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Improving construction project management through the application of AI, BIM and GIS at the construction investment project management board: The case of Viet Nam

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Abstract

This study investigates the impact assessment model of AI, BIM, GIS, and organizational capacity on project management efficiency at regional construction investment project management boards in Vietnam. Data was collected from 250 valid survey responses and analysed using Cronbach's Alpha, EFA, and multiple linear regression. The results show that the model explains 76.6% of the variation in project management efficiency ($R^2 = 0.766$). BIM has the strongest impact ($\beta = 0.318$), followed by AI ($\beta = 0.242$), PME ($\beta = 0.215$), GIS ($\beta = 0.181$), and organizational capacity ($\beta = 0.153$). The study confirms the central role of BIM and the decision-making support role of AI and GIS in the digital project management ecosystem.

Keywords: AI, BIM, GIS, project management, transportation, digital transformation

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1. Introduction

In the world, the application of AI, BIM, and GIS in construction project management is becoming increasingly common and yields many outstanding results. Artificial intelligence (AI) is revolutionizing the field of construction project management through its ability to analyze big data, machine learning, and support automated decision-making. AI helps analyze data, forecast risks, optimize schedules, and support rapid decision-making. BIM allows for the simulation of construction projects in the form of 3D digital models, helping stakeholders coordinate accurately, reduce errors, and save costs. Meanwhile, Geographic Information Systems (GIS) are indispensable spatial management tools for linear infrastructure projects. GIS supports: route selection analysis and geological-hydrological conditions; spatial land acquisition management; construction progress tracking along the route; and real-time field data connectivity. GIS supports spatial information management, construction site analysis, and environmental impact assessment. The combination of these three technologies contributes to improving the quality, efficiency, and sustainability of modern construction projects [1-8].

Transportation projects in Southern Vietnam are increasing in scale and complexity, while management still faces limitations such as delays, cost overruns, and a lack of risk forecasting tools [9-17].

Although AI, BIM, and GIS have been studied individually, integrated studies and empirical validation at the local project management level remain limited [13-15, 17-18].

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2. Current state of construction project management and the application of digital technology in construction project management

2.1. Current situation

Regional Project Management Boards (PMB) in Vietnam are managing numerous construction projects in general and transportation infrastructure projects in particular. However, current management methods still face several limitations: reliance on paper documents and individual experience; lack of tools for forecasting risks related to progress and costs; scattered data that has not been digitized and synchronized; real-time field monitoring; and ineffective coordination among stakeholders. These limitations demonstrate the need for a digital-based project management model [12-13, 17].

2.2. Application

The shift from traditional management models to data-driven project management is becoming an inevitable trend. In the field of transportation projects, three core technologies AI, BIM and GIS play a fundamental role [2-12, 19].

Artificial intelligence (AI) applications enable big data analysis, learning from historical data, and decision support. In construction project management, AI is applied to: predict delays; analyzed the risk of cost overruns; optimize resource allocation; monitor quality and occupational safety; and support decision-making systems. AI helps reduce reliance on subjective experience and improve forecasting accuracy. However, in Vietnam, implementation is limited due to a lack of digitized data, technological infrastructure, and specialized personnel [2, 5, 10].

Building Information Modeling (BIM) is a platform that integrates multidimensional information (3D, 4D, 5D) to support design, schedule, and cost management throughout the project lifecycle. The role of BIM in a project includes: design conflict detection; schedule management (4D); cost management (5D); improved collaboration among stakeholders; and reduced design changes and cost overruns. In Vietnam, BIM has been included in the adoption roadmap but its full potential in local-level project management has not yet been exploited [1, 4, 12].

Geographic Information Systems (GIS) applications are effective spatial management tools, particularly suitable for linear and widely distributed transportation projects. GIS supports: managing route locations and infrastructure status; geological and hydrological analysis; land acquisition support; spatial progress tracking; and real-time field data connectivity. However, the integration of GIS into transportation project management at local project management boards remains limited due to a lack of data interoperability and technological expertise [11, 20].

- AI-BIM-GIS Model Structure: BIM: Design-schedule-cost management platform; GIS: Geographic data and spatial management; AI: Data analysis, risk forecasting, decision support.
- Application Process: Build the BIM model; Link data with the GIS platform; Collect schedule-cost-field data; Apply AI for analysis and forecasting; Support leadership in making timely decisions.

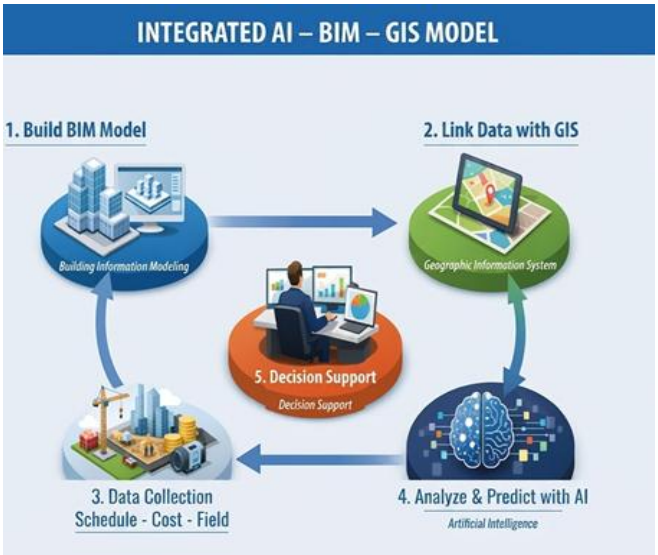

Figure 1. AI-BIM-GIS integration process

Expected benefits: Reduce the risk of delays by 10–15%; Limit additional costs; Enhance transparency and control; Increase coordination efficiency.

3. Research model structure and hypotheses

3.1. Research model structure

- Independent variables: AI (6 observed variables); BIM (6 variables); GIS (6 variables); ORG – Organizational & institutional capacity (6 variables);
- Dependent variable: PME – Project management efficiency (8 variables).
- Total: 32 observed variables

Table 1. Summary of research variables

Variable group	Number of observed variables	Variable code	Content
Artificial intelligence applications (AI);	6	AI1–AI6	AI Applications in Forecasting Schedules, Costs, Risks, and Decision Support
BIM applications in project management (BIM)	6	BIM1–BIM6	Design Management, Schedule Management (4D), Cost Management (5D), Coordination, and Change Control
GIS applications in project management (GIS);	6	GIS1–GIS6	Spatial Management, Route Tracking, Geographic-Site Analysis
Organizational and institutional capacity (ORG).	6	ORG1–ORG6	Management Capabilities, IT Infrastructure, and Policies Supporting Digital Transformation
Project Management Effectiveness (PME)	8	PME1–PME8	Project Efficiency in Schedules, Costs, Quality, Transparency, and Coordination

3.2. Key Hypotheses

- H1: AI application has a positive and statistically significant impact on Project Management Effectiveness (PME).
- H2: The application of BIM has a positive and statistically significant impact on Project Management Effectiveness (PME).
- H3: The application of GIS has a positive and statistically significant impact on Project Management Effectiveness (PME).
- H4: Organizational capacity (ORG) has a positive and statistically significant impact on Project Management Effectiveness (PME).

4. Research Methodology

Scale and questionnaire design.
The study used a cross-sectional survey design with a quantitative method. The analysis unit consists of individual experts involved in managing and implementing transportation construction investment projects at the Southern Region Investment and Construction Project Management Board of Vietnam and related units (design consultants, construction contractors, supervision consultants). Survey period: March–June 2024.

The questionnaire consists of 32 observed variables measuring 5 factors, constructed according to the following process: (1) synthesizing scales from international literature; (2) translating and semantically adjusting to suit the Vietnamese context; (3) expert discussion (n = 5) to check the content; (4) pilot test (n = 15) to check language clarity and scale consistency. The pilot test results showed that the Cronbach's Alpha coefficient of all groups exceeded 0.7 and no variables needed to be removed. Each variable was measured on a 5-point Likert scale (1 = Strongly disagree; 5 = Strongly agree).

This study uses purposive convenience sampling, targeting individuals with practical experience in managing transportation construction projects. The minimum sample size is determined according to the principle of at least 5 observations/variable [22], therefore $n_{min} = 32 \times 5 = 160$. The actual sample of 250 valid questionnaires exceeded this threshold.

Survey Sample: 250 valid questionnaires;

Scale: 05 point Likert;

Analysis: Cronbach’s Alpha; EFA; Linear regression (SPSS) [13].

Data were analyzed in a three-step sequence: (1) Scale reliability testing using Cronbach's Alpha coefficient (threshold $\alpha \geq 0.7$) and item-total correlation coefficient (threshold ≥ 0.3); (2) Exploratory factor analysis (EFA) with Varimax rotation, KMO and Bartlett tests, and factor extraction criteria eigenvalue ≥ 1.0 and loading coefficient ≥ 0.5; (3) Multiple linear regression (OLS) with multicollinearity test (VIF < 10; Tolerance > 0.1), autocorrelation (Durbin-Watson 1.5–2.5), normal distribution of residuals (Normal P-P Plot, Histogram) and homogeneous variance (Scatter Plot). SPSS 23 software was used for the entire analysis.

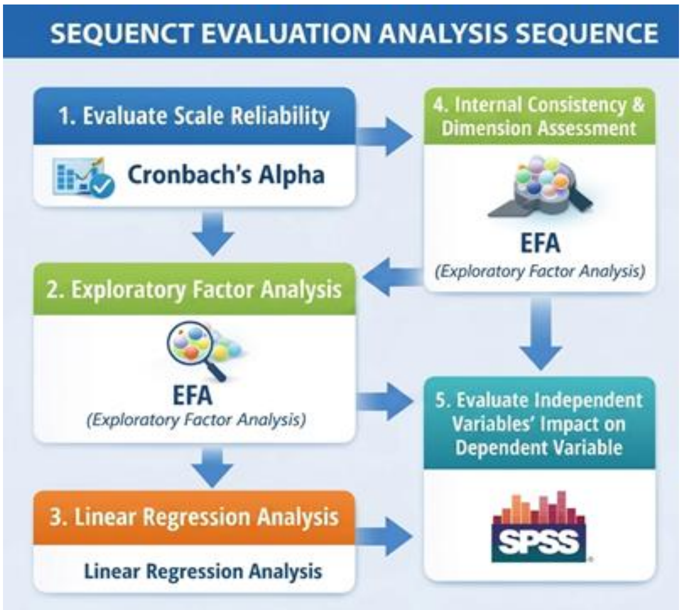

Figure 2. Analysis diagram

4.1. Results of scale validation (Cronbach's Alpha)

The results show that all scales achieved high reliability (Cronbach's Alpha > 0.7)

Table 2. Cronbach's Alpha

Variable group	Alpha
AI	0,892
BIM	0,891
GIS	0,884
ORG	0,857
PME	0,917

No observed variables were removed; - The variable-total correlation coefficients are all > 0.3.
Commentary on results: The scales ensure reliability for further EFA and regression analysis.

4.2. Exploratory Factor Analysis (EFA)

Commentary on results: KMO = 0.874 (>0.5) → data suitable for factor analysis; Bartlett's Test: Sig. = 0.000 (<0.05) → correlation between variables; Eigenvalue > 1; Total variance extracted = 63.695% → good explanatory power. No significant cross-loading is present.
Factor structure is consistent with the initially proposed `

Table 3. EFA results

Indicators	Value	Acceptance threshold
KMO	0,874	≥ 0,8
Bartlett Sig.	0,000	< 0,05
Number of extracted factors	5	Theoretical
Eigenvalue min	1,142	≥ 1,0
Total	63,695%	≥ 60%
Minimum loading coefficient	0,746	≥ 0,50

Table 4. Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4,124	12,889	12,889	4,124	12,889	12,889
2	2,047	6,397	19,286			
3	1,951	6,095	25,382			
4	1,758	5,495	30,877			
5	1,522	4,756	35,633			
6	1,304	4,075	39,708			
7	1,196	3,738	43,446			
8	1,154	3,606	47,052			
9	1,101	3,441	50,493			
10	1,056	3,301	53,794			
11	1,044	3,263	57,057			
12	1,018	3,181	60,238			
13	0,931	2,910	63,147			
14	0,908	2,839	65,986			
15	0,869	2,716	68,703			

16	0,837	2,616	71,319
17	0,786	2,456	73,775
18	0,768	2,399	76,174
19	0,737	2,304	78,478
20	0,716	2,238	80,716
21	0,669	2,090	82,806
22	0,647	2,021	84,827
23	0,618	1,931	86,758
24	0,576	1,801	88,560
25	0,550	1,720	90,280
26	0,516	1,613	91,892
27	0,507	1,584	93,476
28	0,489	1,529	95,005
29	0,446	1,395	96,400
30	0,419	1,309	97,709
31	0,370	1,155	98,865
32	0,363	1,135	100,000

The results in the table above show that the extracted variance is 12.889% < 50%. Thus, there is no presence of CMB [18].

4.3. Regression analysis

Model Sig. = 0.000 (<0.05) → model is statistically significant; - $R^2 = 0.766$ → explains 76.6% of the variation in project management effectiveness; - No multicollinearity (VIF < 2) [13].

Standardized regression equation:

$$Y = \beta_0 + \beta_1 \cdot AI + \beta_2 \cdot BIM + \beta_3 \cdot GIS + \beta_4 \cdot ORG + \varepsilon \quad (1)$$

Y: PME is the average Project Management Efficiency score; β_1–β_4 are the standardized regression coefficients; and ε is the random error.

Table 5. Regression coefficients and multicollinearity test

Variable	B (non-normalized)	SE	β (normalized)	t	Sig.	VIF	Tolerance
Constant	0,312	0,187	—	1,668	0,097	—	—
AI	0,268	0,041	0,242	6,537	0,000	1,483	0,674
BIM	0,351	0,043	0,318	8,163	0,000	1,521	0,658
GIS	0,198	0,038	0,181	5,211	0,000	1,394	0,717
ORG	0,171	0,036	0,153	4,750	0,000	1,352	0,740

All variables had VIF < 2.0 and Tolerance > 0.6, confirming the absence of serious multicollinearity. All hypotheses H1–H4 were supported at a significance level of $p < 0.001$.

4.4. Testing the regression hypothesis of standardized residual Histogram

Mean ≈ 0; - Std. Dev ≈ 1; - Bell-shaped distribution → Residuals are approximately normally distributed.

Normal distribution of residuals: The histogram of the standardized residuals showed an approximately normal distribution with Mean ≈ 0 and Std. Dev. = 0.934 ≈ 1. The Normal P-P Plot shows that the data points closely follow the normal diagonal, confirming that the assumption of normal residual distribution is satisfied.

Table 6. Descriptive statistics of standardized residuals

Indicators	Standardized predicted values	Standardized Residual Values
N	250	250
Mean	0,000	-2.005E-14(≈ 0)
Std. Deviation	0,992	0.934 (≈ 1)
Minimum	-2,821	-2.014
Maximum	2,643	2.166

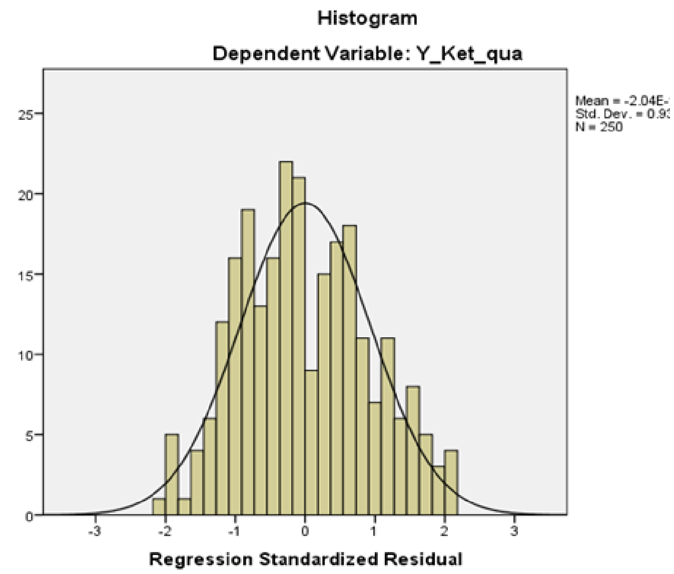

Figure 3. Frequency histogram of standardized residuals

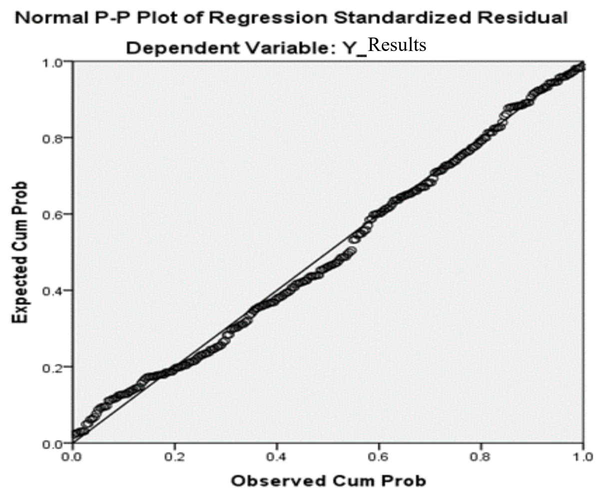

Figure 4. Standardized residual plot Normal P-P Plot

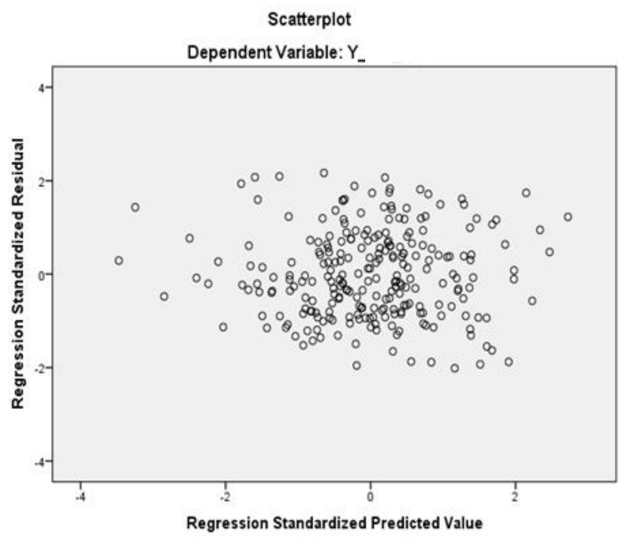

Figure 5. Scatter Plot tests the assumption of linear relationships

Normal P-P Plot: For a Normal P-P Plot, the data points in the residual distribution closely follow the diagonal, indicating a normal residual distribution.

Scatter Plot

Commentary on results: Data points are distributed around the zero axis; - No funnel shape; → Does not violate the assumption of linearity and constant variance.

The regression model meets the statistical assumptions.

5.Conclusion & Recommendations

5.1. Conclusion

Research confirms that artificial intelligence (AI) application has a positive and statistically significant impact on the efficiency of traffic construction project management in Vietnam, in which AI in progress management and decision support has the strongest influence. This result accurately reflects the characteristics of large-scale transportation projects with long implementation periods and many potential risks.

The research model with $R^2 = 0.766$ shows that technological factors (AI, BIM, GIS) explain well the variation of project management effectiveness. This confirms that AI is not just a technical tool but a modern management solution, contributing to improving forecasting, transparency and effective use of public investment capital. However, AI is only effective when deployed on a standardized data platform and in an integrated technology ecosystem.

Further research needs to be carried out: 1. Research on simultaneous integration of AI–BIM–GIS; 2. Quantitative research on a large enough scale in Vietnam; 3. Research the localization context for the local Project Management Board; 4. Clarifying the mediating and regulating role of organizational capacity; 5. Compare the relative impact between technologies.

5.2. Recommendation

To complete the theoretical and practical basis for technology application in construction management, further research should focus on:

- First, in terms of AI, it is necessary to develop and test models to predict delays, cost overruns and safety risks based on real data; At the same time, evaluate data readiness and integration with project management systems in real time.
- Second, regarding BIM, it is necessary to research data standardization and build a shared data environment (CDE), clarifying the role of BIM 4D–5D in controlling progress, costs and connecting to the operational management stage.
- Third, regarding GIS, it is necessary to promote research into BIM–GIS integration for long-distance projects, associated with UAV, satellite and IoT data to improve space monitoring capacity.
- Finally, it is necessary to develop integrated models that evaluate the synergistic impact between AI–BIM–GIS instead of considering each technology individually, thereby providing a complete ecosystem perspective for construction management in the context of digital transformation.

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