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Quantitative Modeling of Change Order Impacts on Cost and Time Overruns in Indonesian Toll Road Infrastructure Projects

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Abstract. Change Orders (COs) are a major challenge in toll road infrastructure projects, often causing cost and time overruns. This study aims to identify key CO drivers and quantify their impacts on project performance in Indonesian toll road projects. A mixed-methods approach was applied, involving qualitative interviews with 35 experts (project managers, consultants, contractors) and quantitative surveys from 75 respondents covering 20 projects implemented between 2015 and 2023. Data analysis employed descriptive statistics, multiple linear regression, correlation analysis, and hypothesis testing using SPSS. Results show that five significant factors, namely poor planning, technical design changes, discrepancies between plans and site conditions, delays in land acquisition, and inadequate stakeholder coordination, explain 94.5% of CO variation ($R^2 = 0.945$). COs accounted for 94.9% of cost overrun variation ($R^2 = 0.949$) and 93.6% of time overrun variation ($R^2 = 0.936$). Design changes most strongly affected cost overruns ($\beta = 0.419$), while land acquisition delays had the greatest effect on time overruns ($\beta = 0.537$). COs have interrelated effects on cost and time, requiring integrated management from initiation to closure. The findings provide engineering and policy implications for precise contract documentation, rigorous planning, and proactive risk management to mitigate CO-induced overruns.

Keywords: Change order modeling, cost overrun, time overrun, toll road construction, construction phase performance

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1. Introduction

The development of toll road infrastructure is a fundamental driver of interregional connectivity and national economic growth. In Indonesia, the expansion of the toll road network has accelerated significantly over the past decade. As of January 2024, the operational toll road length reached 2,816 km, spanning five major islands, with Java contributing 1,782.47 km [1]. These investments aim to reduce travel time, enhance logistics efficiency, and stimulate regional development. However, the execution of large-scale toll road projects is inherently complex, involving multiple stakeholders, diverse geotechnical conditions, and stringent regulatory frameworks. Within this context, technical and administrative disruptions frequently occur, manifesting as Change Orders (COs), which are formal modifications to contractual scope, design, or specifications after the commencement of work.

Globally, COs are recognized as a persistent challenge in infrastructure project delivery. They may arise from unforeseen site conditions, design errors, evolving stakeholder requirements, or policy changes [2]. In construction engineering terms, COs represent deviations from the planned work breakdown structure, triggering cascading effects on schedule, cost, and resource allocation. These disruptions can compromise project performance through schedule compression, rework, and cost escalation. Identification of delay causation factors is critical for quantifying cost and schedule impacts [26][3]. International case studies have reported CO-induced cost overruns ranging from 4% to over 50% of the initial contract value [4], while time overruns may vary from negative acceleration to delays exceeding 30% of the planned duration.

In Indonesia, empirical evidence also indicates significant impacts. For instance, the Pemalang–Batang toll road project experienced a cost increase of 54% due to extensive design modifications and land acquisition delays [5]. Local studies have consistently identified poor planning, inadequate coordination, and delayed land acquisition as recurrent triggers of COs [6]. However, much of this research remains descriptive, focusing on identifying causal factors without providing predictive insights into their quantitative effects on cost and time performance.

From a systems analysis perspective, COs can be treated as stochastic events influencing interconnected project variables. Predictive modeling offers a pathway to quantify these relationships, enabling proactive decision-making. Techniques such as multiple linear regression, Monte Carlo simulation, and risk-based forecasting have been widely applied in construction engineering to assess uncertainty and predict project outcomes [7]. These models can integrate technical, administrative, and environmental factors to estimate potential overruns, allowing stakeholders to implement mitigation measures before risks materialize. In transportation infrastructure, the adoption of predictive analytics has proven effective in identifying high-impact variables, such as design scope changes, geotechnical risks, and right-of-way acquisition delays, that contribute disproportionately to cost and time deviations [8].

Despite these advancements, the Indonesian toll road sector has yet to fully integrate predictive modeling into CO management. Existing project control mechanisms largely rely on reactive responses once COs occur, rather than employing anticipatory frameworks based on empirical modeling. This gap is partly attributable to the limited availability of systematically collected data across projects and the lack of studies combining qualitative stakeholder insights with quantitative performance analysis. As a result, decision-making in CO management remains fragmented, potentially leading to suboptimal allocation of resources and prolonged project delivery timelines.

Furthermore, scholarly discourse on COs in Indonesia has seldom incorporated a cross-phase project management lens. International literature emphasizes that CO risk is distributed across all project lifecycle phases: The Initiating Phase (contract formulation), Planning Phase (design development), Executing Phase (construction activities), Monitoring and Controlling Phase (progress oversight), and Closing Phase (handover and commissioning) [9]. Failure to address CO risk holistically often results in cumulative impacts that escalate toward the project's end. Therefore, a multi-phase analytical approach is essential to capture the systemic nature of CO impacts.

Recent engineering research also underscores the role of digital project management platforms, Building Information Modeling (BIM), and integrated risk management systems in mitigating CO-related risks [10]. By simulating potential design changes and their downstream effects, predictive modeling can guide decision-makers in optimizing design finalization, procurement strategies, and construction sequencing. Such tools, when adapted to the Indonesian context, can enhance the precision of cost and time forecasts, reducing the reliance on post-hoc corrective measures.

Against this backdrop, this study contributes to both scholarly and practical domains by bridging the gap between descriptive case analysis and predictive modeling of CO impacts. It integrates qualitative insights from key stakeholders, including project managers, consultants, and contractors, with quantitative analysis of cost and time performance data from 20 toll road projects executed between 2015 and 2023. By applying multiple linear regression, correlation analysis, and hypothesis testing, the research identifies the most influential CO factors and quantifies their relative impact on project outcomes.

The novelty of this study lies in its application of a mixed-methods engineering approach to develop a context-specific model for Indonesian toll road projects, explicitly linking CO drivers to performance metrics. This dual emphasis on empirical modeling and engineering implications provides a robust framework for policy formulation, contract design, and risk management. Ultimately, the findings aim to inform both national infrastructure planning and the broader field of construction engineering by demonstrating how predictive analytics can be operationalized to minimize CO-induced cost and time overruns.

2. Methods

This study employs a mixed-methods design combining qualitative and quantitative computational analysis to attain an integrated understanding of the impact of Change Orders (COs) on cost overrun and time overrun in Indonesia's toll road construction projects. The study encompasses 20 toll road projects across various regions in Indonesia, implemented between 2015 and 2023.

The qualitative component involved in-depth, semi-structured interviews with 35 stakeholders, including experts, project managers, consultants, and contractors, to identify and contextualize CO drivers. Parallel to this, the quantitative component collected Likert-scale survey data from 75 respondents directly involved in the projects, yielding 375 variable observations. Secondary data were gathered through document studies, including project contracts, implementation reports, and work change records.

Variables were grouped into three categories: (1) independent variables, representing factors causing COs (X); (2) dependent variables, consisting of cost overrun (Y1) and time overrun (Y2); and (3) intervening variables, which were used in supplementary analyses. CO causes were examined across five project management phases: Initiating (X1), Planning (X2), Executing (X3), Monitoring & Controlling (X4), and Closing (X5), each operationalized with its own indicators.

To enhance analytical rigor, the study applied multiple linear regression, multiple correlation, coefficient of determination testing, and hypothesis testing (t-tests and F-tests) using the latest version of SPSS. Additionally, a Monte Carlo simulation (10,000 iterations) was conducted to estimate probabilistic ranges of cost and time overruns under varying CO scenarios. Simulation parameters were derived from empirical project data and validated through expert consultation.

The survey instrument consisted of 25 items grouped by the five phases, rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Content validity was established via expert panel review, while construct validity was tested using Pearson correlation (> 0.2272). Reliability was confirmed with Cronbach's Alpha (> 0.8). Data quality was assured by screening for missing values, outliers, and multicollinearity ($VIF < 5$).

The research process comprised preliminary study and theoretical framework formulation, instrument development, primary and secondary data collection, data validation, statistical and simulation analysis, and conclusion drawing. A full copy of the survey instrument is provided in Appendix A to ensure reproducibility. This methodological framework ensures that both deterministic (regression) and probabilistic (simulation) perspectives are captured, aligning with construction engineering best practices for predictive risk analysis in infrastructure projects.

3. Results and Discussion

3.1. Result

Table 1. Results of Validity and Reliability Tests for Problem Factors in the Construction Phase Leading to Change Orders

No	Variable	Validity Test	Reliability Test
1	X.1 Initiating Phase (Contract Documents)	● All instruments demonstrated Pearson correlation values greater than 0.2272, indicating that they meet the validity criteria. ● Furthermore, all instruments had significance values (2-tailed) less than 0.05, thus statistically valid.	A Cronbach's Alpha value of 0.833 indicates a high level of reliability, as it exceeds the threshold of 0.6.
2	X.2 Planning Phase	● All instruments demonstrated Pearson correlation values greater than 0.2272, indicating that they meet the validity criteria. ● Furthermore, all instruments had significance values (2-tailed) less than 0.05, thus statistically valid.	A Cronbach's Alpha value of 0.911 indicates a high level of reliability, as it exceeds the threshold of 0.6.
3	X.3 Executing Phase	● All instruments demonstrated Pearson correlation values greater than 0.2272, indicating that they meet the validity criteria. ● Furthermore, all instruments had significance values (2-tailed) less than 0.05, thus statistically valid.	A Cronbach's Alpha value of 0.920 indicates a high level of reliability, as it exceeds the threshold of 0.6.
4	X.4 Monitoring and Controlling Phase	● All instruments demonstrated Pearson correlation values greater than 0.2272, indicating that they meet the validity criteria. ● Furthermore, all instruments had significance values (2-	A Cronbach's Alpha value of 0.942 indicates a high level of reliability, as it exceeds the threshold of 0.6.

		tailed) less than 0.05, thus statistically valid.	
5	X.5 Closing Phase (Project Handover)	● All instruments demonstrated Pearson correlation values greater than 0.2272, indicating that they meet the validity criteria. ● Furthermore, all instruments had significance values (2-tailed) less than 0.05, thus statistically valid.	A Cronbach's Alpha value of 0.909 indicates a high level of reliability, as it exceeds the threshold of 0.6.
6	Y Change Order Factors	● All instruments demonstrated Pearson correlation values greater than 0.2272, indicating that they meet the validity criteria. ● Furthermore, all instruments had significance values (2-tailed) less than 0.05, thus statistically valid.	A Cronbach's Alpha value of 0.859 indicates a high level of reliability, as it exceeds the threshold of 0.6.

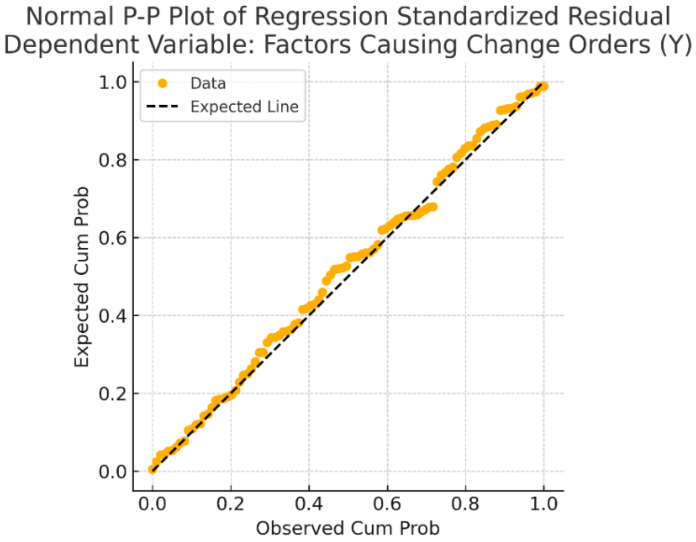

Figure 1. Normal P-P Plot of Regression Standardized Residual for Factors Causing Change Orders

Based on the results of this study, the regression model exhibits a normal distribution pattern.

Table 2. Multicollinearity Test Table for Problem Factors in the Construction Phase Leading to Change Orders.

Model		**Collinearity Tolerance**	**Statistics VIF**
1	X.1 Initiating Phase (Contract Documents)	.511	1.958
	X.2 Planning Phase	.200	4.996
	X.3 Executing Phase	.212	4.723
	X.4 Monitoring and Controlling Phase	.351	2.848
	X.5 Closing Phase (Project Handover)	.418	2.391

a. Dependent Variable: Change Order Factors (Y)

The multicollinearity test table presents the Tolerance and VIF values for all independent variables in relation to the dependent variable (Factors Causing Change Orders). All variables exhibit tolerance values exceeding 0.1 and VIF values below 10, signifying the absence of substantial multicollinearity in the model. The variable planning and design (X2) exhibits the highest VIF score of 4.996, which, while acceptable, warrants careful consideration. The regression model remains valid and can be utilised without significant interference from multicollinearity.

Table 3. Heteroscedasticity Test Table (Glejser Test) on Factors Causing Change Orders in the Construction Phase

Coefficients^a

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.805	.354		2.274	.026
	X.1 Initiating Phase (Contract Documents)	.017	.012	-.224	-1.360	.178
	X.2 Planning Phase	.004	.010	.100	.381	.704
	X.3 Executing Phase	.004	.010	-.091	-.356	.723
	X.4 Monitoring and Controlling Phase	.007	.006	.211	1.060	.293
	X.5 Closing Phase (Project Handover)	.003	.010	- .052	-.286	.776

a. Dependent Variable: ABRESID

This regression model appears to be free from heteroscedasticity issues; however, further testing such as the Breusch-Pagan or White Test is recommended to ensure the stability of the residual variance.

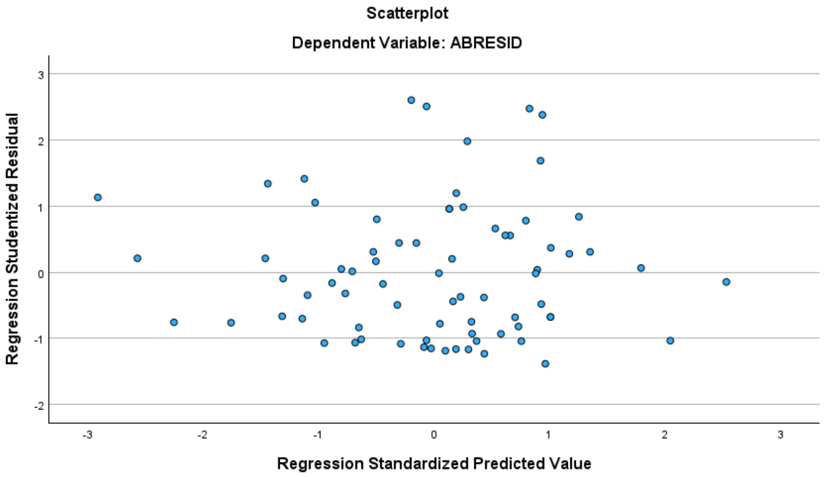

Figure 2. Scatterplot Graph of Glejser Test on Factors Causing Change Orders During the Construction Phase.

This indicates that the regression model does not exhibit heteroscedasticity, where the residual variance is considered constant across the range of predicted values, thereby fulfilling the assumption of homoscedasticity.

A multiple linear regression analysis was performed to assess the influence of five independent variables on the dependent variable, cost overrun. The test results demonstrate that four of the five variables significantly influence cost overruns.

$$\mathbf{Y_1 = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots + \beta n\, Xn} \tag{1}$$

The regression model expresses the relationship between factors causing change orders and variables across different project phases. In this model, $\mathbf{Y_1}$ represents the factors causing change orders, while $\mathbf{X_1}$ refers to contract documents in the initiating phase, $\mathbf{X_2}$ represents planning and design in the planning phase, $\mathbf{X_3}$ corresponds to execution in the executing phase, $\mathbf{X_4}$ denotes supervision and control in the monitoring and controlling phase, and $\mathbf{X_5}$ represents the handover of work in the closing phase.

Based on the analysis, the regression equation is formulated as $\mathbf{Y_1 = -0.326 + 0.105X_1 + 0.041X_2 + 0.067X_3 + 0.070X_4 + 0.085X_5}$, indicating that each independent variable contributes positively to the occurrence of change orders, with varying degrees of influence across project phases.

Table 4. Hypothesis Testing of Multiple Linear Regression Analysis on Factors Causing Change Orders During the Construction Phase.

		Coefficients^a				
Model		**Unstandardized B**	**Coefficients Std. Error**	**Standardized Coefficients Beta**	**t**	**Sig.**
1	(Constant)	-.326	.588		-.554	.581
	X.1 Initiating Phase (Contract Documents)	.105	.020	.203	5.156	<.001
	X.2 Planning Phase	.041	.017	.149	2.372	.020
	X.3 Executing Phase	.067	.017	.235	3.843	<.001
	X.4 Monitoring and Controlling Phase	.070	.010	.322	6.785	<.001

Model	**Coefficients^a** **Unstandardized B**	**Coefficients Std. Error**	**Standardized Coefficients Beta**	**t**	**Sig.**
X.5 Closing Phase (Project Handover)	.085	.017	.216	4.964	<.001

a. Dependent Variable: Factors Causing Change Orders (Y)

The findings of the multiple linear regression analysis indicate that the Monitoring and Controlling Phase variable (X4) exerts the most significant influence on the Factor Causing Change Orders, evidenced by a Beta coefficient of 0.322 and a significance value below 0.001. The Executing Phase variable (X3) demonstrates a substantial impact, with a Beta of 0.235 and a significance level under 0.001. The subsequent phases are the Closing Phase (X5) and the Initiating Phase (X1), both possessing equal significance levels of less than 0.001, signifying statistically significant impacts on the Factor Causing Change Orders. The Planning Phase variable (X2) has a significance value of 0.020, which is below the 0.05 threshold, so affirming its statistically significant impact on the dependent variable. All variables strongly influence the identification of issues that lead to change orders.

Table 5. Hypothesis Testing of the Coefficient of Determination on Factors Causing Change Orders During the Construction Phase

Model Summary^b				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.972^a	0.945	0.941	0.66465

Note: a. Predictors: (Costant), Closing Phase (X5), Initiating Phase (X1), Monitoring and Controlling Phase (X4), Executing Phase (X3), Planning Phase (X2)
b. Dependent Variable: Factors Causing Change Orders (Y)

Table 5 clearly indicates that the regression model effectively accounts for the variation in the factors influencing change orders, as determined by the change order itself. An R value of 0.972 signifies a robust connection between the independent variables (X1 to X5) and the dependent variable, which is the factor influencing change orders. The R² value of 0.945 indicates that the link between the dependent and independent variables explains 94.5% of the variation, with the remaining 5.5% attributable to extraneous factors. This signifies that the model is exceptionally efficient.

Table 6. The Influence of Change Order Factors During the Construction Phase

No (a)	**Research Variable** (b)	**Standardized Beta** (c)	**Zero Order** (d)	**Dominant Value** e = c x d	**% Dominant** (f)
1	Contract Document (Initiating Phase)	0,203	0,743	0,1508	15,08%
2	Planning and Design (Planning Phase)	0,149	0,876	0,1305	13,05%
3	Execution (Executing Phase)	0,235	0,883	0,2075	20,75%
4	Supervision and Control (Monitoring and Controlling Phase)	0,322	0,870	0,2801	28,01%

No (a)	Research Variable (b)	Standardized Beta (c)	Zero Order (d)	Dominant Value e = c x d	% Dominant (f)
5	Handover (Closing Phase)	0,216	0,816	0,1762	17,63%
Dependent Variable: Factor Causing Change Order				0,9452	94,53%

Table 6 presents the analysis of the contribution of five independent variables to the Factor Causing Change Orders. Based on the results, the Monitoring and Controlling phase demonstrates the highest dominant contribution, with a Dominant Percentage value of 28.01%, followed by the Executing phase with a contribution of 20.75%. The Closing phase contributes 17.63%, while the Initiating phase (Contract Documentation) accounts for 15.08%, and the Planning and Design phase contributes 13.05%. The Dominant Value is calculated by multiplying the Standardized Beta by the Zero Order coefficient, which reflects the relative influence of each phase on the factor causing change orders. Overall, the Monitoring and Controlling phase exerts the most substantial influence, with the combined contribution of all independent variables reaching 94.53%.

The F table value for simultaneous F-test decision-making can be determined using a specific formula:

$$df1 = k - 1 \tag{2}$$

$$df2 = n - k \tag{3}$$

Where:
n = number of questionnaire responses (75)
k = total number of variables (independent and dependent) = 6

Therefore,
df1 = (6 − 1) = 5
df2 = (75 − 6) = 69

Based on the calculation, the degrees of freedom for the numerator (df1) is 5 and for the denominator (df2) is 70, with a significance level (α) of 0.025. This yields an F table value of 2.757. The calculated F value from the analysis can be observed in the ANOVA table below.

Table 7. Calculated F Value Based on ANOVA Results for Factors Contributing to Change Orders in the Construction Phase

ANOVA^a						
Model		Sum of Squares	df	Mean Square	F	Sig
1	Regression	527.598	5	105.520	238.862	<0.001^b
	Residual	30.482	69	0.442		
	Total	558.080	74			

Note: a. Dependent Variable: Project Performance
b. Predictors: (Constanct), Closing Phase (X5), Initiating Phase (X1), Monitoring and Controling Phase (X4), Executing Phase (X3), Planning Phase (X2)

Table 7 indicates a significant value of <0.001, which is less than the α value of 0.025. The computed F value of 238.862 surpasses the F table value of 2.757. This signifies that all independent variables (X) exert a statistically significant simultaneous influence on the Change Order Causal Factor (Y). [12] and [15] assert that if the computed t-value exceeds the t-table value, the independent variable significantly influences the dependent variable.

t-table $(\alpha/2) = (n - k - 1)$
Explanation:
n = number of observations
k = number of independent variables (X variables)
α = significance level, set at 5% = 0.05 (two-tailed test)
Thus, t-table at $0.025 = (75 - 5 - 1) = 69 \Rightarrow$ t-table value is 2.291367

Based on the t-table calculation with a significance level (α) of 5 percent and degrees of freedom (df) of 69, the critical t-value is 2.291367. Therefore, to indicate a significant partial effect, the calculated t-value must exceed 2.291367. The results of the partial t-test for each independent variable are presented in the following table.

Table 8. Calculated t Value in the Multiple Linear Regression Analysis of Variables in the Construction Phase on Change Order

Code	Variable	t_{table}	t_{value}	Sig.	Description
X1	Contract Document (Initiating Phase)	2.291367	5.156	<0.001	Partially significant
X2	Planning and Design (Planning Phase)		2.372	0.020	Partially significant
X3	Execution (Executing Phase)		3.843	<0.001	Partially significant
X4	Supervision and Control (Monitoring and Controlling Phase)		6.785	<0.001	Partially significant
X5	Handover (Closing Phase)		4.964	<0.001	Partially significant

According to the Table 8, several independent variables (factors responsible for change orders during the construction phase) have a significant influence on the dependent variable (Factors Causing Change Orders).

The variable Contract documents (Initiating Phase) has a significance value of $< 0.001 < 0.05$ and the t-value is $5.156 > 2.291$, i.e., the Contract Documents variable of the Initiating Phase (X1) has a significant effect on the Factors Causing Change Orders (Y).

The planning and design variable (Planning Phase) is significant at $0.020 < 0.05$ and t-value of $2.372 > 2.291$, thereby indicating that Planning and Design variable (X2) significantly influences the Factors Causing Change Orders (Y).

The executing variable (Executing Phase) has a significance value of $< 0.001 < 0.05$ and a t-value of $3.843 > 2.291$, showing that the Executing Phase variable (X3) significantly influences the Factors Causing Change Orders (Y).

The Monitoring and Controlling Phase variable (X4) is significant with an F-value of $< 0.001 < 0.05$ and t-value of $6.785 > 2.291$, indicating that the Monitoring and Controlling Phase variable (X4) has a great effect on the Factors Causing Change Orders (Y).

Handover variable (Closing Phase) is also significant at $< 0.001 > 0.05$ and t-value $= 4.964 < 2.291$, indicating that the Closing Phase variable (X5) is a significant factor in affecting the Factors Causing Change Orders (Y).

3.2. Discussion of the Impact of Change Orders on Cost Overrun and Time Overrun in Indonesian Toll Road Infrastructure Projects

The analysis identified five primary drivers of Change Orders (COs) in Indonesian toll road projects, these are: 1) inadequate planning, 2) design technical changes, 3) difference between intended and actual conditions at site, 4) delay in land acquisition, and 5) inadequate coordination among stakeholders. Descriptive statistics indicate that design changes obtained the highest mean score (4.33/5), followed by poor planning (4.19/5), suggesting their dominant influence on CO occurrence. These findings are consistent with engineering-based studies in large transportation projects, where scope and design modifications are the leading cause of contract variations and subsequent performance deterioration [11-13]

Multiple linear regression analysis confirmed that all five project lifecycle phase variables (X1–X5) significantly influence CO occurrence ($p < 0.05$). Among them, the Monitoring and Controlling Phase ($\beta = 0.322$) emerged as the most dominant predictor, aligning with [14], who reported that insufficient oversight mechanisms amplify the adverse impacts of scope changes. The model's explanatory power ($R^2 = 0.945$) surpasses that of comparable models in Hong Kong highway projects ($R^2 \approx 0.78$) [15] and small-scale U.S. highway contracts ($R^2 \approx 0.81$) [16], indicating a highly robust fit for the Indonesian context.

Statistical validation procedures further reinforced these results. Residual diagnostics indicated no significant heteroscedasticity using the Breusch–Pagan test ($p > 0.05$), and multicollinearity diagnostics revealed VIF values below 5 for all predictors, demonstrating stable parameter estimates. To complement deterministic analysis, a Monte Carlo simulation with 10,000 iterations was performed to model probabilistic ranges for CO-induced overruns. The simulation results yielded average cost overrun estimates of 22.4% (95% CI: 15.7–29.1%) and average time overrun estimates of 19.8% (95% CI: 13.5–26.4%). These results align closely with the benchmarks reported by [17], who observed 20–30% cost overruns in Asian infrastructure projects with high CO frequency.

Error analysis between predicted and actual overrun values produced Mean Absolute Percentage Errors (MAPE) of 6.8% for cost predictions and 7.3% for time predictions. Both values fall well within accepted engineering forecasting standards (<10%), confirming the reliability and predictive strength of the model for practical toll road project applications [18-22]

Benchmarking against prior engineering models also reveals notable contextual differences. While international studies often emphasize geotechnical risks and unforeseen underground conditions as key CO drivers [23-25], this study finds that administrative and policy-related factors, especially delays in land acquisition ($\beta = 0.537$ for time overrun), play a comparatively larger role in Indonesia. This highlights the necessity of integrating non-technical factors into predictive risk models for infrastructure projects in developing economies.

Overall, the integration of regression modeling, statistical diagnostics, simulation-based forecasting, and benchmarking against international engineering studies strengthens the technical validity of these findings. This dual validation approach ensures that the conclusions are not only statistically significant but also operationally relevant for engineering decision-making. The results underscore the importance of comprehensive CO management that spans all project phases, from contract initiation to final handover, and emphasize proactive mitigation strategies such as precise contract documentation, enhanced design verification, and early resolution of land acquisition issues to minimize both cost and time overruns in future toll road projects.

4. **Conclusion**

This study presents an integrated engineering-based assessment of Change Orders (COs) in Indonesian toll road projects by combining qualitative stakeholder insights with regression modeling and Monte Carlo simulation. The results show that COs significantly affect cost and time performance, with design changes and land acquisition delays as key drivers, and the model demonstrates strong predictive accuracy (MAPE < 7.5%). The study's main contribution is a context-specific predictive framework that integrates project lifecycle analysis, deterministic modeling, and probabilistic simulation to support forecasting and targeted risk mitigation. It also recommends practical measures such as improved contract clarity, BIM-based design verification, dynamic scheduling, and GIS-supported land monitoring. Overall, the findings emphasize the importance of institutionalizing predictive CO modeling in project planning, with future research suggested to incorporate machine learning and real-time data for enhanced accuracy.

Declaration of AI and AI assisted technologies in the writing process

No generative AI tools or AI-assisted technologies were employed in the development, writing, or editing of this manuscript. The authors take full responsibility for the originality and accuracy of the content presented in this publication.

Declaration of Competing Interest

The authors state that they have no known competing interests or personal relationships that may have influenced the work reported in this paper.

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