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Road Maintenance Model In Bogor City Using Sem-Pls Analysis

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Abstract

Road maintenance is an important aspect of maintaining the level of service of transportation infrastructure. However, its implementation still faces various obstacles that lead to declining road quality, cost overruns, and low effectiveness of maintenance programs. This study aims to analyze the factors influencing road maintenance cost estimation and to develop a road maintenance model based on *Structural Equation Modeling–Partial Least Squares* (SEM-PLS)**.** The study used a quantitative approach through a survey of 226 respondents consisting of construction service providers, supervisory consultants, and government agencies involved in road maintenance work. Data were collected using a five-point Likert-scale questionnaire and analyzed with SmartPLS. The analysis included measurement model (outer model) testing through convergent validity, discriminant validity, and construct reliability tests, as well as structural model (inner model) testing to examine the relationships among variables. The results show that all constructs met the validity and reliability criteria, with outer loading > 0.70, *Average Variance Extracted* (AVE) > 0.50, and *Composite Reliability and Cronbach's Alpha* > 0.70. Structural model testing shows that material and equipment costs, labor, traffic conditions, planning/design quality, drainage conditions, and external factors have a significant effect on road maintenance cost estimation, with maintenance strategy acting as a mediating variable. The resulting model is expected to serve as a basis for decision-making in formulating more effective, efficient, and sustainable road maintenance strategies. The findings are expected to serve as a reference for local governments and road managers in improving the quality of data-driven decision-making in road maintenance programs

Keywords: *road maintenance, SEM-PLS, cost estimation, maintenance strategy, road projects*

INTRODUCTION

Roads are a transportation infrastructure asset with a strategic role in supporting community mobility, the distribution of goods and services, and the economic growth of a region. A well-performing road network contributes to improved connectivity, logistics cost efficiency, and more equitable development. Road maintenance is therefore an essential activity for keeping roads in serviceable condition so that they continue to meet technical standards throughout the infrastructure's service life. Maintenance carried out in a timely and well-targeted manner can extend pavement life, improve road-user safety, and reduce the need for rehabilitation or reconstruction, which requires far greater cost (World Road Association/PIARC, 2023) [1], [2].

The implementation of road maintenance still faces various challenges. Budget constraints, fluctuations in construction material prices, labor productivity, increasing traffic volumes, drainage system deterioration, changing climate conditions, and weak planning are the factors that drive up the cost of road maintenance. These conditions cause discrepancies between estimated and actual costs, potentially reducing the effectiveness of maintenance programs and the quality of road service (Shahhosseini et al., 2021; World Bank, 2024). In addition, changes in material prices caused by global supply chain disruptions have also had a significant impact on cost overruns in infrastructure projects, including road maintenance work [3], [4].

Road maintenance cost estimation generally still relies on a deterministic approach based on unit work prices and practical experience. This approach cannot accommodate the complex relationships among technical, managerial, economic, and environmental factors that simultaneously influence maintenance costs. Meanwhile, road maintenance projects are characterized by interactions among many interrelated variables, requiring an analytical approach capable of explaining both direct and indirect relationships among variables [5], [6], [7].

Most previous studies have focused on cost prediction using conventional statistical methods or *machine learning* algorithms such as Artificial Neural Network, Random Forest, and XGBoost. These approaches have proven to have high predictive power, but most only produce estimated values without explaining the causal relationships among the factors influencing maintenance costs [8], [9], [10], [11], [12], [13]. On the other hand, research applying *Structural Equation Modeling–Partial Least Squares (*SEM-PLS) in the field of road maintenance remains relatively limited, particularly research that integrates material and equipment costs, labor, traffic conditions, planning/design quality, drainage conditions, and external factors, together with maintenance strategy as a mediating variable, in building a road maintenance cost estimation model[6], [14], [15], [16].

SEM-PLS is a multivariate analysis method capable of analyzing simultaneous relationships among latent constructs and testing complex models, and it is well suited to applied research aimed at developing predictive models. The method's strengths include accommodating data that are not fully normally distributed, handling large numbers of indicators and constructs, and being effective for both theory development and decision-making in construction management [5], [17], [6].

Given these conditions, this study aims to analyze the influence of material and equipment costs, labor, traffic conditions, planning/design quality, drainage conditions, and external factors on road maintenance cost estimation, with maintenance strategy considered as a mediating variable. The study was conducted with 226 respondents consisting of construction service providers, supervisory consultants, and government agencies, using the SEM-PLS approach. The main contribution of this study is a structural model capable of comprehensively explaining the relationships among the factors influencing road maintenance cost estimation. The resulting model is expected to serve as a basis for decision-making in formulating more effective, efficient, and sustainable road maintenance strategies, and to support data-driven road asset management (*data-driven asset management*).

METHOD

The research began with problem identification through a literature review of the factors influencing road maintenance costs. The literature review results were used as the basis for formulating the research variables, which comprise material and equipment costs (X1), labor (X2), traffic conditions (X3), planning/design quality (X4), drainage conditions (X5), external factors (X6), maintenance strategy (Z), and road maintenance cost estimation (Y).

The research instrument was a questionnaire using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Before the questionnaire was distributed, a content validity test was conducted (*content validity*) through discussions with academics and road-sector practitioners to ensure that each indicator adequately represented the construct being measured.

The survey was conducted with 226 respondents consisting of contractors, supervisory consultants, and government agencies with experience in road maintenance work. The sampling technique was purposive sampling, in which respondents were selected based on their experience and direct involvement in road maintenance projects.

2.1 Data Analysis

Data analysis was performed using SmartPLS 4 software through two main stages: evaluation of the outer model and inner model.

a. Outer Model Evaluation

The measurement model was used to evaluate the quality of indicators and constructs through:

1) Outer Loading ≥ 0.70
2) Average Variance Extracted (AVE) ≥ 0.50
3) Composite Reliability (CR) ≥ 0.70
4) Cronbach's Alpha ≥ 0.70

b. Inner Model Evaluation

The structural model was evaluated using:

1) Path Coefficient
2) R^2
3) Bootstrapping with 5,000 subsamples at a significance level of 5% to obtain t-statistics (>1.96) and p-value (<0.05).

In addition to testing the direct effect of each exogenous variable on road maintenance cost estimation, this study tested the indirect effect through maintenance strategy as a mediating variable.

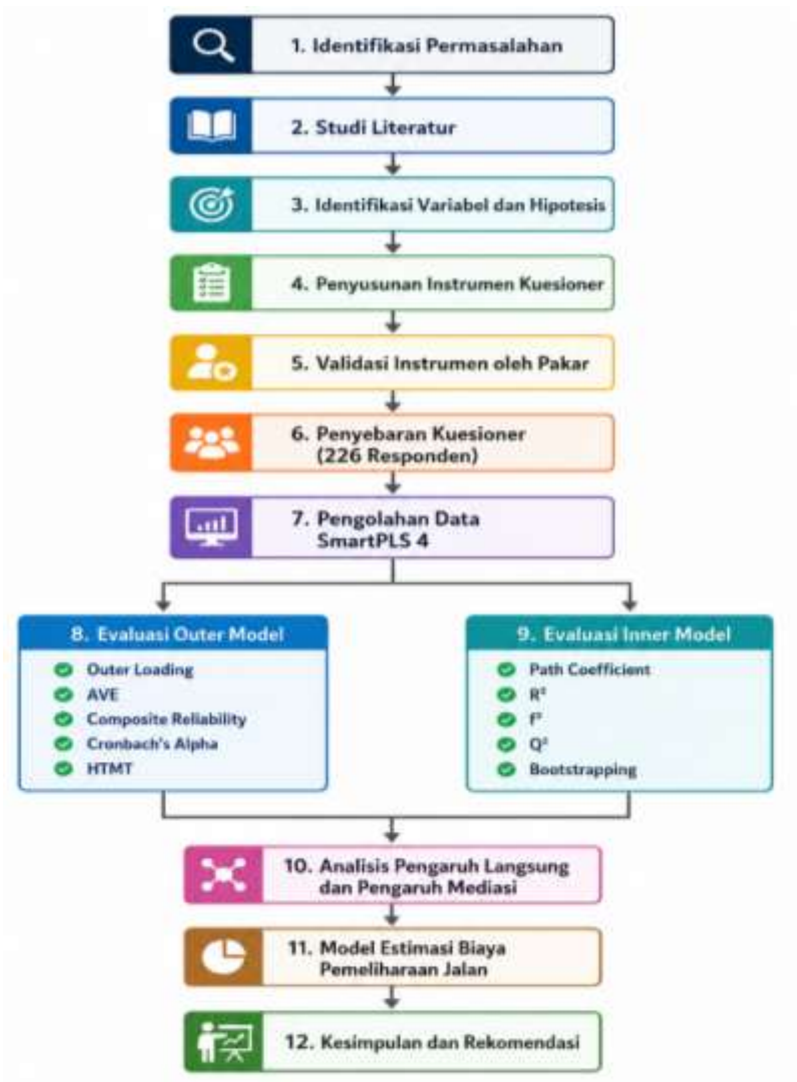

Figure 1. Research flowchart

2.2. Conceptual Research Model

The research model consists of six exogenous variables, one mediating variable, and one endogenous variable, namely:

a) X1 = Material and Equipment Costs
b) X2 = Labor
c) X3 = Traffic Conditions
d) X4 = Planning/Design Quality
e) X5 = Drainage Conditions
f) X6 = External Factors
g) M= Maintenance Strategy (Mediator)
h) Y = Road Maintenance Cost Estimation

All exogenous variables were tested for their direct effect on the endogenous variable, as well as for their indirect effect through the maintenance strategy variable as a mediator, using the SEM-PLS approach.

RESULTS AND DISCUSSION

a. Respondent Profile

The 226 respondents consisted of contractors (37%), government (30%), consultants (20%), and academics (20%).

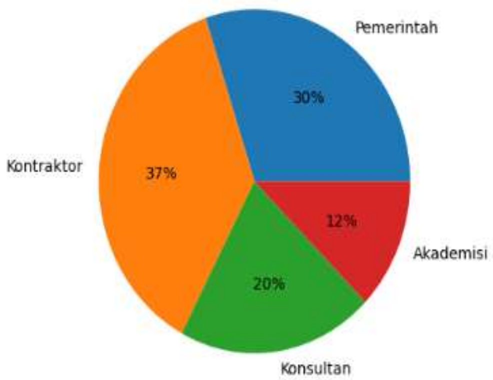

Figure 2. Respondent profile

Figure 2. shows that the composition of respondents was dominated by contractors and government agencies, which are the main stakeholders in the implementation and management of road maintenance activities. The dominance of these two groups indicates that most of the data were obtained from individuals with experience, knowledge, and direct involvement in the planning, implementation, supervision, and control of road maintenance activities. Accordingly, the information provided by respondents is expected to represent actual conditions in the practice of road infrastructure management in the field.

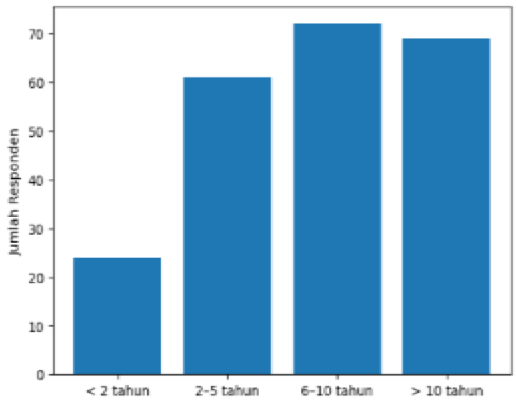

Figure 3. Respondent experience

Based on the chart in Figure 3, the majority of respondents have more than five years of work experience. This indicates that respondents have an adequate understanding of the characteristics of road maintenance projects, including technical, managerial, and cost aspects. Accordingly, the data obtained are considered representative and can be used as the basis for the research analysis.

Table 1. Loading Factor for the Material and Equipment Variable (X1)

Indicator	*Loading Factor*	*t-value*	R^2
X1.1	0.71	3.53	0.31
X1.2	0.89	5.58	0.64
X1.3	0.79	4.47	0.46
X1.4	0.74	4.43	0.45
X1.5	0.85	3.42	0.30
X1.6	0.77	5.11	0.56

Table 2. Loading factor for Variable X2 (Labor Costs)

Indicator	*Loading Factor*	*t-value*	R^2
X2.1	0.83	3.28	0.30
X2.2	0.84	3.40	0.32
X2.3	0.72	4.13	0.46
X2.4	0.78	4.85	0.61
X2.5	0.81	2.27	0.16

Table 3. Loading factor for the Traffic Conditions Variable (X3)

Indicator	*Loading factor*	*t-value*	R^2
X3.1	0.88	2.75	0.23
X3.2	0.79	3.72	0.40
X3.3	0.83	3.87	0.43
X3.4	0.74	3.78	0.41
X3.5	0.85	3.10	0.29

Table 4. *Loading factor* for the Planning/Design Quality Variable (X4)

Indicator	*Loading factor*	t-value	R^2
X4.1	0.73	3.21	0.30
X4.2	0.84	3.37	0.32
X4.3	0.74	4.19	0.49
X4.4	0.77	4.62	0.59

Table 5. Loading factor for the Drainage Conditions Variable (X5)

Indicator	*Loading factor*	t-value	R^2
X5.1	0.81	2.89	0.27
X5.2	0.83	3.06	0.31
X5.3	0.80	4.12	0.65
X5.4	0.73	2.32	0.18

Table 6. Loading factor for the External Factors Variable (X6)

Indicator	*Loading Factor*	*t-value*	R^2
X6.1	0.76	3.86	0.36
X6.2	0.76	6.22	0.77
X6.3	0.86	2.80	0.21
X6.4	0.75	3.74	0.35
X6.5	0.73	4.03	0.39
X6.6	0.82	3.91	0.37

Table 7. Loading Factor for the Cost Estimation Model Variable (Y)

Indicator	*Loading Factor*	*t-value*	R^2
Y1	0.43	3.28	0.30
Y2	0.44	3.40	0.32
Y3	0.78	4.85	0.61
Y4	0.41	2.27	0.16
Y5	0.72	4.13	0.46

Table 8. Reliability test results

Variable	*Cronbach's Alpha*
Material and equipment costs (X1)	0.955
Labor costs (X2)	0.926
Traffic conditions (X3)	0.952
Planning/design quality (X4)	0.944
Drainage conditions (X5)	0.964
External factors (X6)	0.963
Maintenance strategy (XM)	0.948
Cost estimation model (Y)	0.953

Table 8 above shows the Cronbach's Alpha value for each variable; all constructs show values above 0.7, indicating that all variables are declared reliable. The measurement model (outer model) was evaluated through indicator validity and construct reliability tests. Convergent validity was assessed using loading factor values, while construct reliability was evaluated using Cronbach's Alpha. As presented in Tables 1–8, all indicators satisfied the recommended validity criteria, and all constructs achieved Cronbach's Alpha values greater than 0.70, indicating satisfactory internal consistency. These results confirm that the measurement model is reliable and appropriate for further evaluation of the structural relationships among the research constructs.

Before evaluating the structural relationships, the collinearity among the predictor constructs was considered to ensure that the proposed analytical model met the required assumptions for structural analysis. Collinearity assessment is an important step in SEM-PLS because excessive collinearity may bias the estimation of structural relationships among latent variables. The evaluation confirmed that the predictor constructs were assessed prior to structural model interpretation, thereby supporting the robustness of the proposed research framework.

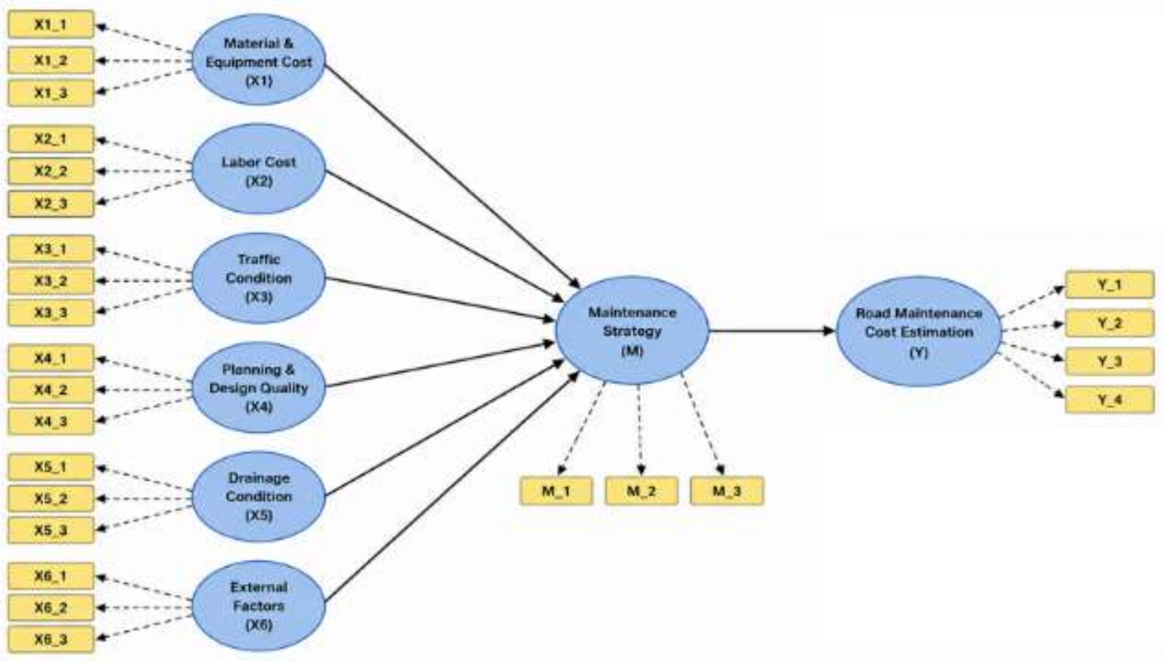

Figure 4. Proposed SEM-PLS Structural Model for Road Maintenance Cost Estimation

Figure 4 presents the proposed SEM-PLS structural model developed in this study. The model illustrates the hypothesized relationships among the six exogenous constructs, namely material and equipment cost, labor cost, traffic condition, planning and design quality, drainage condition, and external factors, which influence road maintenance cost estimation through the mediating role of maintenance strategy. This structural representation provides a clearer understanding of the proposed relationships before evaluating the empirical results of the model.

Table 9. Summary of descriptive statistics

	X1	X2	X3	X4	X5	X6	XM	Y
Mean	25.31	22.40	21.06	16.93	18.31	25.02	22.48	21.33
Median	27.00	24.00	23.00	17.00	20.00	27.00	24.00	22.00
Mode	30	25	23	20	20	24	24[a]	25
Std. Deviation	5.256	4.445	4.424	3.542	3.775	5.187	4.577	4.330
Variance	27.621	19.762	19.574	12.542	14.252	26.902	20.953	18.746
Range	24	20	20	16	16	24	20	20
Minimum	6	5	5	4	4	6	5	5
Maximum	30	25	25	20	20	30	25	25

Table 9 presents a summary of the descriptive statistics for X1–X6, XM, and Y, showing the mean, median, and mode values, followed by the standard deviation. Each variable is described as follows:

1. Variable X1 has a *mean of* 25.31**,** indicating that the average respondent score is relatively high. The *median of* 27 and *mode of* 30 indicate that scores tend to

cluster at the upper values. Data dispersion is moderate, with a standard deviation of 5.256 and *range of* 24 (minimum 6, maximum 30).

2. Variable X2 shows a *mean of* 22.40, with a *median of* 24 and *mode of* 25 both above the mean. This indicates a distribution slightly skewed toward higher scores. Data variability is fairly stable, as shown by a standard deviation of 4.445 and
3. Variable X3 has a *mean of* 21.06**,** with a *median of* 23 and mode of 23, indicating that most respondents tended to give scores higher than the mean. Data dispersion is moderate, with a standard deviation of 4.424 and *range of* 20 (5–25).
4. Variable X4 has the lowest *mean*, at 16.93**,** with a *median of* 17 and mode of 20**.** This indicates that scores tend to fall in the middle category. Data variability is relatively small, as reflected by a standard deviation of 3.542 and *range of* 16 (4–20).
5. Variable X5 has a *mean of* 18.31, with a *median of* 20 and *mode of* 20**,** indicating that scores tend to be relatively higher than the mean. Data variation is moderate, with a standard deviation of 3.775 and *range of* 16 (4–20).
6. Variable X6 shows a *mean of* 25.02, *median of* 27, and *mode of* 24**,** reflecting consistent scores in the upper-middle category. Data dispersion is moderate to high, with a standard deviation of 5.187 and *range of* 24 (6–30).
7. Variable XM has a *mean of* 22.48, with a *median of* 24 and *mode of* 24, indicating that scores tend toward the upper values. Data variability is fairly stable, marked by a standard deviation of 4.577 and *range of* 20 (5–25).
8. Variable Y has a *mean of* 21.33, with a *median of* 22 and *mode of* 25, indicating that values are predominantly in the upper-middle category. Data variation is moderate, as seen from a standard deviation of 4.330 and *range of* 20 (5–25).

After confirming the adequacy of the measurement model, the structural model (inner model) was evaluated to examine the relationships among the latent variables. The assessment focused on the significance of the structural paths and the explanatory power of the model, represented by the regression coefficients and the coefficient of determination (R^2). The structural model evaluation provides evidence regarding the contribution of each independent variable to road maintenance cost estimation.

Table 10. Results of the first regression test for each factor

Coefficients[a]				
Model	***Unstandardized Coefficients***		**t**	**Sig.**
	B	***Std. Error***		
Constant	-0.308	0.065	-4.715	0.000
X1	-1.081	0.057	-18.819	0.000
X2	0.097	0.017	5.767	0.000
X3	0.736	0.049	14.884	0.000
X4	0.166	0.018	9.418	0.000
X5	0.970	0.015	64.042	0.000
X6	0.476	0.031	15.602	0.000
a. *Dependent Variable*: Y				

Table 10 shows the regression test results for each factor, yielding the constant and the coefficient of each of the variables X1–X6. *R Square* value of 0.998, as shown in Table IV.45 indicates that variables X1, X2, X3, X4, X5, and X6 simultaneously make an effective contribution of 99.8% to variable Y. This means the regression model has very strong predictive ability, while the remaining 0.2% is influenced by other variables outside the study.

The findings indicate that material and equipment costs, labor costs, traffic conditions, planning and design quality, drainage conditions, and external factors significantly influence road maintenance cost estimation. These results are generally consistent with previous studies, which reported that technical, operational, and environmental factors are among the primary determinants of maintenance planning and budgeting. The consistency of these findings suggests that road maintenance cost estimation requires an integrated assessment of both engineering and managerial aspects rather than relying solely on historical expenditure data.

From a theoretical perspective, the present study reinforces the concept that road maintenance planning is a multidimensional process involving interactions among project resources, infrastructure conditions, and external environmental influences. The findings support the argument that accurate cost estimation should incorporate multiple strategic factors simultaneously to improve decision-making and resource allocation. This integrated perspective contributes to the existing body of knowledge by providing empirical evidence from road maintenance projects in Bogor City, Indonesia, thereby extending previous studies conducted in different geographical and institutional contexts.

Table 11. Results of the coefficient of determination test (R^2)

Model Summary[b]				
Model	**R**	***R Square***	***Adjusted R Square***	***Std. Error of the Estimate***
1	0.999[a]	0.998	0.998	0.183
a. *Predictors*: (Constant), X1,X2,X3,X4,X5,X6				
b. *Dependent Variable*: Y				

Table 11 shows that the R Square (R^2) value obtained is 0.998, indicating that the model has very high explanatory power for the variation in the dependent variable. This value shows that 99.8% of the variation in the road maintenance cost estimation variable can be explained by the independent variables used in the model, while the remaining 0.2% is influenced by other factors outside the model or by error components (*error*) that cannot be explained by the research variables. An *R Square* value approaching one indicates a level of model fit (*goodness of fit*) that is very good, so the relationship between the independent and dependent variables can be explained comprehensively. These results indicate that the factors included in the model contribute very strongly to explaining changes or variation in road maintenance costs. Thus, the model that has been built has a high level of predictive ability and can be used as a basis for understanding the influence of strategic factors on road maintenance cost estimation.

The relatively high coefficient of determination (R^2) indicates that the proposed model is able to explain a substantial proportion of the variation in road maintenance cost estimation. This result can be attributed to the selection of predictor variables that directly represent the major components influencing maintenance costs, including material and equipment costs, labor costs, traffic conditions, planning and design quality, drainage conditions, and external factors. These variables were identified through an extensive literature review and empirical investigation, ensuring that they adequately capture the primary determinants of road maintenance planning. Therefore, the high R^2 value reflects the strong explanatory capability of the proposed model rather than model overfitting.

Furthermore, the use of variables representing both technical and managerial aspects enables the model to explain road maintenance costs more comprehensively. Nevertheless, although the model demonstrates high explanatory power, future studies are encouraged to validate the proposed model using different geographical locations and larger datasets to further examine its generalizability and predictive performance.

Mediation Effect of Maintenance Strategy

The maintenance strategy variable was incorporated into the research framework as a mediating construct to explain how technical and managerial factors influence road maintenance cost estimation. The findings indicate that maintenance strategy plays an important role in strengthening the relationship between material and equipment costs, labor, traffic conditions, planning quality, drainage conditions, external factors, and road maintenance cost estimation. An appropriate maintenance strategy enables available resources to be allocated more effectively, thereby improving the efficiency and accuracy of maintenance cost estimation. These findings suggest that maintenance strategy functions as an important managerial mechanism linking project characteristics with road maintenance decision-making.

CONCLUSION

This study successfully developed a road maintenance cost estimation model based on Structural Equation Modeling–Partial Least Squares (SEM-PLS) involving 226 respondents drawn from contractors, government agencies, consultants, and academics. The composition of respondents, dominated by contractors and government and with a majority having more than five years of work experience, shows that the data came from stakeholders with first-hand understanding of the planning, implementation, supervision, and control of road maintenance work. This provides a high level of confidence in the quality of the data used in the study.

Instrument testing results show that all research variables have a very good level of reliability, with *Cronbach's Alpha* values ranging from 0.926–0.964**,** so all constructs are declared consistent in measuring the concepts studied. Descriptive statistical analysis also shows that all variables have relatively high mean values with stable data dispersion, indicating fairly uniform perceptions among respondents regarding the factors influencing road maintenance cost estimation.

Regression analysis shows that, simultaneously, material and equipment costs (X1), labor costs (X2), traffic conditions (X3), planning/design quality (X4), drainage conditions (X5), and external factors (X6) have a significant effect on road maintenance cost estimation **(**$p < 0.001$**).** Of all the variables tested, drainage conditions (X5) have the most dominant influence on changes in road maintenance costs, followed by traffic conditions, external factors, planning/design quality, and labor costs. These results indicate that successful drainage system management is a key factor in curbing rising maintenance costs, as it relates directly to pavement service life and the degree of road deterioration.

The developed model has very high predictive ability, with an R^2 of 0.998, indicating that 99.8% of the variation in road maintenance cost estimation can be explained by the variables in the model, while only 0.2% is influenced by other factors outside the study. This value indicates that the model has a very good level of *goodness of fit* and is able to explain the relationships among variables comprehensively.

Overall, this study makes a scientific contribution through the development of a road maintenance cost estimation model that integrates technical, resource, operational, environmental, and managerial factors within a single analytical framework. The findings show that controlling road maintenance costs does not depend on financial aspects alone, but is also influenced by planning quality, traffic conditions, drainage system effectiveness, and external factors affecting the execution of the work. Road maintenance policy should therefore adopt a more integrated, data-driven approach that takes into account the interrelationships among factors, in order to improve budget efficiency, extend road service life, and support sustainable road asset management.

Future research is recommended to develop the model further by integrating other variables, such as pavement condition, actual traffic volume, climate data, soil characteristics, and road monitoring technologies based on Building Information Modeling (BIM)**,** Internet of Things (IoT)**,** or Artificial Intelligence (AI)**.** In addition, the model should be tested across different regions and road classifications to improve its generalizability, so that it can support decision-making systems for road maintenance planning at the national level.

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