Available online at www.CivileJournal.org

Civil Engineering Journal

(E-ISSN: 2476-3055; ISSN: 2676-6957)

Vol. 11, No. 01, January, 2025

Assessment for Evaluation of Local Roads Based on Infrastructure Data and Budget Allocation

Desi Meriana [1*], Bambang S. Subagio [2], Najid [1]

[1] Civil Engineering Program, Tarumanagara University, Jakarta, Indonesia.

[2] Faculty of Civil and Environmental, Bandung Institute of Technology, Bandung, 40132, Indonesia.

Received 19 September 2024; Revised 16 November 2024; Accepted 04 December 2024; Published 01 January 2025

Abstract

Technical criteria are one of the determining factors in calculating the technical index amount of the allocation budget for road infrastructure. The technical criteria include pavement deterioration, bridge condition, road performance, local budget allocation for road capital expenditure, allocation of local budget government for routine maintenance of roads, e-monitoring reporting, and SHP map reporting. Evaluation is required to determine the influence of each of these criteria and highlight the importance of comprehensive and continuous data testing to provide an overview of road infrastructure data and budget allocations. This study aims to analyze the influence of each technical criterion based on infrastructure data and the allocation of funding for local road maintenance in Indonesia. Two regression methods, Multiple Linear Regression with Dummy (MLRD) and Binary Logistic Regression (BLR), were used to identify and evaluate each variable and the potential of the resulting criteria. The results show that pavement deterioration (PD) and road performance (RP) are the criteria that significantly influence the assessment of infrastructure data and are the best models. This finding highlights the need for comprehensive data testing to provide an accurate overview of local road infrastructure from the data submitted by local governments to the central government.

Keywords: Infrastructure; Road; Special Allocation Fund; Local Road; Regression Method.

1. Introduction

Adequate and quality road infrastructure is essential for improving the economy and regional connectivity [1]. However, this needs to be supported by the availability of budget allocations and complete technical data according to conditions and needs. Therefore, the correlation between available budget allocations and road maintenance practices is fundamental to ensuring sustainable infrastructure maintenance [2]. However, in several countries, there are instances where the criteria and budget allocations are inefficient and inappropriate in planning and implementation [3]. In addition to budget limitations [4, 5], fiscal disparities [6, 7], and political interests can also hinder development in the regions, particularly in locations where surrounding communities are at threat of conflict [8]. Therefore, program monitoring and evaluation are critical to ensure influence and targeted use of resources to minimize risks associated with budget limitations, fiscal gaps, and political interests. Several studies have explored the assessment of road maintenance based on technical criteria and budget allocation.

Setyawan et al. (2024) identified a strong relationship between maintenance budget allocation and road stability, with a regression value of $R^2 = 0.94$. This finding underscores that increased maintenance funding significantly enhances road stability [2]. Additionally, the study highlights the importance of adopting sustainable road construction practices

* Corresponding author: dmeriana1405@gmail.com

http://dx.doi.org/10.28991/CEJ-2025-011-01-04

and ensuring adequate budget allocation for maintenance to achieve and sustain road stability effectively. Jayakody et al. (2024) have developed an integrated budget allocation of roads. The findings benefit asset managers in deciding the maintenance budget allocation optimization for a cross-asset system consisting of road and water pipe assets [9]. Another study by Kaba & Assaf (2019) developed a maintenance priority for roads in sub-Sahara considering technical criteria such as pavement performance, international roughness index (IRI), traffic survey, annual average daily traffic (AADT), assessment of the functional condition, and pavement structure, economic, social, and cultural indicators use of principal components analysis (PCA) for weighting to help select priority road construction and preservation projects [10]. In addition, Obeti et al. (2024) showed that the relationship between the road maintenance cost criterion and the length of road to be maintained criterion has a significant impact and is the dominant determinant for sustainable road maintenance [11]. Identifying and selecting the factors that affect fund allocation based on the criteria and characteristics of the road is a prerequisite for establishing a scientific and reasonable road maintenance allocation model [12].

In other words, budget allocation decisions should be considered based on numerous criteria, and researchers have proposed various approaches. A regression technique approach can be comprehensively applied. Multiple Linear Regression with Dummy (MLRD) and Binary Logistic Regression (BLR) techniques are simple and easy-to-use computational tools to investigate the relationship between multiple independent and dependent variables in complex linear and non-linear relationships among various parameters [13, 14]. Likewise, this approach allowed us to assess the influence and determine the best model for the overall criteria tested. Several studies are limited to road quality and performance improvement models for budget allocation, weighting models, and prioritization of road infrastructure maintenance. However, it is essential to highlight how these criteria can be evaluated comprehensively by the established criteria. In other words, to improve the quality of infrastructure data and budget allocation, it is necessary to reinforce criteria with a data-driven approach to accurately and on-target identify infrastructure needs [15].

This study aims to analyze the influence of each technical criterion based on infrastructure data and the allocation of funding for local road maintenance in Indonesia. The findings highlight the necessity for comprehensive data testing to provide an accurate overview of local road infrastructure from the data submitted by local governments to the central government. Another finding is that the budget allocation data in this study can help identify whether the technical criteria allocated from the central government to local governments influence the allocation of funds for local road maintenance in Indonesia.

Section 1 reviews the literature to establish the research context and highlight its contributions. Section 2 clearly defines key terms related to infrastructure data criteria and budget allocations in Indonesia. Section 3 details the methodology employed in the study. Finally, Sections 4 and 5 present a series of statistical tests conducted to ensure accurate interpretation and reliability of the analysis.

2. Infrastructure Data Assessment of the Special Allocation Fund

The special allocation fund, known in Indonesia as DAK, is one type of transfer from the state budget allocated to fund regional infrastructure development to support national and regional priorities in Indonesia [16]. In addition, the purpose of the special fund allocation for the road infrastructure sector is to finance certain areas that are national priorities but are the responsibility of local governments [17].

In reality, the determination of DAK has been regulated in Government Regulation Number 55/2005 on balance funds. The allocation of DAK assistance is based on three criteria: general criteria, specific criteria, and technical data criteria [16]. The special allocation fund (DAK) allocation is determined by general criteria (e.g., financial capacity of a sub-national government), specific criteria (e.g., specific characteristics of a region), and technical criteria (e.g., guidelines established by the responsible line ministry), as shown in Figure 1.

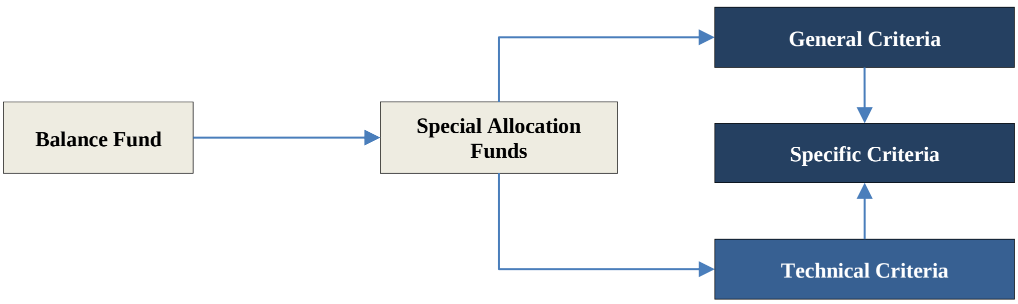

Figure 1. Criteria of the special allocation fund 'DAK'

One of the criteria used in our study is the technical criteria. These criteria are established by the relevant technical ministries, specifically the Regional Infrastructure Facilitation Center, the Regional Infrastructure Facilitation Planning Section, and the General Secretariat of the Ministry of Public Works and Housing. In addition, the technical criteria for the road sector are based on established guidelines from the relevant technical ministries. These guidelines are essential for determining local technical data. The specific criteria are shown in Figure 2 and detailed in Table 1 [18].

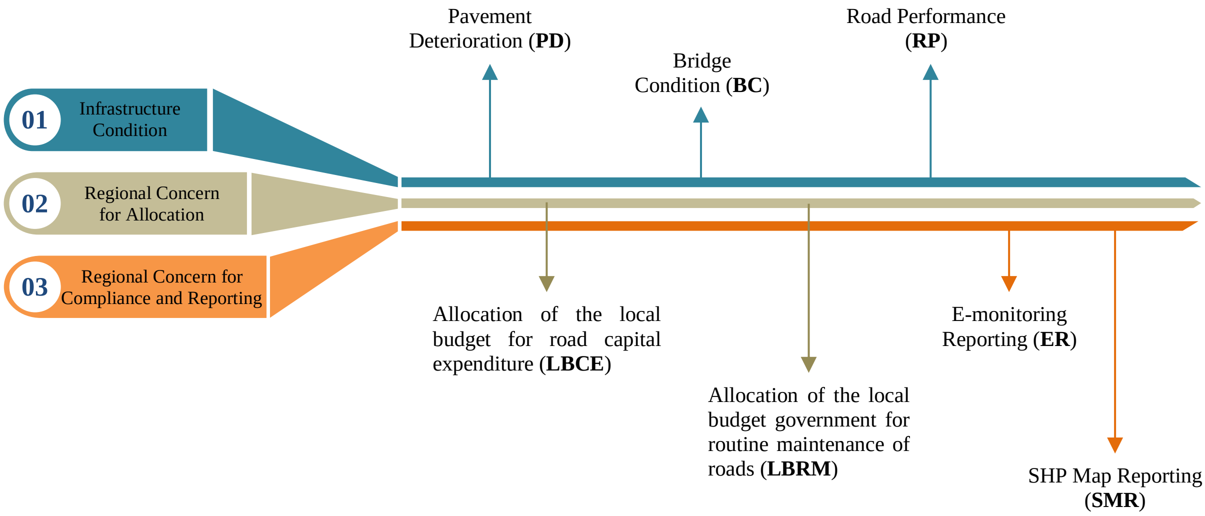

Figure 2. Classification of technical criteria

Table 1. Assessment of DAK technical criteria for roads

Technical Criteria for Roads	Definition
Pavement deterioration	Total length of roads with light and major damage level.
Bridge condition	Data of bridge dimension, type, and condition based on bridge management system (BMS) guidelines [19].
Road performance	Increase in percentage of stable condition from the previous year. That is the last year (N-1) to the next year (N+1).
Allocation of the local budget for road capital expenditure	Contribution of local government budget funding (excluding DAK) to the road sector, compared to the total local government budget for road development.
Allocation of the local budget government for routine maintenance of roads	The local budget government focuses on maintaining road conditions and routine maintenance of roads and bridges.
E-monitoring reporting	Commitment of local governments in the implementation of DAK as measured by reporting the e-monitoring, which consists of physical and financial budget progress.
SHP Map Reporting	Compliance with the assessment of verified SHP maps that have been uploaded into the local road management information system.

Technical criteria are classified into three categories, as shown in Figure 2. The three main categories provide an understanding of the criteria used to assess infrastructure condition (PD, BC, and RP), regional concern for allocation (LBCE and LBRM), and regional concern for compliance and reporting to central government (ER and SMR). In addition, seven technical criteria are one of the determining factors in calculating the technical index amount of the allocation budget for local road infrastructure in Indonesia.

3. Research Methodology

The methodology consists of several stages. The first stage is the collection of primary data obtained directly from the first author when verifying the technical data of the DAK for roads in 2021 through the regional road management information system known as SiPDJD [20]. The second stage is the selection of study sites, and the third stage is data compilation. The seven criteria are used and classified based on ratio/numeric, ordinal, or interval scales. This classification helps in understanding how each criterion can be analyzed and interpreted.

The fourth stage is a series of analysis techniques performed using Multiple Linear Regression with Dummy (MLRD) and Binary Logistic Regression (BLR) to investigate the pattern and potential of correlation and influence between the dependent and independent variables of each technical criteria variable and determine the best model. In addition, it is necessary to ensure the robustness of the analysis results and the accuracy of interpretation in the field [7], as shown in Figure 3.

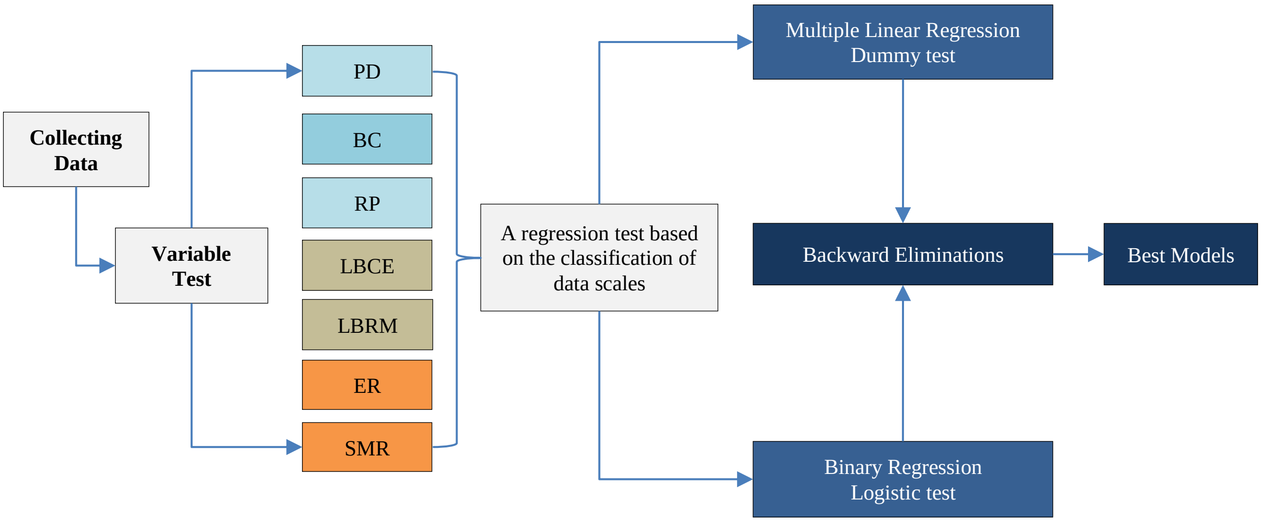

Figure 3. Variables and test methods of the research

3.1. Collecting data and Area of Study

As previously explained, the results of data collection on road infrastructure criteria in the proposed road maintenance budget allocation. This study is limited to three representative data locations in Indonesia: Riau Island, East Kalimantan, North Maluku, and Bali Island. In each study area, there are different provinces, districts/municipalities. The selection of the study areas was derived from an assessment of local pro-activity in DAK activities in the road sector [21]. The number of regions designated as study areas in each province is present in Figure 4.

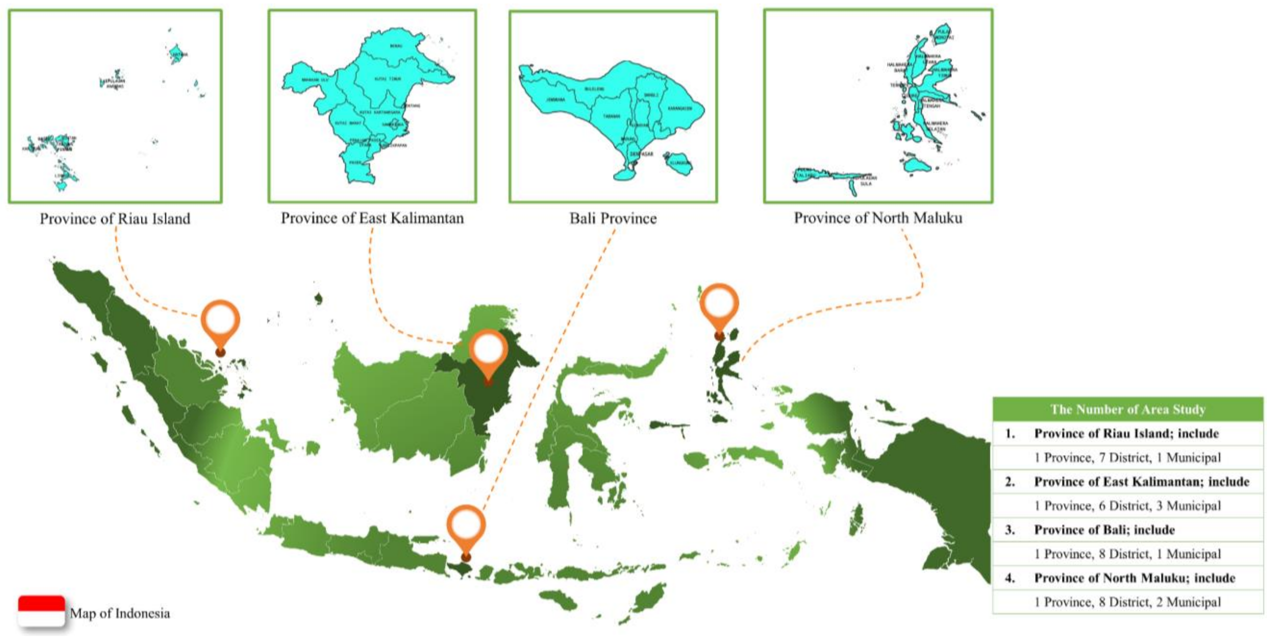

Figure 4. Area and number of Study

The data collected consisted of seven criteria obtained from each study area, and seven criteria are presented in Table 1. Several technical criteria were gathered from road and bridge condition surveys and map surveys, encompassing essential data attributes related to road networks and GIS-based regional conditions. In addition to the technical data obtained from these survey activities, the other essential data from several regional agencies proposing DAK, such as data in the form of evaluation reports and monitoring of DAK activities as regional compliance in reporting SHP maps. In addition, APBD data for road capital expenditures and APBD allocations for routine road maintenance are aspects and forms of regional concern in maintaining road assets in their regions.

3.2. Determination of Variables and Attributes

The variables in this study are defined as a set of logical conditions utilized to this point in the criteria for calculating the local budget allocation index in Indonesia and the adoption from Minister of Public Works regulation No. 5 on operational guidelines for the implementation of DAK infrastructure for roads in 2021 [18]. The variables and attributes identified are present in Table 2, which were derived based on the form and scale of the collected data

Table 2. Variables coding criteria

Technical Criteria For Roads (Variable)	Acronym/symbol	Definition a Coding
Pavement Deterioration	PD	Km (length)
Bridge Condition	BC	1 : Yes 0 : No
Road Performance	RP	1 : Up 0 : Down
Allocation of the local budget for road capital expenditure	LBCE	1 : Yes 0 : No
Allocation of the local budget government for routine maintenance of roads	LBRM	1 : Yes 0 : No
E-Monitoring Reporting	ER	0 : 0 × Reporting 4 : 1 × Reporting 6 : 2 × Reporting 8 : 3 × Reporting 10 : 4 × Reporting
SHP Map Reporting	SMR	1 : Yes 0 : No

3.3. Statistical Test MLRD Method

Multiple linear regression with Dummy (MLRD) variables generally shows the availability or lack of quality or attributes. Dummy variables are nominal/ordinal scale independent variables grouped by code with a value of 1 or 0 [22]. The dependent variable uses an interval/ratio or ratio/numeric scale, as in Table 1. The equation for the multiple linear regression model is present in Equation 1.

$$Y = \beta_0 \pm \beta_i X_i \dots\dots\dots\dots \pm \beta_n X_n \tag{1}$$

where, y is the dependent variable, X_i is with X_n represents the independent variable, β_1; coefficient of regression variable x_1, β_0 is (intercept point) regression line and y-axis, $\beta_1$is coefficient of regression variable x_1, β_n is coefficient of regression variable X_n.

The problem: To investigate the influence of pavement damage (PD) and e-monitoring reporting (ER) on other variables, PD and ER are treated as dependent variables (*y*). Meanwhile, BC, RP, LBCE, LBRM, and SMR variables were used as independent variables (*x*). Based on this, we propose our first hypothesis as follows H1: variables bridge condition (BC), road performance (RP), allocation of the local budget for road capital expenditure (LBCE), allocation of the local budget government for routine maintenance of roads (LBRM), e-monitoring reporting (ER) and SHP Map reporting (SMR) were in classified as independent variables or (*x*) has a significant influence on pavement deterioration (PD).

H2: variables pavement deterioration (PD), bridge condition (BC), road performance (RP), allocation of the local budget for road capital expenditure (LBCE), allocation of the local budget government for routine maintenance of roads (LBRM), and SHP Map reporting (SMR) were in classified as independent variables or (*x*) has a significant influence on e-monitoring reporting (ER). Furthermore, the hypothesis and goodness of fit data should be considered when determining the regression test. Analysis regression is used based on backward eliminations [23]. In the multiple linear regression with dummy, the coefficient of determination (R^2) followed the f-test and t-test [24]. It aims to analyze data, describe variables and their relationships, and influence and present the results empirically.

3.4. Statistical Test BLR Method

Logistic regression is utilized to model a binary variable (0,1) based on one or more other variables. Binary Logistic Regression is an extension of linear regression. This is used when the dependent variable is categorical and the independent variable is continuous, discrete, or mixed. If the dependent variable is a yes/no variable expressed as 1 and 0, then this model is called binary logistic regression. [22]. In addition, binary logistic regression (BLR) models are flexible and intuitive for significant interpretation [25]. In particular, the BLR technique investigates the influence of multiple independent variables (x) on a dependent variable (y) with binary characteristics. The binary logistic regression equation used is in Equation 2.

$$\pi(x_i) = \frac{e^{x_i'\beta}}{1+e^{x_i'\beta}} = \frac{e^{\beta_0+\beta_1 x_1+\ldots+\beta_p x_p}}{1+e^{\beta_0+\beta_1 x_1+\ldots+\beta_p x_p}} \tag{2}$$

where: $\pi(x_i)$ is probability of dependent variable, e is exponential, β_0 is Constanta, β_1 is coefficient of regression independent variable x_1.

In this study, the binary properties of the variables bridge condition (BC), road performance (RP), allocation of the local budget government for routine maintenance of roads (LBRM), allocation of the local budget for road capital expenditure (LBCE), and SHP map reporting (SMR) were classified as dependent variables or (y) respectively, these variables work as subsequent hypotheses (hypotheses H3 to H7) to analyze the logistic regression model described in Table 3.

Table 3. The variables and hypotheses used for BLR

Variable	Description/Acronym/symbol	Variable	Description/Acronym/symbol
$Y_1^{(3)\ dependent}$	BC	$Y_1^{(4)\ dependent}$	RP
X_1	PD	X_1	PD
X_2	RP	X_2	BC
X_3	LBCE	X_3	LBCE
X_4	LBRM	X_4	LBRM
X_5	ER	X_5	ER
X_6	SMR	X_6	SMR
$X_{1..}\ X_6^{\ (3)\ Independent}$		$X_{1..}\ X_6^{\ (4)\ Independent}$	
$Y_1^{(5)\ dependent}$	LBCE	$Y_1^{(6)\ dependent}$	LBRM
X_1	PD	X_1	PD
X_2	BC	X_2	BC
X_3	RP	X_3	RP
X_4	LBRM	X_4	LBCE
X_5	ER	X_5	ER
X_6	SMR	X_6	SMR
$X_{1..}\ X_6^{\ (5)\ Independent}$		$X_{1..}\ X_6^{\ (6)\ Independent}$	
$Y_1^{(7)\ dependent}$	SMR		
X_1	PD		
X_2	BC		
X_3	RP		
X_4	LBCE		
X_5	LBRM		
X_6	ER		
$X_{1..}\ X_6^{\ (7)\ Independent}$			

In binary logistic regression (BLR) using backward elimination, the hypotheses and model fit parameters tested include Nagelkerke R-Square, the omnibus test, and the Wald test. This makes it possible to describe the variables and their correlations, analyze their influence, and present the results of the study empirically.

4. Results and Discussion

Conceptually, the relationship between variables, in statistics, the value of the correlation coefficient varies between +1 and -1. The relationship between the two variables is weaker as the correlation coefficient value is close to 0 [24, 26]. The calculation results are in Table 4 using the Pearson coefficient correlation matrix. Based on the calculation results, although the coefficient value = 0.377, close to 0, which confirms the absence of a strong relationship, the calculation results show a significant positive correlation between the variables of pavement damage (PD) and road performance (RP). It means that when the value of the PD variable increases, the RP variable tends to increase.

Table 4. Summary of the correlation test

		PD	BC	RP	LBCE	LBRM	ER	SMR
PD (Pavement Deterioration)	Pearson Correlation	1	0.091	0.377*	0.075	-0.224	0.254	-0.041
	Sig. (2-tailed)		0.581	0.018	0.649	0.171	0.118	0.806
	N	39	39	39	39	39	39	39
BC (Bridge Condition)	Pearson Correlation	0.091	1	0.065	-0.380*	0.088	0.191	0.212
	Sig. (2-tailed)	0.581		0.695	0.017	0.596	0.244	0.195
	N	39	39	39	39	39	39	39
RP (Road Performance)	Pearson Correlation	0.377*	0.065	1	0.296	-0.182	0.192	-0.104
	Sig. (2-tailed)	0.018	0.695		0.067	0.267	0.240	0.529
	N	39	39	39	39	39	39	39
LBCE (Allocation of the Local Budget for Road Capital Expenditure)	Pearson Correlation	0.075	-0.380*	0.296	1	-0.095	0.205	-0.380*
	Sig. (2-tailed)	0.649	0.017	0.067		0.564	0.210	0.017
	N	39	39	39	39	39	39	39
LBRM (Allocation of the Local Budget Government for Routine Maintenance of Roads)	Pearson Correlation	-0.224	0.088	-0.182	-0.095	1	-0.102	0.250
	Sig. (2-tailed)	0.171	0.596	0.267	0.564		0.536	0.124
	N	39	39	39	39	39	39	39
ER (E-Monitoring Reporting)	Pearson Correlation	0.254	0.191	0.192	0.205	-0.102	1	-0.101
	Sig. (2-tailed)	0.118	0.244	0.240	0.210	0.536		0.540
	N	39	39	39	39	39	39	39
SMR (SHP Map Reporting)	Pearson Correlation	-0.041	0.212	-0.104	-0.380*	0.250	-0.101	1
	Sig. (2-tailed)	0.806	0.195	0.529	0.017	0.124	0.540	
	N	39	39	39	39	39	39	39

* Correlation is significant at the 0.05 level (2-tailed).

Furthermore, the bridge condition (BC) variable is significantly related to the variable of allocation of the local budget for road capital expenditure (LBCE). In addition, other variables producing a positive correlation relationship are the BC and LBCE variables from the resulting correlation coefficient value of 0.380. One limitation of this study is that the coefficient correlations test value remains relatively low. These findings are similar to those of Altaie & Dishar (2024), who reported average correlation coefficients ranging from 0.2 to 0.3 [27]. While the correlation coefficient in this study is similar to previous findings, it indicates a significant relationship. The results of this study can be further explored by exploring more complex relationships between independent and dependent variables [28]. Further analysis utilized a regression approach, which made it possible to identify the influence of each variable. This method provides a comprehensive analysis of how each factor contributes to the results observed in this study.

4.1. Analysis and Result: The MLRD

Model estimation results for the pavement damage (PD) variable and the e-monitoring reporting (ER) model are shown in Equations 3 and 4, respectively. In addition, the R^2 reliability factors for each equation are 0.142 for PD and 0.127 for ER.

$$\mathrm{PD} = 4.427 + 0.873\,_{\mathrm{RP}} \tag{3}$$

$$\mathrm{ER} = 4.303 + 1.697_{\mathrm{BC}} + 4.000\,_{\mathrm{LBCE}} \tag{4}$$

where, PD is a variable indicating pavement deterioration, RP is a variable indicating road performance, ER is a variable indicating e-monitoring reporting, BC is a variable indicating bridge condition, and LBCE is a variable indicating allocation of the local budget for road capital expenditure.

Based on the first model (Equation 3) and Table 5, it can be seen that the RP variable has a simultaneous influence on the PD variable. In addition, every time there is an increase of 1 unit in the RP variable, the PD value will increase by 0,873. In other words, when there is an increase in the RP variable, the value of the PD variable will also increase. The second model (Equation 4) shows that the BC and LBCE variables influence the ER variable. Every one-unit increase in the BC variable will increase the ER value by 1,697, assuming that the LBCE variable remains constant. In addition, every one-unit increase in the LBCE variable will change the ER variable by 4,000 units.

Table 5. The variables and hypotheses used for MLRD

Variable	Description/Acronym/symbol	Variable	Description/Acronym/symbol
$Y_1^{(1)\ \text{dependent}}$	PD	$Y_1^{(2)\ \text{dependent}}$	ER
X_1	BC	X_1	PD
X_2	RP	X_2	BC
X_3	LBCE	X_3	RP
X_4	LBRM	X_4	LBCE
X_5	ER	X_5	LBRM
X_6	SMR	X_6	SMR
$X_{1..}\ X_6^{(1)\ \text{Independent}}$		$X_{1..}\ X_6^{(2)\ \text{Independent}}$	

The hypothesis and goodness of fit model should be considered when determining the regression test. Analysis regression is used based on backward eliminations [23]. The coefficient of determination (R^2) is a higher R^2 value in the multiple linear regression with a dummy (MLRD). It is generally considered better as it indicates a stronger relationship between *x* and *y* can be used for prediction or another purpose. However, a negligible R^2 does not mean *x* is impractical in explaining *y*. Instead, a negligible R^2 might indicate that *y* is also influenced by other significant factors [25]. Likewise, the R^2 results on the PD and ER variables generate a coefficient of determination of 0.142 and 0.127, respectively. It means that the independent variables in this study can explain the dependent variable PD (14.2%), and other independent variables excluded from observation explain the remaining 85.8%. In addition, the dependent variable for ER (12.7%), along with other independent variables excluding observations, explains the remaining 87.3%. The results of the analysis and hypothesis testing of the pavement deterioration (PD) and e-monitoring reporting (ER) models in this study are referred to in Table 6, using backward elimination [23, 29].

Table 6. Summary of the statistical result for DP and ER

Dependent	Independent	F-test		T-Test		R^2
		F-stat	Sig.	F-stat	Sig.	
PD	*Constant*	6.144	0.018*	14.330	0.000	0.142
	RP			2.479	0.018*	
ER	*Constant*	2.613	0.087**	2.050	0.048	0.127
	BC			1.868	0.070**	
	LBCE			1.929	0.062**	

Description: * indicates significance at a confidence level below 0.05%, ** indicates significance at a confidence level of more than 0.05%.

Second, the F-test and T-tests were followed [24]. It is carried out to test the data, describe the influence, and deliver empirical study results. The simultaneous F-test results, as stated in Table 6, show that both F-stat values have a value of (6.144) for the PD model and the ER model F-stat has a value of (2.613) with a p-value of 0.018 for PD and 0.087 for ER respectively. Thus, it hypothesized a significant influence of the two dependent variables. Furthermore, it is to evaluate the independent variables on the dependent variable partially. Third, the significance test (T-Test) of the PD model variables is carried out to identify these variables. According to this test, only the RP variable ($0.018 < 0.05$) has a significant influence. There are no significant variables for the ER model, as presented in Table 6.

Based on statistical tests, it shows that the two models simultaneously have a significant influence on the dependent variable. It can be seen that the RP variable significantly affects the PD variable model compared to other model variables. Another study states that pavement damage can have a significant influence on pavement performance, where damage that occurs on the pavement can simultaneously weaken the pavement structure and reduce its ability to withstand traffic loads [2 ,11, 30]. In such a way that, when viewed from the perspective of road performance, it also influences the type of damage that occurs on the road. Demonstrates that the PD models (Equation 3) can be used to predict or evaluate the dependent variable by considering the influence of RP.

4.2. Analysis and Result of BLR

The results were analyzed using the BLR method and tested with many combinations to find the most significant influence variables. All five variables were modelled as dependent variables, as shown in Table 4. The results are presented in Equations 5 to 9 and details of Table 7 using the best model through backward elimination

$$\mathrm{RP} = \frac{e^{-3.457+0.950\ \mathrm{PD}}}{1 + e^{-3.457+0.950\ \mathrm{PD}}} \tag{5}$$

$$\mathrm{BC} = \frac{e^{-8.599-42.406\ \mathrm{LBCE}\ +4.967\ \mathrm{ER}}}{1+e^{-8.599-42.406\ \mathrm{LBCE}\ +4.967\ \mathrm{ER}}} \tag{6}$$

$$\mathrm{LBCE} = \frac{e^{-35.337-37.750\ \mathrm{BC}\ +9.217\ \mathrm{ER}}}{1+e^{-35.337-37.750\ \mathrm{BC}\ +9.217\ \mathrm{ER}}} \tag{7}$$

$$\mathrm{LBRM} = \frac{e^{-0.833+20.370\ \mathrm{SMR}}}{1+e^{-0.833+20.370\ \mathrm{SMR}}} \tag{8}$$

$$\mathrm{SMR} = \frac{e^{-1.526+19.677\ \mathrm{LBRM}\ +22.729\ \mathrm{LBCE}}}{1+e^{-1.526+19.677\ \mathrm{LBRM}\ +22.729\ \mathrm{LBCE}}} \tag{9}$$

where, RP is a variable of road performance, PD is a variable of pavement deterioration, BC is a variable of bridge Condition, LBCE is the allocation of the local budget for road capital expenditure, LBRM is the allocation of the local budget government for routine maintenance of roads, SMR is a SHP map reporting, and ER is the e-monitoring reporting.

Table 7. Summary of the statistical result for BC, RP, LBRM, LBCE, and SMR

Variables		Omnibus-Test			Wald-Test		Nagelkerke' R
Dependent	**Independent**	**Chi χ^2**	**df**	**Sig.**	**Chi χ^2**	**Sig.**	**R^2**
BC	*Constant*	8.924	2	0.012*	0.000	1.000	0.355
	LBCE				0.000	0.999**	
	ER				0.000	0.999**	
RP	*Constant*	5.446	0.020*	0.020*	2.448	0.118	0.197
	PD				4.375	0.036*	
LBRM	*Constant*	3.918	0.048*	0.048*	4.835	0.028	0.141
	SMR				0.000	0.999**	
LBCE	*Constant*	9.301	0.010*	0.010*	0.000	0.998	1.000
	BC				0.000	0.997**	
	ER				0.000	0.997**	
SMR	*Constant*	7.211	0.027*	0.027*	0.000	1.000	0.293
	LBRM				0.000	0.999**	
	LBCE				0.000	1.000**	

Description: * indicates significant at a confidence level below 0.05%, ** indicates significant at a confidence level of more than 0.05%.

At this stage, there are three types of hypotheses. First, the omnibus test is similar to the F-test in regression with a significance level of 5% or 0.05 [22, 25]. The results showed that all tested models (BC, RP, LBCE, LBRM, and SMR) are significant. Indicates that the independent variables significantly influence the dependent variable, with a significance level of p-value < 0.05. Therefore, these models are considered valid for further analysis, as presented in Table 7. Hypothesis acceptance depends on the independent variable's significant influence on the dependent variable [14].

Second, Wald Tests whether partial independent variables are sufficient to influence the dependent variable. Wald-test testing is also commonly known as T-test [25]. In the test results that have been carried out, as shown in Table 7, the RP model partially indicates a significant value of 0.036. There are no significant results in partial checks on BC, LBCE, LBRM, and SMR variables.

Third, Nagelkerke's R Square is the value of the independent variables' ability to explain the dependent variable's variability. In contrast, the residual is explained by other variables excluded from the research model; as shown in Table 7, the bridge condition (BC) model gives the maximum value of R^2 of 0.355. Unlike the LBCE model, R^2 is 100%. This indicates a relatively large number that cannot be predicted [29].

Table 7 shows the final state of all variables tested in the final equation and decision model. The BLR analysis results indicate that Variable RP has the highest influence significance, and bridge condition (BC) criteria as an alternative second model has the highest influence significance. Based on the statistical parameter test results presented in Table 7, it can be seen that the selected model is derived from the road performance (RP) variable in Equation 5 and the bridge condition (BC) variable in Equation 6. Based on the BLR statistical results, the final conditions of all variables tested in the equations and decision models show that the road performance variable (RP) in Equation 5 has a significant influence. Furthermore, the bridge condition (BC) in Equation 6 is the second alternative model.

4.3. Validation of the Model

Based on the model validation test, the two methods resulted in seven technical criteria models based on infrastructure data and budget allocations for road maintenance funding in Indonesia. One of the best models was selected from the seven obtained models, resulting in a significant statistical test value. Several statistical tests were conducted to validate the selected models, including normality, autocorrelation, and multicollinearity tests. Among the seven models analyzed, the PD model had a significant influence. The first step is to perform a normality test for the selected model. This test is essential to ensure the residuals are normally distributed, with a p-value > 0.05 [31]. The significance value (2-tailed) obtained a value of 0.924 > 0.05. This indicates that the PD model has a normal distribution at the 95% confidence level, as shown in Table 8. The Kolmogorov-Smirnov test results are presented in Table 8. Additionally, the results indicate that there is no significant difference between the distribution of unstandardized residuals and the normal distribution. This confirms that the normality assumption for the residuals has been satisfied. The significance value (2-tailed) obtained a value of 0.924 > 0.05. It is indicated that the PD model has a normal distribution at the 95% confidence level.

Table 8. Result of the normality test of the PD model

One-Sample Kolmogorov-Smirnov Test		
		Unstandardized Residual
N		39
Normal Parameters [a,b]	Mean	0E-7
	Std. Deviation	0.91462178
Most Extreme Differences	Absolute	0.088
	Positive	0.065
	Negative	-0.088
Kolmogorov-Smirnov Z		0.549
Asymp. Sig. (2-tailed)		0.924

a. Test distribution is Normal.

b. Calculated from data.

Based on the residual histogram and Normal P-P plot, it can be concluded that this regression model generally satisfies the assumption of residual normality. The histogram shows a near-normal distribution of residuals with a mean value close to zero (-9.25E-16) and a standard deviation of 0.987, although there is a slight asymmetry (skewness). The Normal P-P plot shows that most of the dots follow the diagonal line, which indicates that the residuals follow a normal distribution, although there are some slight deviations at either end of the plot. The overall normality assumption is satisfied, indicating that the regression model should be used to explain the data. Therefore, based on Figure 5, the histogram of residuals, and the Normal P-P plot, this regression model largely satisfied the assumptions of residual normality. Thus, the regression model is robust and reliable.

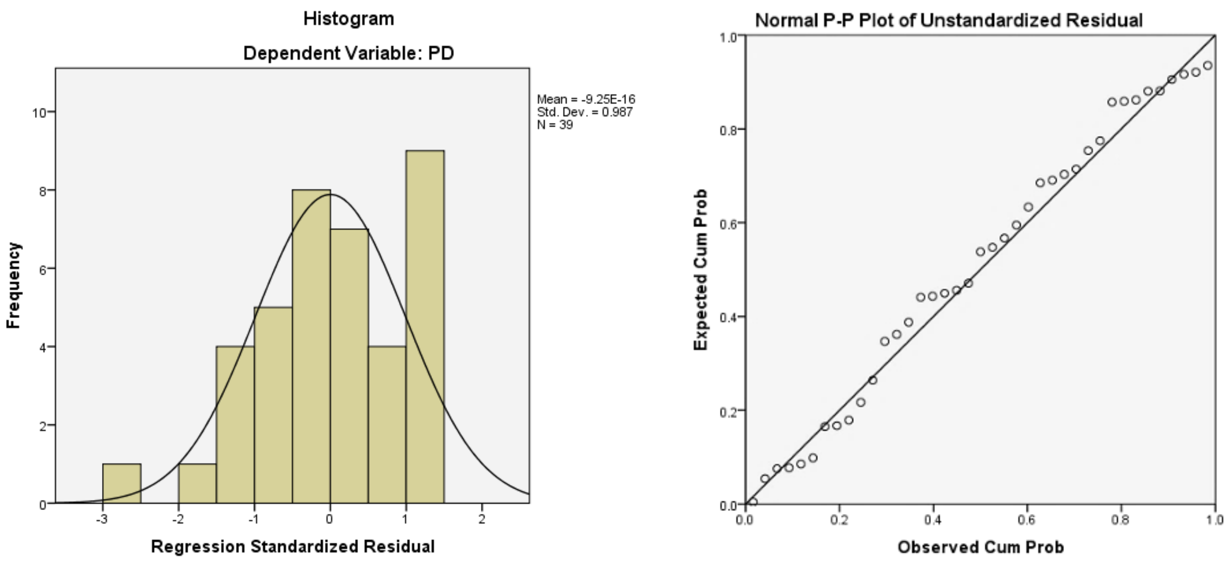

Figure 5. Histogram and P-Plot test of the PD model

The summary model in Table 9 shows that the model with the RP variable produces an adjusted R^2 value of 0.05, which adjusts for the number of independent variables making a small contribution. In addition, the standard error value of the calculation in the model is 0.926 with a Durbin-Watson (D-W) value of 1.486. The D-W test is a statistical test used to detect autocorrelation in the residual of a model [23]. The resulting D-W value is then compared with the critical value (dL). Based on the resulting D-W value greater than dL, the model does not experience autocorrelation. This indicates that the resulting model has good accuracy because the resulting errors are not correlated with each other so the independent variables can explain the dependent variable influenceively.

Table 9. Statistically selected model test results with road performance (PD) variables

Model Summary [f]					
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Durbin-Watson**
5	0.377[e]	0.142	0.119	0.92690	1.486

e. Predictors: (Constant), RP

f. Dependent Variable: PD

In addition to testing for auto-correlation, the variables in the model are also tested for collinearity. Multicollinearity is done to check the correlation between independent variables in the model [30]. Multicollinearity can be seen from the tolerance and VIF values generated in a model as seen in Table 10. The results showed that the tolerance and VIF values generated are 1.000, which indicates that there is no collinearity problem with the model. This states that the model is reliable because there is no intercorrelation between the independent variables in the models.

Table 10. (PD) Multicollinearity test result for road performance variable

Coefficients [a]								
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
		B	**Std. Error**	**Beta**			**Tolerance**	**VIF**
1	(Constant)	4.427	0.309		14.330	0.000		
	RP	0.873	0.352	0.377	2.479	0.018	1.000	1.000

The F-test result on the selected model variables, as shown in Tables 9 and 11, indicated that the model significantly influences the dependent variable, the PD variable. In addition, this model shows a p-value of 0.018, which means that the influence of RP on PD is statistically significant. This indicates that RP consistently contributes to the variation in PD. Although the significance value generated in this model tends to be minor, the RP variable shows that the variable influences the prediction of the value of the PD variable. Based on some of these things related to the statistical data tests carried out, the RP variable can be used as one of the references in decision-making.

Table 11. F-Test result of road performance variable

Variables in the Equation							
		B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**
RP	PD	0.950	0.454	4.375	1	0.036	2.585
	Constant	-3.457	2.209	2.448	1	0.118	0.032

Predictors: (Constant), RP.

ANOVA[a]						
	Model	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	5.279	1	5.279	6.144	.018[f]
	Residual	31.788	37	.859		
	Total	37.067	38			

Predictors: (Constant), RP.

5. Conclusion

Based on the analysis of seven technical criteria related to budget allocation, the criteria that have a role and influence the assessment based on infrastructure data for local budget allocation are the variable of pavement deterioration (PD) and road performance (RP). The PD-RP relationship is significant, both technically and when the data is statistically tested. When road quality deteriorates, road performance also deteriorates, and vice versa. So, if there is a decrease in road quality, it will significantly affect maintenance costs, affecting the overall performance of the road.

In addition to these two best model options, other criteria, namely bridge condition criteria (BC) and e-monitoring reporting criteria (ER), can be used as alternative models. In its implementation, bridge condition and road condition are two things that are closely related to performance variables and cannot be separated as part of the infrastructure conditions. Furthermore, the e-monitoring criteria (ER) with the bridge condition criteria (BC) can be interpreted as the better or more compliant the DAK e-monitoring reporting, the better the bridge condition database, and vice versa. If the database related to infrastructure condition data is good, then the implementation of funds for maintenance activities will also be adequately realized. Based on the result of the model test, it can be seen that it is essential to conduct comprehensive and continuous data testing on the seven technical criteria used in assessing budget allocations for regional roads, especially in Indonesia. If the data used is tested comprehensively, it can provide more accurate condition assessment results to make implementing budget allocation activities more influential.

Overall, the findings of this research study translate into actionable recommendations for local governments in Indonesia. Specifically, the first change that the budget allocation process should make based on the results of this study is to improve the quality of infrastructure data. Local governments should focus on improving the quality of infrastructure data to ensure accurate and consistent data collection every year. Local governments should focus on improving the quality of infrastructure data to ensure accurate and consistent data collection each year. Good data will provide a solid basis for planning and making the right decisions. The second is to set priorities based on needs. Local governments should set priorities based on the needs identified in the road infrastructure condition evaluation. By prioritizing budget allocations for maintenance based on needs, localities can direct resources to areas that need the most attention, thereby maximizing the impact of each expenditure. Third, conduct regular monitoring and evaluation. The central government conducts monitoring and evaluation. Local governments conduct e-monitoring to ensure that the physical treatment plan in the field is by the initial handling targets. This process will help identify whether the criteria set and the budget allocated are achieving the expected results. Further research can recommend other criteria models based on issues and phenomena that occur on regional roads, one of which is connectivity. Given that there are still isolated areas in Indonesia that have not been connected with an adequate road network, it is recommended that the central government consider additional criteria to support infrastructure criteria and budget allocations in the future.

6. Declarations

6.1. Author Contributions

Conceptualization, D.M., B.S.S., and N.N.; methodology, D.M., B.S.S., and N.N.; formal analysis, D.M.; data curation, D.M.; writing—original draft preparation, D.M.; writing—review and editing, D.M., B.S.S., and N.N.; visualization, D.M.; supervision, B.S.S. and N.N.; project administration, D.M.; funding acquisition, D.M. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Acknowledgements

The author would like to thank the Center for Regional Infrastructure Facilitation, the Regional Infrastructure Facilitation Planning Division, and the Secretariat General of the Ministry of Public Works and Housing.

6.5. Conflicts of Interest

The authors declare no conflict of interest.

7. References

[1] Azaki, N., & Lutfi, A. (2023). The Allocative Efficiency Analysis of Special Allocation Fund for Road Sector in 2015-2019. Jurnal Transformative, 9(1), 84–101. doi:10.21776/ub.transformative.2023.009.01.5.

[2] Setyawan, A., Hermani, W. T., Yulianto, B., & Gravitiani, E. (2024). Influence of Maintenance Funds on Improve Road Steadiness with the Curva Expert Program. Civil Engineering Journal (Iran), 10(2), 546–554. doi:10.28991/CEJ-2024-010-02-014.

[3] Shah, A. (2012). Autonomy with Equity and Accountability: Toward a More Transparent, Objective, Predictable and Simpler (TOPS) System of Central Financing of Provincial-Local Expenditures in Indonesia. Policy Research Working Papers, The World Bank, Washington, United States. doi:10.1596/1813-9450-6004.

[4] Gertler, P. J., Gonzalez-Navarro, M., Gračner, T., & Rothenberg, A. D. (2024). Road maintenance and local economic development: Evidence from Indonesia's highways. Journal of Urban Economics, 143. doi:10.1016/j.jue.2024.103687.

[5] Akita, T., Riadi, A. A., & Rizal, A. (2021). Fiscal disparities in Indonesia in the decentralization era: Does general allocation fund equalize fiscal revenues? Regional Science Policy and Practice, 13(6), 1842–1865. doi:10.1111/rsp3.12326.

[6] Iliopoulos, P., & De Witte, K. (2024). The expenditure composition and trade-offs in local government budgets. Socio-Economic Planning Sciences, 93. doi:10.1016/j.seps.2024.101900.

[7] Välilä, T. (2024). Fiscal sustainability and the composition of government investment: The case of investment in road infrastructure. Transport Policy, 145, 105–125. doi:10.1016/j.tranpol.2023.10.001.

[8] Kanwal, S., Rasheed, M. I., Pitafi, A. H., Pitafi, A., & Ren, M. (2020). Road and transport infrastructure development and community support for tourism: The role of perceived benefits, and community satisfaction. Tourism Management, 77, 104014. doi:10.1016/j.tourman.2019.104014.

[9] Jayakody, J. A. N. N., Nasvi, M. C. M., Robert, D. J., Navaratnarajah, S. K., Kurukulasuriya, L. C., Giustozzi, F., Gunasekara, C., & Setunge, S. (2024). Development of a Cross-Asset Model for the Maintenance of Road and Water Pipe Assets using AHP Method. Civil Engineering Journal (Iran), 10(2), 336–361. doi:10.28991/CEJ-2024-010-02-01.

[10] Kaba, E. K., & Assaf, G. J. (2019). Roads funding priority index for Sub-Saharan Africa using principal components analysis. Case Studies on Transport Policy, 7(4), 732–748. doi:10.1016/j.cstp.2019.09.002.

[11] Obeti, A. M., Muhwezi, L., Kakitahi, J. M., & Byaruhanga, C. B. (2024). Investigating the cost of mechanized unpaved road maintenance operations in Uganda. Transportation Research Interdisciplinary Perspectives, 25. doi:10.1016/j.trip.2024.101135.

[12] Cao, L., Tan, T., Hou, X., & Dong, Z. (2024). Decision-making optimization model for the targeted sustainable maintenance of a complex road network. Journal of Cleaner Production, 434. doi:10.1016/j.jclepro.2023.139891.

[13] Zhao, D., Liu, Y., & Chen, H. (2024). Are Mini and full-size electric vehicle adopters satisfied? An application of the regression with dummy variables. Travel Behaviour and Society, 35. doi:10.1016/j.tbs.2024.100744.

[14] Yuniarsih, E. T., Salam, M., Jamil, M. H., & Nixia Tenriawaru, A. (2024). Determinants determining the adoption of technological innovation of urban farming: Employing binary logistic regression model in examining Rogers' framework. Journal of Open Innovation: Technology, Market, and Complexity, 10(2), 100307. doi:10.1016/j.joitmc.2024.100307.

[15] Amir, A., & Henry, M. (2023). Reverse Engineering of Maintenance Budget Allocation Using Decision Tree Analysis for Data-Driven Highway Network Management. Sustainability (Switzerland), 15(13), 10467. doi:10.3390/su151310467.

[16] Government Regulation. (2005). Government Regulation Number 55 of 2005 Concerning Balancing Funds. Government of Indonesia. (In Indonesian).

[17] Parbinoto, A. G. (2018). Evaluation of the Use of Physical Special Allocation Funds for Infrastructure Sector and Its Effect on Infrastructure Provision. Jurnal Defis, Desentralisasi Fiskal, Ekonomi Dan Keuangan Daerah, 3, 31-46.

[18] The Government of the Republic of Indonesia. (2021). Regulation of the Minister of Public Works and Public Housing of the Republic of Indonesia Number 5 of 2021 Concerning Operational Instructions for Management of Special Allocation Funds for Public Works and Public Housing Infrastructure In Fiscal Year 2021. Ministry of Public Works and Public Housing, Jakarta, Indonesia. (In Indonesian).

[19] Directorate General of Highways. (1993). Bridge Management System, Ministry of Public Works Republic of Indonesia, Republic of Indonesia, Jakarta, Indonesia.

[20] SiPDJD No:18/PRT/M/2011. (2011). Concerning Technical Guidelines for the Provincial and Regency/City Road Database Management System. Peraturan Menteri Pekerjaan Umum: Government of the Republic of Indonesia, Jakarta, Indonesia. (In Indonesian).

[21] Meriana, D., Subagio, B. S., & Najid, N. (2023). Technical Criteria Model for Special Allocation Funds (DAK) for Roads throughout Indonesia. Jurnal Teknik Sipil, 30(3), 437–448. doi:10.5614/jts.2023.30.3.12.

[22] Hilbe, J. M. (2016). Practical Guide to Logistic Regression. Chapman and Hall/CRC, New York, United States. doi:10.1201/b18678.

[23] Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2015). Introduction to time series analysis and forecasting. John Wiley & Sons, Hoboken, United States.

[24] Siegel, A. F. (2016). Practical business statistics. Academic Press, Cambridge, United States.

[25] Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied Logistic Regression. Wiley Series in Probability and Statistics, John Wiley & Sons, Hoboken, United States. doi:10.1002/9781118548387.

[26] Zaid, M. A. (2015). Correlation and Regression Analysis. The Statistical, Economic and Social Research and Training Centre for Islamic Countries (SESRIC), Ankara, Turkey.

[27] Altaie, M. R., & Dishar, M. M. (2024). Integration of Artificial Intelligence Applications and Knowledge Management Processes for Construction Projects Management. Civil Engineering Journal (Iran), 10(3), 738–756. doi:10.28991/CEJ-2024-010-03-06.

[28] Herianti, E., Marundha, A., & Haryanto, H. (2024). An accounting review of regional and central budgeting dynamics in Indonesia. Journal of Infrastructure, Policy and Development, 8(8). doi:10.24294/jipd.v8i8.6355.

[29] Montgomery, D. C., Runger, G. C., & Hubele, N. F. (2015). Engineering Statistics (5th Ed.). John Wiley & Sons, Hoboken, United States.

[30] Abu Dabous, S., Zeiada, W., Al-Ruzouq, R., Hamad, K., & Al-Khayyat, G. (2021). Distress-based evidential reasoning method for pavement infrastructure condition assessment and rating. International Journal of Pavement Engineering, 22(4), 455–466. doi:10.1080/10298436.2019.1622012.

[31] Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2013). Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences. Routledge, New York, United States. doi:10.4324/9780203774441.