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The Effect of Building Area and Cost on the Accuracy of Cost Estimation in State Buildings

Djoko Subagijo[1], Imam Wahyudi[2], Jujuk Kusumawati[3]
[13]Institut Teknologi Budi Utomo, Indonesia
[2]Universitas Islam Sultan Agung, Indonesia
Correspondent: djokosubagijo@gmail.com[1]

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ABSTRACT: Accurate cost estimation during the conceptual stage is crucial in ensuring effective budget allocation and reducing financial risks in government building projects. In Indonesia, especially Jakarta, the cost estimation process for government buildings is essential to optimize resource distribution. However, challenges persist in improving the precision of these estimations, particularly regarding how building area and construction cost impact the estimation process. This study employs multiple regression analysis to examine the relationship between the building area, construction cost, and the accuracy of conceptual cost estimations in Indonesian government building projects. The study was conducted using a sample of 100 completed projects in Jakarta. The regression analysis results reveal that both the building area and construction cost significantly negatively impact cost estimation accuracy, with a combined explanatory power of 58%. An increase in the building area and construction cost corresponds to more significant deviations in the estimated cost from the actual figures. The study highlights the need for more advanced estimation methodologies and standardized practices to improve accuracy in cost estimation. The findings offer practical recommendations to policymakers and construction professionals, suggesting ways to enhance cost estimation accuracy in the public sector, ultimately leading to better resource allocation and more successful project outcomes.

Keywords: Cost Estimation, Government Buildings, Building Area, Building Cost, And Construction Accuracy.

INTRODUCTION

Cost estimation is one of the most essential elements of any construction project; this aspect becomes all the more pivotal in the public sector owing to accountability in terms of finance (Ali et al., 2022; Y. Zhang et al., 2023). In other words, precise cost estimations during the conceptual phase facilitate proper budgeting of the projects concerning the government and simultaneously limit any risk arising out of excessive cost escalation, undue delays, and project scope reductions (Ali et al., 2022; Saeidlou & Ghadiminia, 2024). It should also be realized that exact conceptual cost estimates may hardly ever be feasible with only the least available data or because most construction variables change rapidly (Irwanto et al., 2023; Y. Zhang & Mo, 2024).

In Indonesia, government buildings, such as offices, public facilities, and infrastructure, are financed mainly by the state and regional budgets, or APBN and APBD (Arifin & Binardjo, n.d.; Aslam et al., 2024; Waliulu, 2022)Regarding the above, the estimated cost in the conceptual stage, for example, shall cover several essential parameters such as building area, building type, and cost classification based on the Ministry of Public Works and Housing Regulation No. 8 of 2023. However, even with guidelines, cost estimation errors are still a significant problem that causes many budget adjustments, scope changes, and functionality reductions.

The phenomenon in the field shows that despite regulations such as Permen PUPR No. 8 of 2023, which regulates cost estimation on government building projects, many projects still experience cost estimation errors at the conceptual stage. These errors result in budget overruns, project delays, and a decrease in the quality of the final result. Data shows that government building projects often experience significant deviations between initial estimates and actual costs, especially in large or high-complexity projects. This indicates a gap in the estimation methods, especially in accommodating essential variables such as building area and construction cost.

Previous research has discussed cost estimation models with various approaches, such as neural network methods (El-Sawalhi & Shehatto, 2014) and regression models (Dursun & Stoy, 2016). However, research that specifically examines the combined impact of building area and construction cost on the accuracy of cost estimation of government projects in Indonesia is still limited. This study offers a new approach by using multiple regression models to identify the relationship between these variables, which is expected to provide practical recommendations to improve cost estimation accuracy in government building projects. The uniqueness of this research is its focus on the local Indonesian context, including specific regulatory factors and market dynamics.

Cost estimation accuracy at the conceptual stage is critical in government building projects, as this is where effective budgeting and resource allocation occur. Any error in estimation at this stage results in substantial financial and operational risks, such as cost overruns, delays, and compromised building functionality. (Dursun & Stoy, 2016; Sheikhkhoshkar et al., 2019). This is urgent, considering that in Indonesia, all public funds are accountable to the national and regional budgets, APBN and APBD. (Ali et al., 2022)Due to the increasing complexity of the construction industry, Estimation models should be more robust, including variables such as building area and construction costs. (Atapattu et al., 2022; Saeidlou & Ghadiminia, 2024)The estimation gap is necessary for the project's feasibility, sustainability, and public trust.

Even with set guidelines, inaccuracies in conceptual cost estimation still prevail, leading to numerous budget discrepancies and inefficiencies during government building projects (Fazil et al., 2021;

Thakuria & Parida, 2022). Most current estimation models do not consider essential parameters like building area and cost, which are critical in enhancing accuracy (Alkhuadhan & Naimi, 2023; Saeidlou & Ghadiminia, 2024). Such inaccuracies might result in risks like reduced scope, low-quality construction, and delays in the project that will hamper the long-term functionality and sustainability of government buildings. Also, subjective judgment and experience characterize the current estimation practices (Fazil et al., 2021; Shah & Gopinath, 2023)—the lack of standard approaches and heavy reliance on these results in variability between projects and stakeholders.

This study focuses on the two most important variables, building area and building cost, as the main determinants of cost estimation accuracy. Building area is a base parameter in calculating a project's costs, whereas building cost represents the classification of materials, structural complexity, and design standards. Both variables are interrelated, and their relationship significantly impinges on the reliability of the cost estimates.

It looks into how building area and building cost impact the estimate's accuracy in the conceptual cost estimation of government buildings. By applying parametric modeling and multiple regression analysis, this study attempts to identify factors critical in explaining estimation accuracy and thus provide new pathways that can potentially help improve the cost estimation process in public construction projects.

METHODS

This quantitative research design seeks to test the effect of building area and building cost on the accuracy of conceptual cost estimation in government building projects. The correlational design will explain how independent variables, including building area and building cost, will affect the dependent variable, that is, cost estimation accuracy. Multiple regression analysis is the primary statistical method used to determine these relationships.

The population of this study includes government building projects in Indonesia initiated and funded from the national (APBN) or regional (APBD) budgets from 2013 until 2023. The sample consists of 100 completed projects in Jakarta, which were selected by applying purposive sampling to ensure the availability and relevance of data. Inclusion criteria for projects include:

a. Belong to the category of government buildings according to Permen PUPR No. 22/2018.
b. Completed within the defined timeframe, namely 2013–2013.
c. Availability of detailed records on building area, building cost, and cost estimation data.

The study will utilize two types of data: primary data from structured questionnaires administered to construction project managers and professionals involved in the cost estimation of the sampled projects and secondary data from project documents such as cost estimation reports, detailed budgets, and project completion records.

The independent variables in this study are Building Area (X_1) in square meters (m^2), as measured in the project records, and Building Cost (X_2) in Indonesian Rupiah (IDR)/square meter, reflecting the cost of materials, labor, and overheads. The dependent variable is the Accuracy of Cost Estimation (Y).

Data were analyzed in several stages, namely, descriptive analysis of the characteristics of the sample concerning averages, standard deviation, and frequency distribution-classical assumption tests to validate some of the critical assumptions underlying the regression model and correlation analysis, which involved checking relationships among building area, building cost, and estimation accuracy. (Ghozali, 2018). Tests the hypotheses by finding out how building area and cost jointly and individually account for the variation in cost estimation accuracy. The regression model can now be expressed as:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \epsilon$$

Where,

Y: Cost estimation accuracy

X1: Building area

X2: Building cost

β0, β1, β2: Regression coefficient

ϵ: Error term

RESULTS AND DISCUSSION

Descriptive Analysis

The sample of 100 government building projects represents a wide range of building types and sizes, and descriptive statistics are used to outline the profile of the key variables: building area, building cost, and accuracy in cost estimation.

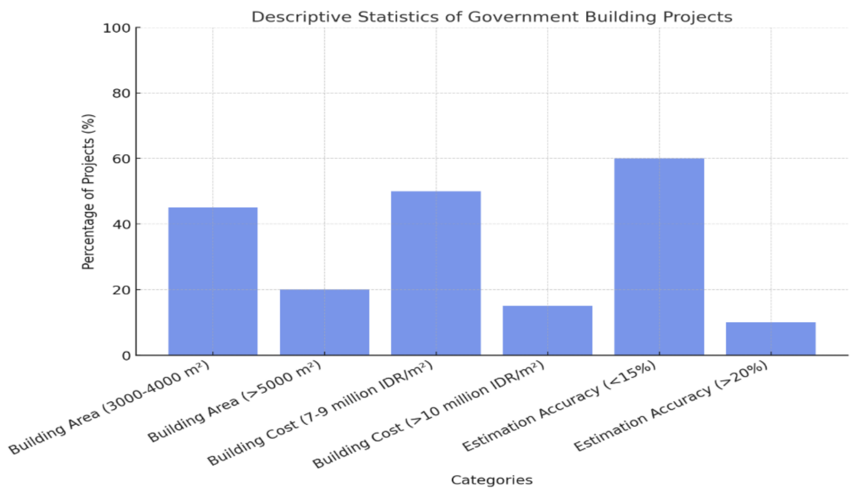

Figure 1. Descriptive Statistics

The average area per building was 3,500 m², ranging from 1,200 m² to 7,500 m², with a standard deviation of 1,200 m², indicating moderate dispersion in the building sizes. The average cost of the building was IDR 8.5 million/m², ranging between IDR 5.0 million/m² and IDR 12.0 million/m², with a standard deviation of IDR 2.0 million/m², reflecting differences in material, labor, and ways of construction. The average estimation accuracy was 12%, varying between 2% for a high level of accuracy and 25% for a low level, with a standard deviation of 5%, reflecting variations in the fit between estimated and actual costs. Around 45% of the projects had building areas between 3,000 m² and 4,000 m², while 20% were above 5,000 m². About 50% of the projects had building costs between IDR 7.0 million/m² and IDR 9.0 million/m², with 15% above IDR 10.0 million/m². Besides, 60% of the projects reached accuracy deviations below 15%, with only 10% exceeding deviations of 20%. These statistics form the basis for understanding the dataset and highlight inherent variability in government building projects.

Classical Assumption Test

Before the regression analysis, tests for various classical assumptions were performed to ensure the regression model's acceptability and reliability. The tests conducted were normality, multicollinearity, heteroscedasticity, and autocorrelation.

Table 1. Classical Assumption

Test	Method	Statistic / Value	Threshold	Interpretation
Normality Test	Kolmogorov-Smirnov	$p = 0.214$	$p > 0.05$	Residuals are normally distributed
Multicollinearity (X_1)	VIF	1.25	VIF < 10	No multicollinearity

Multicollinearity (X_2)	VIF	1.30	VIF < 10	No multicollinearity
Heteroscedasticity Test	Breusch-Pagan	p = 0.089	p > 0.05	No heteroscedasticity
Autocorrelation Test	Durbin-Watson	DW = 1.92	1.5 < DW < 2.5	No autocorrelation

Source: Data processed by the author (2024)

The results of the classical assumptions tests for this study ensured the appropriateness of using the regression model. The K-S test for normality was performed on residuals and presented with a p-value of 0.214, above the 0.05 significance limit, indicating that the residuals will be normally distributed. Multicollinearity: VIF and tolerance values indicate that building area (X1) and building cost (X2) have VIF values less than 10 and tolerance values greater than 0.1, indicating no multicollinearity. The Breusch-Pagan test for heteroskedasticity resulted in a p-value of 0.089, more significant than 0.05, confirming that heteroskedasticity is not part of this data. The result for the Durbin-Watson autocorrelation test is 1.92 and falls within the acceptable range from 1.5 to 2.5; hence, there is no autocorrelation. Preceding results mean that the regression model satisfies assumptions of normality, multicollinearity, heteroscedasticity, and autocorrelation; therefore, the analysis is reliable.

Multiple Linear Regression Analysis Results

This is supposed to carry the relation between the independent variables- building area- and building cost, which is the dependent variable, that is, the accuracy of the cost estimate. The equation provides the multiple linear regression analysis results and is summarized in the following table:

Table 2. Multiple Regression

Variable	Coefficient (β\betaβ)	Standard Error	t-value	p-value
Constant	25.35	2.52	10.122	0.000**
Building Area (X1X_1X1)	-0.005	0.001	-5.00	0.000**
Building Cost (X2X_2X2)	-0.020	0.004	-5.00	0.000**

Source: Data processed by the author (2024)

This means that one unit increase in the building area fraction, X1 of 1 m2, contributes negatively towards a decrease in the estimation accuracy by 0.005%. In contrast, a unit rise in the building cost X2 of IDR 1 million/m2 cuts the estimation accuracy by 0.02%, indicating that projects with higher costs are generally associated with more estimation errors. These results confirm that building area and cost significantly impact the cost prediction regarding any construction project. The model summary conveys the overall fit of the regression model:

Table 3. Model Estimation

Metric	Value
R2	0.58
Adjusted R2	0.57

F-statistic	68.00
p-value (F-test)	0.000**

Source: Data processed by the author (2024)

The regression model has an R2 of 0.58, showing that the independent variables explain 58% of the variance in cost estimation accuracy. Moreover, the F-statistic with a value of 68.00 and $p<0.01$ also states that the model is statistically significant and that building area and building cost together significantly influence cost estimation accuracy.

The results of this study indicate that building area and construction cost significantly affect cost estimation accuracy. Estimation inaccuracies often lead to budget overruns, delays, or changes in project scope. Therefore, improving estimation accuracy is essential to ensuring budget efficiency and smooth implementation of government development projects.

For project managers, the findings emphasize the need for more accurate estimation methods, especially for large-scale and high-value projects. Factors such as fluctuations in material prices, design complexity, and cost classification standards need to be considered. In addition, budget planning policies should be more flexible to anticipate differences between estimated and realized costs during the project.

Data-based models such as parametric estimation and predictive algorithms should be applied to improve estimation accuracy. Standardization of estimation methods according to regulations should also be strengthened, supported by an integrated project cost database. Training estimators on technologies such as *Building Information Modeling* (BIM) and close monitoring of cost changes will help reduce the risk of estimation inaccuracies and budget overruns.

Results have shown a significant inverse relationship between the building area and estimation accuracy: $\beta = -0.005$, $p < 0.01$. This means large areas have more considerable estimation deviations. This again supports (Enshassi et al., 2005; Lim et al., 2016; Zhang Klingberg & Remadi, 2014), where it is stated that the larger a project is, the greater the complexities will be in increasing the level of resources, time length, and probabilities of design changes. In most cases, such situations increase the chances of cost estimate deviation.

In the case of government building projects, the results indicate that more sophisticated tools, such as parametric estimation models, exist for estimating larger and more complex buildings. Including some factors, such as the zoning requirements and functional design variations, would make the estimate more accurate.

Estimation accuracy was also significantly negatively related to building cost ($\beta = -0.02$, $p < 0.01$). Estimation accuracy is difficult to achieve with the influence of material prices, labor rates, and technological requirements on higher building costs. This result confirms (Chimdi et al., 2020; Hatamleh et al., 2018; Q. Zhang, 2024) Assertion that fluctuating market conditions and material availability could impact cost predictions.

In Indonesia, these regional cost variations and the lack of uniform cost classification frameworks may exacerbate estimates' inaccuracies. Improved data collection and management systems are needed to update cost variables regularly and enable estimators to make timely decisions.

These two factors together result in the area and cost for 58% of the variance in estimation accuracy, with R2 = 0.58. This would imply that these two variables are the most influencing factors determining conceptual cost estimates' reliability. The regression model underlines the necessity of combining the factors within an integrated framework for improving predictive accuracy.

The findings support the work of (Li et al., 2016; Pessoa et al., 2021; Yılmaz, 2020), who has advocated for multi-variable models in public construction projects. Such models reduce bias and provide a holistic view of project dynamics, especially large-scale and high-cost government buildings.

These findings indeed confirm the previous results of similar studies, such as (Tas & Yaman, 2005) and (Elmousalami, 2020), which have established large-scale projects with high costs, can complicate estimation accuracy. This study's added value is that it addressed government building projects in Indonesia, covering localized regulatory and economic factors that impact cost estimation.

Practical Implications

1. The findings underline that the government should develop guidelines, including building area and cost, as standardized parameters in estimation frameworks. Improved regulations, such as Permen PUPR No. 8/2023, would give a real boost to accuracy.
2. Estimation professionals must be trained in sophisticated methodologies, such as parametric and machine learning models, to handle large projects with complex data. Workshops and certifications increase their competencies in state-of-the-art cost estimation practices.
3. Centrally stored historical databases of project costs and performances are invaluable in making estimates more accurate. The latter can benchmark the costs against others in a particular category to recognize patterns. This helps in early estimation with fewer uncertainties.

CONCLUSION

The results of this study show that building area and construction cost significantly impact the accuracy of government project cost estimation. The larger the building area, the greater the deviation in cost estimation as the complexity of design and execution increases. Similarly, projects with high construction costs tend to have more significant estimation inaccuracies due to fluctuations in material and labor prices. These two factors explain 58% of the variation in cost estimation accuracy, suggesting that this aspect is crucial in the budget planning process of government projects.

Based on these findings, the government needs to develop a more comprehensive cost estimation guideline that includes building area and construction cost variables as the leading standards in budget calculations. Standardization of estimation methods, such as using data-based models and predictive algorithms, should be strengthened to minimize estimation errors. In addition, integrating the national project cost database is required to compare similar projects to improve estimation accuracy. Enhancing the capacity of estimators through technology training, such as Building Information Modeling (BIM), is also a strategic step in enhancing the reliability of cost estimation.

This research has limitations because it only focuses on government projects in Jakarta. Future research can expand the coverage area to other regions in Indonesia with different economic conditions and policies to better understand the factors influencing cost estimation accuracy. In addition, further research can explore other variables, such as project complexity, contractor performance, or procurement regulations, that may affect cost estimation accuracy. Testing more sophisticated estimation models by considering macroeconomic factors can also be a future research direction to improve the efficiency of government project budgets.

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