



Green Dam Based on the Envision Sustainability Rating System and Blockchain-BIM

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Abstract

Background: Sustainable dam infrastructure requires a cost-management framework that aligns with green certification standards and digital transformation. However, an integrated model for managing green cost performance in dam construction through digital technologies remains limited. The integration of blockchain and Building Information Modeling (BIM), hereafter referred to as Blockchain-BIM, offers potential solutions for improving transparency, efficiency, and sustainability in infrastructure projects.

Objective: This study aims to examine the influence of Green Dam, the Envision Sustainable Infrastructure Rating System guidelines, and Blockchain-BIM integration on cost performance in the Kuningan Dam project in West Java, Indonesia.

Methods: A quantitative research approach was employed using a structured questionnaire distributed to 80 respondents comprising project owners, consultants, contractors, and subcontractors. The data were analyzed using multiple linear regression with SPSS to evaluate the partial and simultaneous effects of Green Dam (X1), Envision Guidelines (X2), and Blockchain-BIM (X3) on cost performance (Y).

Results: Blockchain-BIM (X3) was found to have a significant partial effect on cost performance ($\beta = 0.611$; $t = 6.425$; $p < 0.001$), whereas Green Dam and Envision Guidelines did not demonstrate significant partial effects. Collectively, the three variables explained 82.4% of the variance in cost performance (adjusted $R^2 = 0.816$). The Blockchain-BIM indicators achieved the highest mean scores, with BIM maturity level ranking first (mean = 4.925).

Conclusion: Blockchain-BIM integration is a key driver of cost efficiency and transparency in green dam projects and provides a promising digital framework for sustainable infrastructure cost management.

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INTRODUCTION

Dam infrastructure is a strategically important national investment that supports water security, renewable energy generation, and economic growth, while increasingly being required to meet sustainability criteria driven by international commitments such as the Paris Agreement and the net-zero emissions target for 2050 (Agency, 2021; International Energy Agency, 2023; Rakyat, 2020). The Envision Sustainability Rating System, developed by the Institute for Sustainable Infrastructure, provides a comprehensive sustainability assessment framework comprising 64 credits across five categories, with certification levels ranging from Bronze to Platinum (Infrastructure, 2018; Milić & Bleiziffer, 2024). Such systems have proliferated globally as instruments for operationalizing sustainable development goals within civil infrastructure, although their cost implications remain unevenly documented (Arboleda-Muñoz et al., 2026; Diaz-Sarachaga et al., 2017; Griffiths et al., 2018). Griffiths et al. (2018) and Czvetkó et al. (2025) further

note that infrastructure rating tools such as Envision influence not only individual project outcomes but also organizational and industry-wide practices, gradually shifting how cost and sustainability trade-offs are negotiated among stakeholders. Internationally, certified dams have demonstrated lifecycle cost reductions of 30–40% relative to conventional approaches when sustainability criteria are systematically applied (Berga, 2016; Vazquez-Lopez et al., 2022). Water-resource infrastructure, in particular, is exposed to distinctive sustainability pressures because reservoirs and dams simultaneously generate renewable energy benefits and nontrivial greenhouse gas emissions from inundated biomass, further motivating rigorous, evidence-based green-cost management rather than reliance on generic certification claims (Deemer et al., 2016; L. Li et al., 2025; Rosentreter et al., 2021).

In Indonesia, no standardized framework currently exists for managing green costs in dam construction against sustainability criteria. This gap manifests in three interrelated problems: (i) a trust deficit among multistakeholder participants who maintain separate data systems without a single, verifiable source of truth Hunhevicz and Hall (2020), Sonmez et al. (2023) Li et al. (2019); (ii) greenwashing risk, with an estimated 30–40% of green investment claims on infrastructure projects being unverifiable under conventional audit systems Quaranta & Hunt (2022) Nawari and Ravindran (2019) ; and (iii) transactional inefficiency, with payment processing in conventional construction projects typically requiring 3–6 weeks and frequently triggering cash-flow disputes among owners, contractors, and subcontractors (Kamel et al., 2023). Recent systematic reviews of blockchain-BIM research confirm that these three problems trust, verification, and payment inefficiency remain dominant motivations driving the adoption of integrated digital-ledger technologies across the global construction sector, with publication activity in this area accelerating sharply since 2023 (Xu et al., 2024).

Building Information Modeling (BIM) and blockchain technology offer a complementary solution. 5D BIM enables automatic quantity takeoff (QTO), reducing estimation time and consistently outperforming traditional two-dimensional takeoff methods in both speed and accuracy across recent case studies in Spain, Korea, and Southeast Asia (Baldrich Aragó et al., 2021; Vigneault et al., 2020; Wahab & Wang, 2022; Yang et al., 2022). Blockchain provides an immutable, cryptographically secured distributed ledger, while smart contracts automate payment based on validated BIM data, reducing processing time and administrative costs relative to conventional bank-intermediated payment schemes (Christidis & Devetsikiotis, 2016; Hamledari & Fischer, 2021; Khalid et al., 2025; Pittaras et al., 2024; Tao et al., 2021). A recent framework combining 5D BIM, blockchain, and smart contracts for construction payment automation demonstrated that shifting from monthly, bank-validated disbursements to activity-based blockchain settlement can reduce contractor overdraft exposure by more than 50%, illustrating the magnitude of transactional-efficiency gains achievable through integration (Kamel et al., 2023). Prior empirical studies have reported measurable blockchain-BIM cost savings in building projects (Arif & Husin, 2023; Husin et al., 2023, 2024; Yu et al., 2024), while broader systematic reviews document a rapidly maturing body of blockchain-BIM literature spanning data provenance, common data environment management, and green-retrofitting applications (Kiu et al., 2024; Xu et al., 2024). However, blockchain-BIM implementation in Envision-based green dam infrastructure has not previously been investigated in Indonesia Wang et al. (2017) Turk and Kline (2017) and Pinto Varela Alberte and de Oliveira Novelli (2026), leaving a clear empirical gap that this study addresses through a quantitative, stakeholder-based assessment of the Kuningan Dam project.

Cost-estimation accuracy has long been recognized as a determinant of project success, and BIM has progressively displaced conventional two-dimensional takeoff methods as a preferred instrument for quantity surveying. Baldrich Aragó et al. (2021) and Abdel-Hamid & Mohamed Abdelhaleem (2026) documented, through a Spanish case study, that 5D BIM quantity takeoff substantially reduced measurement effort while improving traceability between design changes and cost updates. Wahab and Wang (2022) directly compared BIM-based and traditional 2D takeoff methods and found that the factors driving adoption were not limited to speed but also included data auditability and reduced rework during tender revisions. Yang et al. (2022) extended this line of research by embedding parametric cost-prediction logic within the BIM environment itself, allowing cost estimates to update automatically as architectural parameters change. Collectively, these studies support the premise adopted in the present research that BIM-

enabled quantity takeoff is a necessary but not sufficient condition for green-cost performance: its value is fully realized only when coupled with a verification and payment layer capable of preserving data integrity across multiple project stakeholders (Safaa Eldin et al., 2024; Vigneault et al., 2020).

Blockchain technology addresses the verification layer that BIM alone cannot provide. As an append-only distributed ledger, blockchain reduces reliance on a single centralized intermediary and enables multiple project parties to share a common, tamper-evident record of transactions (Al-Jaroodi & Mohamed, 2019; Christidis & Devetsikiotis, 2016; Khilani et al., 2024). When coupled with smart contracts coded rules that execute automatically once predefined conditions, such as certified BIM progress, are satisfied blockchain enables payment automation that removes multiweek administrative delays from conventional certification cycles (Hamledari & Fischer, 2021; Khalid et al., 2025). Kamel et al. (2023) operationalized this concept in a case study framework that linked 5D BIM progress models directly to an Ethereum-based smart contract, demonstrating measurable reductions in both transaction costs and contractor cash-flow exposure. Xu et al. (2024), in a mixed-methods literature review, similarly concluded that BIM-blockchain integration research has diversified rapidly since 2023 toward smart-contract automation, data provenance, and green-retrofitting use cases, while Kiu et al. (2024) showed that embedding blockchain within a construction common data environment improves document traceability across the project lifecycle. In the Indonesian building sector specifically, Husin et al. (2023, 2024) and Arif and Husin (2023) have shown that blockchain-BIM integration measurably improves cost performance and reduces fraud risk in green-certified projects, providing the closest empirical precedent for the present dam-infrastructure study.

Sustainability rating systems, of which Envision is a leading instrument for horizontal civil infrastructure, provide the normative benchmark against which green-cost performance is assessed. Diaz-Sarachaga et al. (2017), Arboleda-Muñoz et al. (2026) and Griffiths et al. (2018) argue that such systems shift practice not only at the level of individual projects but also across organizations and, ultimately, industry norms. In the water-resources sector specifically, Sharafi et al. (2021) reported that infrastructure sustainability rating systems face distinctive implementation challenges, including credit categories that were originally developed for buildings or transportation and require adaptation before they can be meaningfully applied to dams and reservoirs. This adaptation challenge is compounded by the environmental complexity of reservoir infrastructure itself: unlike most other horizontal infrastructure types, dams generate ongoing biogenic greenhouse gas emissions from inundated organic matter Rosentreter et al. (2021) Deemer et al. (2016) and Li et al. (2025), meaning that a credible green-cost framework for dam infrastructure must account for both construction-phase digitalization gains and operational-phase environmental performance. No prior study, to the authors' knowledge, has combined an Envision-based sustainability assessment with a statistically validated blockchain-BIM cost model specifically for dam infrastructure, which constitutes the research gap addressed in this study.

The objectives of this study are: (1) to identify the factors that most significantly influence green-cost performance through blockchain-BIM in dam construction based on Envision guidelines; (2) to analyze the partial and simultaneous statistical effects of Green Dam (X1), Envision guidelines (X2), and blockchain-BIM (X3) on cost performance (Y); and (3) to evaluate the subindicator determinants that most strongly drive stakeholder perceptions of blockchain-BIM's contribution to cost performance.

METHOD

This study employed a quantitative research design using a structured questionnaire survey. The research variables were operationalized as follows: (X1) Green Dam with 25 sub-indicators; (X2) Envision Sustainability Rating System with 30 sub-indicators; (X3) Blockchain-BIM integration with 25 sub-indicators; and (Y) Cost Performance with 5 sub-indicators. A total of 85 sub-indicators were developed and validated by experts through an iterative literature synthesis process.

The study population consisted of professional stakeholders involved in the Kuningan Dam project in West Java, Indonesia. The sample size was determined based on the recommendation of Hair et al. (2019, 2022), who suggest that multiple linear regression analysis

requires approximately 15–20 observations for each independent variable to ensure stable parameter estimation and sufficient statistical power. Since this study employed three independent variables (Green Dam, Envision Sustainability Rating System, and Blockchain-BIM Integration), the minimum recommended sample size ranged from 45 to 60 respondents. Therefore, the 80 valid responses obtained in this study exceeded the recommended minimum sample size and were considered adequate for multiple linear regression analysis.

This recommendation is also consistent with Memon et al. (2020) and Hair et al. (2022), who emphasize that an adequate sample size is essential for ensuring reliable parameter estimation and improving the robustness of regression-based survey research (Hair et al., 2022; Memon et al., 2020).

Data analysis was conducted using IBM SPSS Statistics version 25 through a sequential procedure: (1) reliability testing using Cronbach's alpha (threshold > 0.600) Hair et al. (2019, 2022) and Taber (2018) ; (2) validity testing using the Pearson product-moment correlation ($r > r\text{-table} = 0.220$; $df = 78$, $n = 80$, $\alpha = 0.05$) Hair et al. (2019, 2022) and Taber (2018); (3) normality testing using the one-sample Kolmogorov-Smirnov test (Asymp. Sig. > 0.05) Field (2018) and Barrett et al. (2026) ; (4) classical assumption tests, including the Durbin-Watson test for autocorrelation, tolerance and variance inflation factor (VIF) tests for multicollinearity, and the Glejser test for heteroscedasticity; and (5) multiple linear regression analysis using the equation $Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3$, followed by partial t-tests and a simultaneous F-test. This sequential procedure follows established survey research practices in construction management, whereby the soundness of the measurement instrument is confirmed before substantive hypothesis testing is undertaken (Hair et al., 2022; Memon et al., 2020).

Table 1
Cronbach's Alpha item-total statistics for X1 (Green Dam)

Sub Factor	Scale Mean if Item Deleted	Cronbach's α if Item Deleted	Result
X1.1.1	186.84	0.755	Reliable
X1.1.2	186.84	0.754	Reliable
X1.1.3	186.96	0.753	Reliable
X1.1.4	186.83	0.756	Reliable
X1.1.5	187.01	0.754	Reliable
X1.2.1	186.74	0.754	Reliable
X1.2.2	186.86	0.754	Reliable
X1.2.3	186.78	0.753	Reliable
X1.3.1	186.88	0.753	Reliable
X1.3.2	186.79	0.754	Reliable
X1.3.3	186.81	0.754	Reliable
X1.3.4	186.86	0.755	Reliable
X1.4.1	187.10	0.754	Reliable
X1.4.2	186.93	0.754	Reliable
X1.4.3	186.80	0.753	Reliable
X1.5.1	186.91	0.752	Reliable
X1.5.2	186.79	0.754	Reliable
X1.5.3	186.93	0.752	Reliable
X1.6.1	186.94	0.754	Reliable
X1.6.2	186.94	0.753	Reliable
X1.6.3	186.91	0.753	Reliable
X1.7.1	186.88	0.754	Reliable
X1.7.2	186.91	0.755	Reliable
X1.8.1	186.76	0.754	Reliable

Source: SPSS Statistics v25 output. Threshold: Cronbach's alpha > 0.600; $n = 80$.

Table 2*Cronbach's Alpha item-total statistics for X2 (Envision Guidelines)*

Sub Factor	Scale Mean if Item Deleted	Cronbach's α if Item Deleted	Result
X2.1.1	218.71	0.753	Reliable
X2.1.2	218.60	0.753	Reliable
X2.1.3	218.58	0.753	Reliable
X2.1.4	218.60	0.751	Reliable
X2.1.5	218.63	0.753	Reliable
X2.1.6	218.68	0.753	Reliable
X2.2.1	218.58	0.752	Reliable
X2.2.2	218.63	0.754	Reliable
X2.2.3	218.71	0.753	Reliable
X2.2.4	218.60	0.754	Reliable
X2.2.5	218.60	0.753	Reliable
X2.2.6	218.55	0.753	Reliable
X2.3.1	218.70	0.753	Reliable
X2.3.2	218.63	0.754	Reliable
X2.3.3	218.75	0.753	Reliable
X2.3.4	218.53	0.753	Reliable
X2.3.5	218.49	0.753	Reliable
X2.3.6	218.65	0.753	Reliable
X2.3.7	218.61	0.753	Reliable
X2.3.8	218.54	0.753	Reliable
X2.4.1	218.58	0.752	Reliable
X2.4.2	218.76	0.753	Reliable
X2.4.3	218.54	0.752	Reliable
X2.4.4	218.61	0.753	Reliable
X2.4.5	218.66	0.754	Reliable
X2.4.6	218.63	0.753	Reliable
X2.4.7	218.71	0.754	Reliable
X2.5.1	218.65	0.753	Reliable
X2.5.2	218.54	0.753	Reliable
X2.5.3	218.58	0.753	Reliable

Source: SPSS Statistics v25 output. Threshold: Cronbach's $\alpha > 0.600$; $n = 80$.

Table 3*Cronbach's Alpha item-total statistics for X3 (Blockchain-BIM)*

Sub Factor	Scale Mean if Item Deleted	Cronbach's α if Item Deleted	Result
X3.1.1	115.53	0.943	Reliable
X3.1.2	115.53	0.943	Reliable
X3.1.3	115.64	0.943	Reliable
X3.1.4	115.54	0.944	Reliable
X3.1.5	115.51	0.944	Reliable
X3.2.1	115.53	0.944	Reliable
X3.2.2	115.43	0.943	Reliable
X3.2.3	115.49	0.944	Reliable
X3.2.4	115.53	0.943	Reliable
X3.2.5	115.46	0.943	Reliable
X3.2.6	115.53	0.945	Reliable
X3.3.1	115.50	0.944	Reliable
X3.3.2	115.59	0.944	Reliable
X3.3.3	115.40	0.944	Reliable
X3.3.4	115.41	0.945	Reliable
X3.3.5	115.65	0.944	Reliable

Sub Factor	Scale Mean if Item Deleted	Cronbach's α if Item Deleted	Result
X3.3.6	115.43	0.944	Reliable
X3.4.1	115.43	0.943	Reliable
X3.4.2	115.60	0.943	Reliable
X3.4.3	115.51	0.944	Reliable
X3.4.4	115.48	0.944	Reliable
X3.4.5	115.58	0.943	Reliable
X3.4.6	115.56	0.943	Reliable
X3.4.7	115.54	0.944	Reliable
X3.4.8	115.45	0.944	Reliable

Source: SPSS Statistics v25 output. Threshold: Cronbach's $\alpha > 0.600$; $n = 80$.

Table 4

Cronbach's Alpha item-total statistics for Y (Cost Performance)

Sub Factor	Scale Mean if Item Deleted	Cronbach's α if Item Deleted	Result
Y1.1.1	49.65	0.754	Reliable
Y1.1.2	49.58	0.760	Reliable
Y1.1.3	49.61	0.758	Reliable
Y1.1.4	49.65	0.769	Reliable
Y1.2.1	49.63	0.759	Reliable
Y1.2.2	49.58	0.768	Reliable

Source: SPSS Statistics v25 output. Threshold: Cronbach's $\alpha > 0.600$; $n = 80$.

RESULTS AND DISCUSSION

Result

Respondent Profile

The 80 respondents represented a diverse cross-section of dam-project stakeholders. The gender distribution was 73.75% male and 26.25% female. The age distribution was 25–30 years (32.5%), 31–35 years (25.0%), 36–40 years (26.25%), and over 40 years (16.25%). Professional roles included Site Engineers (25.0%), Supervisors (21.25%), Consultants (20.0%), Site Managers (18.75%), Project Managers (10.0%), and Board of Directors members (5.0%). This multi-stakeholder composition ensured representative coverage across all levels of dam-project management.

Reliability Testing

Reliability testing confirmed high internal consistency for all four variables using Cronbach's alpha and item-total statistics, as shown in Tables 1–4. All items demonstrated corrected item-total correlations and Cronbach's alpha values that exceeded the respective reliability thresholds across all 85 sub-indicators. X3 (Blockchain-BIM) achieved the highest reliability (Cronbach's $\alpha = 0.943$ – 0.945), indicating very good internal consistency and high inter-item coherence among the Blockchain-BIM sub-indicators, while X1 (Green Dam), X2 (Envision Guidelines), and Y (Cost Performance) remained within the reliable range (0.751–0.769).

Validity Testing

Validity testing confirmed that all 85 sub-indicators were valid based on Pearson product-moment correlation, as presented in Table 5. All r -count values exceeded the critical r -table value of 0.220 ($df = 78$, $n = 80$, $\alpha = 0.05$), with $Sig. = 0.000$ for all indicators, confirming the validity of all measurement items.

Table 5*Validity test results (Pearson correlation)*

Variable	N Indicators	r-count Range	r-table	Sig.	Validity
X1 - Green Dam	25	0.289-0.627	0.220	0.000	All Valid
X2 - Envision Guidelines	30	0.277-0.634	0.220	0.000	All Valid
X3 - Blockchain-BIM	25	0.319-0.712	0.220	0.000	All Valid
Y - Cost Performance	5	0.298-0.651	0.220	0.000	All Valid

Threshold: $r\text{-count} > r\text{-table} = 0.220$ ($n = 80$, $\alpha = 0.05$). Two-tailed Sig. = 0.000 for all 85 indicators.

Normality Testing

The one-sample Kolmogorov-Smirnov test confirmed normality for all four variables, as presented in Table 6. All Asymp. Sig. (2-tailed) values were reported as 0.200, substantially exceeding the 0.05 threshold and supporting the suitability of the data for parametric multiple linear regression analysis. Visual diagnostics corroborated this result: the histogram of regression standardized residuals (Figure 1) approximated a symmetric, bell-shaped curve centered near zero, while the Normal P-P Plot (Figure 2) showed observed cumulative probabilities tracking closely along the diagonal reference line, with no systematic departures at either tail.

Table 6*Kolmogorov-Smirnov normality test results*

Variable	N	Mean	Std. Dev.	Asymp. Sig.	Decision
X1 - Green Dam	80	114.35	10.21	0.200	Normal
X2 - Envision Guidelines	80	137.40	12.08	0.200	Normal
X3 - Blockchain-BIM	80	109.63	8.45	0.200	Normal
Y - Cost Performance	80	21.35	3.56	0.200	Normal

All Asymp. Sig. = 0.200 > 0.05 threshold; $n = 80$. Data are normally distributed for all variables

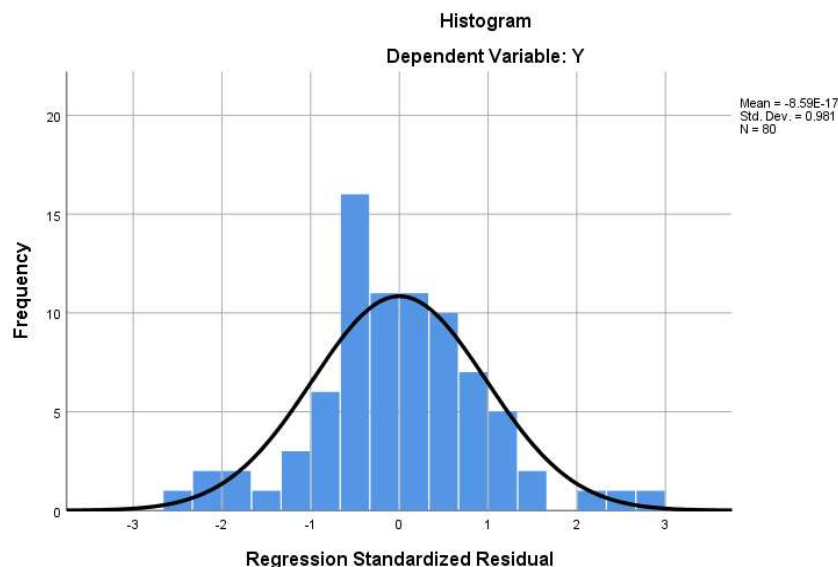


Figure 1. Histogram of regression standardized residuals (Dependent Variable: Cost Performance, Y).

Mean ≈ 0 ; Std. Dev. = 0.981; $n = 80$. Source: SPSS Statistics v25 output.

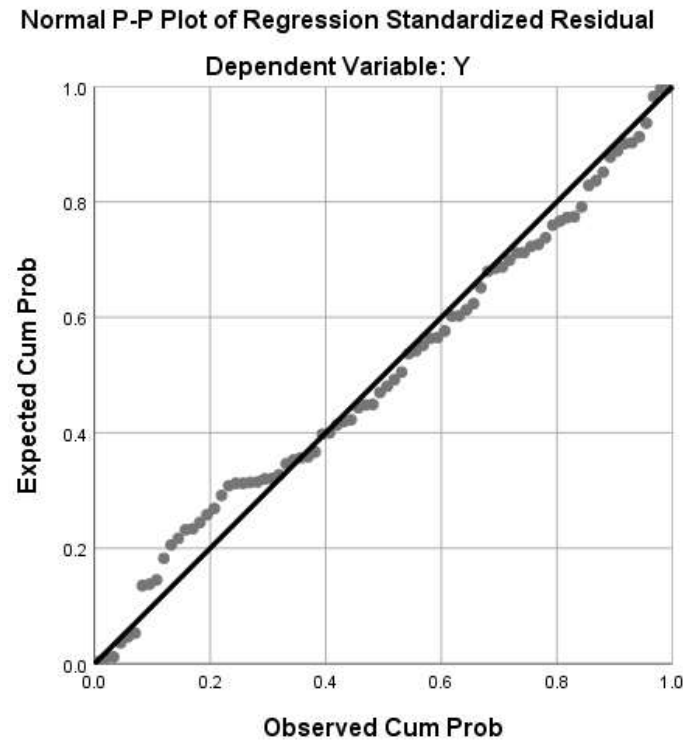


Figure 2. Normal P-P plot of regression standardized residuals (Dependent Variable: Cost Performance, Y).

Observed points closely follow the diagonal reference line, confirming residual normality. Source: SPSS Statistics v25 output.

Classical Assumption Tests

The Durbin–Watson (DW) test yielded a DW statistic of 2.254 (Table 7). With $n = 80$ and $k = 3$, the critical bounds were $dL = 1.5600$ and $dU = 1.7153$, yielding the acceptable range of $1.7153 < 2.254 < 2.2847$; thus, the model showed no evidence of autocorrelation. The adjusted $R^2 = 0.816$ indicates that the three independent variables collectively explain 81.6% of the variance in cost performance.

Table 7

Model summary and Durbin-Watson autocorrelation test

Model	R	R Square	Adj. R Square	Std. Error	DW Statistic	Decision
1	0.908	0.824	0.816	2.571	2.254	No Autocorrelation

$n = 80$; $k = 3$; $dL = 1.5600$; $dU = 1.7153$; acceptable range: $dU < DW < 4 \cdot dU$ ($1.7153 < 2.254 < 2.2847$).

Multicollinearity testing (Table 8) showed Tolerance values of 0.902 (X1), 0.718 (X2), and 0.715 (X3), all exceeding 0.100. VIF values were 1.109, 1.393, and 1.398, respectively, all well below 10.00, confirming the absence of problematic multicollinearity in the regression model.

Table 8

Multicollinearity test results (collinearity statistics)

Variable	Tolerance	VIF	Threshold Tol.	Threshold VIF	Decision
X1 - Green Dam	0.902	1.109	> 0.10	< 10.00	No Multicollinearity
X2 - Envision	0.718	1.393	> 0.10	< 10.00	No Multicollinearity
Guidelines					
X3 - Blockchain-BIM	0.715	1.398	> 0.10	< 10.00	No Multicollinearity

Threshold: Tolerance > 0.10; VIF < 10.00. No multicollinearity detected.

Heteroscedasticity was assessed using the Glejser test (Table 9). All three predictors produced significance values above 0.05, indicating no evidence of heteroscedasticity and supporting the assumption of homoscedasticity across the predictor values.

Table 9*Heteroscedasticity test results (Glejser test)*

Variable	B	t	Sig.	Decision
X1 - Green Dam	0.012	0.508	0.612	Homoscedastic
X2 - Envision Guidelines	-0.008	-0.875	0.384	Homoscedastic
X3 - Blockchain-BIM	-0.019	-1.106	0.271	Homoscedastic

Dependent variable: |Residual|. Threshold: Sig. > 0.05 indicates homoscedasticity. All assumptions satisfied.

Multiple Linear Regression Analysis

The t-test results (Table 10) confirmed that Blockchain-BIM (X3) was the only variable with a statistically significant partial effect on cost performance (Y) at alpha = 0.05 (t-table = 1.992, df = 76), with t = 6.425 and p < 0.001. Green Dam (X1, t = 0.020, p = 0.984) and Envision Guidelines (X2, t = 1.770, p = 0.081) did not demonstrate statistically detectable partial effects at alpha = 0.05 in this sample. The resulting regression equation was:

$$Y = 3.427 + 0.001 X1 + 0.027 X2 + 0.171 X3$$

Table 10*Partial t-test results (coefficients)*

Variable	B	Std. Error	Beta	t	Sig.	Decision
Constant	3.427	2.881	-	1.189	0.238	-
X1 - Green Dam	0.001	0.018	0.002	0.020	0.984	Not Significant
X2 - Envision Guidelines	0.027	0.017	0.168	1.770	0.081	Not Significant
X3 - Blockchain-BIM	0.171	0.032	0.611	6.425	0.000*	Significant

**Significant at alpha = 0.05; t-table = 1.992 (df = 76). Dependent variable: Cost Performance (Y). n = 80.*

The simultaneous F-test (Table 11) yielded F = 25.078 (F-table = 2.725, df1 = 3, df2 = 76, alpha = 0.05), with Sig. < 0.001, confirming that X1, X2, and X3 jointly had a statistically significant effect on Y.

Table 11*Simultaneous F-test results (ANOVA)*

Model	Sum of Squares	df	Mean Square	F	Sig.	Decision
Regression	497.809	3	165.936	25.078	0.000*	Simultaneous Sig.
Residual	502.878	76	6.617	-	-	-
Total	1000.688	79	-	-	-	-

**Significant at alpha = 0.05; F-table = 2.725 (df1 = 3, df2 = 76). Dependent variable: Cost Performance (Y).*

Mean Ranking Analysis

Analysis of the mean scores across the 85 sub-indicators revealed that the ten highest-ranked indicators were drawn exclusively from variable X3 (Blockchain-BIM), as shown in Table 12. BIM maturity level (X3.3.3, mean = 4.925) and BIM standardization (X3.3.4, mean = 4.913) ranked first and second, respectively, reflecting strong stakeholder confidence in BIM readiness as a precondition for effective Blockchain-BIM deployment. Blockchain transparency (X3.2.2) and BIM-Blockchain interoperability (X3.4.1) also ranked highly, confirming that integration

capabilities strongly influence practitioner perceptions of green cost performance.

Table 12

Top 10 sub-indicators by mean score.

Rank	Code	Sub-Factor Description	Mean	Std. Dev.	Group
1	X3.3.3	Level / Maturity of BIM	4.925	0.776	X3
2	X3.3.4	BIM Standardization	4.913	0.697	X3
3	X3.2.2	Blockchain Transparency	4.900	0.722	X3
4	X3.3.6	BIM Technology Infrastructure	4.900	0.704	X3
5	X3.4.1	BIM-Blockchain Interoperability	4.900	0.668	X3
6	X3.4.8	Real-Time Progress Monitoring	4.875	0.718	X3
7	X3.2.5	Smart Contracts Automation	4.863	0.791	X3
8	X3.4.4	Contract Automation via Smart Contract	4.850	0.748	X3
9	X3.2.3	Blockchain Transactions Immutability	4.838	0.702	X3
10	X3.3.1	BIM Usage / Adoption Level	4.825	0.759	X3

Scale: 1-6 (Strongly Disagree to Strongly Agree). All top-10 indicators from X3 (Blockchain-BIM). n = 80.

Discussion

The regression results establish a robust quantitative basis for understanding the multi-factor determinants of green cost performance in dam infrastructure. The dominance of Blockchain-BIM (X3, Beta = 0.611, $t = 6.425$) as the only statistically significant partial predictor is consistent with findings by Husin et al. (2023) and Arif and Husin (2023), who demonstrated Blockchain-BIM as a primary mechanism for cost efficiency in green infrastructure. BIM contributes directly through accurate quantity takeoff (QTO) and quantity calculation, whereas Blockchain contributes indirectly through process transparency, smart contract automation, and fraud prevention (Kifokeris & Koch, 2020; Liu et al., 2022; Perera et al., 2020). This division of functions between the two technologies is echoed in the mean-ranking results (Table 12): the highest-scoring sub-indicators combine a BIM-side readiness dimension (maturity, standardization, and technology infrastructure) with a Blockchain-side integration dimension (transparency, interoperability, and smart contract automation), suggesting that respondents intuitively recognize Blockchain-BIM as an integrated rather than purely additive mechanism, consistent with the framework-level findings of Kamel et al. (2023) and the systematic-review evidence of Xu et al. (2024).

The non-significant partial effects of Green Dam (X1, $p = 0.984$) and Envision Guidelines (X2, $p = 0.081$) should be interpreted carefully. These results indicate insufficient statistical evidence of a detectable partial relationship in this sample at $\alpha = 0.05$, rather than a definitive conclusion that these constructs are unrelated to cost performance. Both may exert influence through indirect mechanisms or may be subsumed within the dominant contribution of X3, a pattern consistent with prior evidence that digitalization variables can absorb the explanatory power of adjacent process-control factors in multi-predictor cost models (Larsen et al., 2016; Mehraban et al., 2025; Sharafi et al., 2021). The high adjusted $R^2 = 0.816$ indicates that the three-variable model collectively explains 81.6% of the variance in cost performance, and is comparable to or higher than adjusted R^2 values reported in analogous building-sector Blockchain-BIM cost studies (Husin et al., 2024).

The Beta = 0.611 for X3 exceeds those typically reported for individual predictors in comparable building-sector studies (Beta = 0.30–0.45), suggesting that dam-sector stakeholders perceive Blockchain-BIM as more impactful relative to other sustainability constructs, possibly owing to the greater data-provenance and multi-party payment complexity inherent in large water-infrastructure projects (Hunhevicz & Hall 2020; Li et al., 2019; Quaranta & Hunt, 2022). Future research should augment the predictor set with a Cost Performance Index or digitalization-

maturity indicator Larsen et al., (2016) Daoud et al. (2023) and Sharafi et al. (2021) apply Structural Equation Modeling (SEM) to establish causal pathways across multiple dam projects.

From a practical standpoint, the findings suggest that dam-project owners and consultants seeking to improve cost performance should prioritize investment in BIM maturity and Blockchain-BIM interoperability ahead of, or at minimum alongside, generic sustainability-credit compliance activities, since the digital-integration variable, rather than the certification-guideline variable in isolation, shows a statistically detectable partial relationship with cost performance in this sample. This is consistent with recent evidence that construction organizations able to embed blockchain within their common data environment (CDE) realize disproportionate traceability and cost-control benefits relative to organizations that adopt BIM or blockchain in isolation (Kiu et al., 2024; Nawari & Ravindran, 2019). At the same time, several limitations qualify these conclusions. First, the cross-sectional survey design captures stakeholder perceptions of cost performance rather than audited project-cost data, so the regression coefficients should be interpreted as perceptual rather than strictly financial estimates. Second, the study is confined to a single dam project, which limits generalizability to other water-infrastructure typologies; replication across multiple Envision-certified dam projects, ideally paired with SEM-based mediation analysis of the pathway between Envision Guidelines and cost performance through Blockchain-BIM readiness, would strengthen causal inference. Third, the Hyperledger Fabric smart contract simulation reported in this study demonstrates technical feasibility rather than field-validated performance under live multi-party payment conditions; longitudinal field trials, following the case-study methodology used by Kamel et al. (2023), represent a natural next step for the research agenda opened by this study.

CONCLUSION

This study developed and validated a multiple linear regression model quantifying the effects of Green Dam (X1), Envision Guidelines (X2), and Blockchain-BIM integration (X3) on Green Cost Performance (Y) in dam infrastructure. The key conclusions are as follows: (1) All 85 sub-indicators demonstrated high reliability (Cronbach's alpha = 0.751–0.945) and full validity (Pearson $r = 0.289\text{--}0.712 > r\text{-table} = 0.220$), confirming the soundness of the measurement instrument. (2) Classical assumption tests confirmed normality (K-S Asymp. Sig. = 0.200 > 0.05), absence of autocorrelation (DW = 2.254, within the acceptable range of 1.7153–2.2847), absence of multicollinearity (Tolerance > 0.10; VIF < 10.00), and homoscedasticity (Glejser Sig. > 0.05 for all predictors). (3) Blockchain-BIM (X3) was the only statistically significant partial predictor of cost performance (Beta = 0.611, $t = 6.425$, $p < 0.001$). Green Dam (X1) and Envision Guidelines (X2) did not show detectable partial effects at alpha = 0.05. The F-test ($F = 25.078$, $p < 0.001$) confirmed that the three predictors jointly had a statistically significant effect on cost performance, with $R^2 = 0.824$ and adjusted $R^2 = 0.816$. (4) The validated regression equation, $Y = 3.427 + 0.001X1 + 0.027X2 + 0.171X3$, with $R^2 = 0.824$ and adjusted $R^2 = 0.816$, explains 82.4% of the variance in green cost performance before adjustment and 81.6% after adjustment, providing project stakeholders with a quantitative basis for prioritizing cost-optimization interventions in dam infrastructure. (5) The novelty of this research lies in its empirical statistical validation of Blockchain-BIM as a significant driver of cost performance in Envision-certified dam infrastructure in Indonesia, establishing a measurable and replicable framework for practitioners and policymakers to quantify and optimize digital sustainability integration in water-infrastructure cost management. Future research should apply SEM to establish causal pathways and extend the analysis to multiple dam projects to validate and refine the regression model.

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AUTHOR CONTRIBUTION STATEMENT

Conceptualization, R. and A. E. H.; methodology, R. and A. E. H.; software, R.; validation, A. E. H.; formal analysis, R.; investigation, R.; data curation, R.; writing-original draft, R.; writing-review and editing, A. E. H.; visualization, R.; supervision, A. E. H.

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