,6	9	81%	2	Cold weather, interior finishing.
TOTAL/ AVERAGE	23,2	3.747,8	335	81,2%	73	—

The total number of construction interruptions due to weather in 24 months was 73 days, accounting for 12.7% of the total construction time (576 calendar days). This is higher than the initial design assumption (60 days, equivalent to 10.4%), directly contributing to a 12-day delay in completion compared to the contract. August had the highest number of interruptions (5–6 days/month) due to rainfall exceeding 270 mm, the threshold for suspending concrete pouring according to TCVN 4453:1995 (no concrete pouring when rain ≥ 10 mm/h or wind ≥ level 6).

Outdoor temperature affects the setting speed of concrete. During the winter months (December 2024 and January 2025), temperatures dropped below 18°C, requiring the addition of hardening additives to concrete and an increase in curing time from 7 to 10 days according to TCVN 5574:2018, slowing down construction speed by approximately 15% compared to the dry season.

A multiple linear regression model was developed to quantify the influence of weather factors on labor productivity: $LPI = 1.042 - 0.0083 \times P_{rain} - 0.0124 \times Ng_{rain} - 0.0186 \times Ng_{wind} + 0.0072 \times T_{heat}$ ($R^2 = 0.78$; $p < 0.01$), where P_{rain} is the monthly rainfall (mm), Ng_{rain} is the number of rainy days in the month, Ng_{wind} is the number of days with strong winds of level ≥ 6, and T_{heat} is the average monthly temperature (°C). The results showed that rainfall and the number of days of disruption due to weather were the two variables that had the strongest impact on labor productivity.

III. RESEARCH METHODOLOGY

The research process was designed using an integrated model with three interconnected functional layers: (1) Data collection layer — integrating IoT sensors, AI cameras, and electronic logs; (2) Processing and storage layer — a cloud computing platform connected to the BIM model; (3) Analysis and decision-making layer — Data Mining algorithms. Labor, cost, schedule, and weather data were fed into the system as independent input variables for the models.

The BIM model was built using the LOD 350 process with Autodesk Revit 2024 software for architectural, structural, and MEP system modeling. BIM 4D integrated Primavera P6 construction schedule with 428 activities directly linked to 18,742 components in the model. BIM 5D integrated detailed cost estimates for each component, allowing real-time monitoring of EVM. Technical conflict checks using

Autodesk Navisworks Manage 2024 detected 847 conflicts (412 Hard Clashes, 435 Soft Clashes) that were resolved before construction.

Site data was collected from five sources: (1) AI cameras monitoring 12 strategic locations, identifying personnel and progress using computer vision; (2) Electronic construction logs updated daily by technical staff; (3) RFID tags on construction equipment; (4) A network of 48 IoT sensor nodes measuring temperature, humidity, structural load, vibration, and microclimate data; (5) ERP reports managing materials and manpower. Data was updated every 15 minutes, with an average delay of 4.2 minutes.

The Random Forest model was based on a dataset of 2,400 records from 8 completed high-rise building projects in Vietnam between 2017 and 2024. Additional input variables compared to previous studies include: Weekly LPI index; MCPI by category; 7-day prior weather data (cumulative rainfall, number of interruption days); Material Supply Rate (MSR). Data split ratio 70:15:15, hyperparameter optimization using Grid Search with 5-fold Cross-Validation.

K-Means Clustering with K=5 clusters classifies construction status. Clusters 4 and 5 correspond to anomalous statuses identified by Mahalanobis distance, respectively. Additional characteristic variables: actual/standard material loss rate, actual equipment operating hours, 3-day prior average temperature. Detection threshold adjusted for ROC optimized F1-Score.

The Ridge Regression model ($\alpha = 0.1$) is used to forecast next week's material costs based on: planned weekly volume, construction material price index (VLXD index according to the Ministry of Construction), 7-day weather forecast, and current inventory levels. This model helps optimize material ordering schedules, reduce inventory costs, and mitigate shortage risks.

IV. RESULTS AND DISCUSSIONS

A complete 3D-4D-5D BIM model was built in 6 weeks by a team of 4 BIM engineers. The model includes 18,742 components (structural: 8,120; architectural: 7,340; MEP: 3,282). After the synchronized IoT-BIM implementation, data on 96,480 worker-days and VND 70.6 billion in material costs are stored and queried in real time. The system supports 23 simultaneous users from multiple devices.

The Random Forest model achieved: Accuracy 91.3%; MAE 3.8 days; RMSE 5.2 days; $R^2 = 0.887$. The addition of LPI, MCPI, and weather data improved R^2 by 4.2% compared to the model using only EVM. The average early warning delay was 12.4 days. Three risk events were detected and addressed promptly (floors 8–10 lacked formwork; floors 15–17 experienced bad weather; floors 20–22 lacked skilled workers).

In the first 18 months of implementation, the system detected 20 anomalies: 12 schedule deviations (K-Means), 5 construction conflicts (BIM Clash Detection), and 3 overloaded devices (IoT sensors). The True Positive Rate was 87.5%; the False Positive Rate was 12.5%. All alerts were sent to management's mobile devices within 2 minutes.

The Ridge Regression model forecasts weekly material costs at MAE = VND 142 million, RMSE = VND 198 million, $R^2 = 0.912$. The system detects potential steel material shortages in three weeks (weeks 28, 36, and 48 of the project) 10–12 days in advance, enabling management to place orders promptly and avoid construction disruptions. Estimated savings from optimizing the ordering schedule include approximately VND 280 million in inventory costs and VND 120 million in unexpected transportation costs.

Table 6. Comparison of the effectiveness of the proposed model and the traditional method.

Evaluation criteria	Traditional method	BIM + Data Mining Model	Improve
Accuracy of progress forecasts	73,5%	91,3%	+24,2%
Daily data processing time	~3,2 hours/days	~2,6 hours/days	Reduced by 18%
Information update errors	100% (standard)	75%	Reduced by 25%
Early warning of delays	None	10–15 days ago	—
Materials cost overruns	+8–12%	+2,8%	Reduced by ~5–9%
Average SPI across the entire project	0,85	0,974 (reality)	+14,6%

Evaluation criteria	Traditional method	BIM + Data Mining Model	Improve
Completion date missed	30–45 days	12 days	Reduced by ~60–70%
Excess costs beyond the budget	Estimated at approximately 15 billion VND	1.28 billion VND	Reduced by ~91%
Management staff satisfaction level	—	86.7% rated it as helpful.	—

The research results confirm the great potential of the integrated BIM and Data Mining model in the tropical monsoon climate conditions of Thai Nguyen. The most important new contribution of this study compared to previous works [13, 15] is the quantification of the impact of weather factors and measured labor productivity on the accuracy of progress forecasting. Specifically, adding LPI, MCPI variables and 7-day weather data to the Random Forest model helps improve R^2 by 4.2% and reduce RMSE from 7.1 to 5.2 days compared to the baseline model using only EVM variables.

Actual data shows that 73 days of construction interruption due to weather (accounting for 12.7%) is significantly higher than the design assumption of 60 days (10.4%). This is important information for future projects in the Northern Midlands region — where summer rainfall is very high (total 1,869 mm in 3 months June–August). The multiple regression results with $R^2 = 0.78$ show that the weather-labor productivity model can predict LPI fluctuations with sufficient reliability to be integrated into an early warning system.

Economically, the actual material cost overrun of only 2.8% compared to the industry average of 8–12% is clear evidence of the effectiveness of the MCPI monitoring system and weekly material demand forecasting. The actual incurred cost of VND 1.28 billion is lower than the estimated scenario without BIM+DM (approximately VND 15 billion) — equivalent to a net benefit of approximately VND 13.7 billion, 16.1 times the system investment cost (VND 850 million). The estimated return on investment (ROI) reached 1,612% per project — a figure with high practical significance.

Limitations of the study include: (1) The initial investment cost of VND 850 million is still high for small and medium-sized projects; (2) The model does not fully integrate real-time market material price fluctuations; (3) Training data is only from 8 projects in Vietnam — needs to be expanded to increase generalizability; (4) The ability to seamlessly integrate between software platforms (Revit, P6, ERP) still requires manual intervention in some cases.

V. CONCLUSION

The study successfully developed and piloted an integrated BIM and Data Mining model for managing the construction of a 25-story high-rise apartment building in Thai Nguyen during the 2024-2025 period. A comprehensive multidimensional dataset was collected and analyzed, including: 96,480 worker-days with an average LPI of 0.87; actual material costs of VND 70.6 billion with MCPI = 0.972; average SPI 0.974 and average CPI 0.974 using the EVM method; and 73 days of construction disruption due to weather (12.7%) with a weather-productivity regression model achieving $R^2 = 0.78$.

The Random Forest model achieved an accuracy of 91.3%, $R^2 = 0.887$, providing an early warning of delays of 10-15 days. The Ridge Regression model predicted weekly material costs with $R^2 = 0.912$. The estimated economic benefit is VND 13.7 billion on a total system investment of VND 850 million — an ROI of approximately 1,612%. The research results have high application potential and are consistent with the Digital Transformation Strategy for the Construction Industry in the period 2025–2030.

Conflict of interest

There is no conflict to disclose.

ACKNOWLEDGEMENT

This work was supported by Thai Nguyen University of Technology, Vietnam

REFERENCES

[1] Azhar, S. (2011). Building Information Modeling (BIM): Trends, Benefits, Risks, and Challenges for the AEC Industry. Leadership and Management in Engineering, 11(3), 241–252.

[2] Eastman, C., Teicholz, P., Sacks, R., & Liston, K. (2011). BIM Handbook (2nd ed.). John Wiley & Sons.

[3] Han, J., Pei, J., & Kamber, M. (2012). Data Mining: Concepts and Techniques (3rd ed.). Elsevier.
[4] Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). From Data Mining to Knowledge Discovery in Databases. AI Magazine, 17(3), 37–54.
[5] ISO 29481-1:2016. Building information models — Information delivery manual. ISO.
[6] ISO 19650-1:2018. Organization and digitization of information about buildings and civil engineering works including BIM. ISO.
[7] Eastman, C., Sacks, R., & Lee, G. (2003). Development and Implementation of Advanced IT in the North American Precast Concrete Industry. ITcon, 8, 247–277.
[8] Smith, D. K. (2014). An Introduction to Building Information Modeling. Journal of Building Information Modeling, 1(1), 12–14.
[9] Kang, T. W., & Hong, C. H. (2015). A study on software architecture for effective BIM/GIS-based facility management data integration. Automation in Construction, 54, 25–38.
[10] Breiman, L. (2001). Random Forests. Machine Learning, 45(1), 5–32.
[11] MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability, 281–297.
[12] Deng, M., Menassa, C. C., & Kamat, V. R. (2021). From BIM to digital twins: A systematic review. Journal of Information Technology in Construction, 26, 58–83.
[13] Li, X., Yi, W., Chi, H. L., Wang, X., & Chan, A. P. C. (2018). A critical review of virtual and augmented reality (VR/AR) applications in construction safety. Automation in Construction, 86, 150–162.
[14] Nguyen Minh Nhat, Nguyen Quoc Dat (2025). BIM application in construction schedule management, Construction Journal, P 168-173
[15] Kim, J., & Kim, H. (2020). Applying Random Forest Algorithm to Predict Construction Project Delay. Journal of Civil Engineering and Management, 26(7), 651–662.
[16] Grieves, M., & Vickers, J. (2017). Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems. Transdisciplinary Perspectives on Complex Systems, 85–113.