International Journal of Transport Development and Integration
https://www.acadlore.com/journals/IJTDI

Vehicle Composition and Flexible Pavement Condition: A Multiple Linear Regression Analysis of the Ciganea–Cijantung Road, Indonesia

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Received: 04-22-2026 **Revised:** 06-26-2026 **Accepted:** 07-08-2026

Citation: Bahtiar, Joni, Falderika, T. A. Aziis, D. Patabang, and M. R. Kaiway, "Vehicle composition and flexible pavement condition: A multiple linear regression analysis of the Ciganea–Cijantung Road, Indonesia," *Int. J. Transp. Dev. Integr.*, vol. 10, no. 3, pp. 600–616, 2026. https://doi.org/10.56578/ijtdi100302.

Abstract: Flexible pavements are essential transportation assets, and their deterioration under mixed traffic conditions creates significant maintenance, safety, and economic challenges. Although traffic loading is widely recognized as being associated with pavement performance, relatively few studies have developed locally calibrated and easily interpretable regression models that quantify the contribution of different vehicle classes to pavement condition at the corridor level. This study applies multiple linear regression (MLR) to analyze the relationship between vehicle composition and the Pavement Condition Index (PCI) along a 3.5 km road section in Purwakarta, Indonesia, consisting of 35 pavement segments. Primary data were collected through pavement distress surveys and traffic observations categorized into light, medium, and heavy vehicles. The surveyed corridor exhibited a mean PCI of 61.89, indicating generally good pavement condition, although variability in distress severity was observed, with rutting and potholes as dominant types. The MLR model explained 79.4% of PCI variability (R^2 = 0.794, $p <$ 0.001). Heavy vehicles exhibited the strongest statistically significant negative association with PCI, followed by medium vehicles, whereas light vehicles were not statistically significant after adjustment for the remaining traffic categories. These findings indicate that traffic composition, particularly heavy-vehicle traffic, provides valuable information for pavement maintenance planning.

Keywords: Pavement Condition Index; Flexible pavement; Vehicle composition; Multiple linear regression; Pavement deterioration

1 Introduction

Road infrastructure is a central determinant of accessibility and regional economic performance, and in Indonesia it also remains the dominant carrier of mobility and freight: approximately 75% of human and goods transport is served by roads [1]. This reliance makes pavement performance, commonly operationalized through serviceability indicators such as road "stability" measured using the International Roughness Index (IRI), a critical basis for network-level governance and investment prioritization [1]. Yet Indonesia's road-management challenge is structurally complex because regional roads (provincial/district/city) constitute ∼90% of the national road network (528,202 km in 2019) and are primarily managed by local governments, where maintenance capacity and fiscal space can be constrained [1, 2]. National monitoring also indicates persistent performance gaps among road classes. National roads achieved a stability level of 92%, whereas provincial and district/city roads reached only 69% and 57%, respectively, remaining below the national stability target of 75% [1]. These disparities become increasingly important as large-scale connectivity investments, including toll-road expansion and corridor development across Java, continue to increase traffic exposure and the operational importance of strategic road links [3–6]. Within this context, regression-based empirical models provide a practical means of quantifying relationships between traffic characteristics and pavement condition while maintaining a level of interpretability that is valuable for infrastructure management [1]. However, despite extensive work on connectivity-driven transformation and on road-governance/maintenance constraints, the literature base remains more developed on macro-corridor change than on segment-level, locally calibrated predictive condition modeling that can directly support pavement-management decisions under local constraints, an imbalance that motivates the remainder of the manuscript's methodological direction [1–4, 6].

The urgency for locally grounded road-condition modeling is particularly salient in West Java: a province repeatedly identified as a strategic growth and industrial region within Java's core economic geography. For example, West Java hosts one of Indonesia's largest concentrations of industrial estates, covering approximately 3.71 million hectares and comprising at least 32 industrial estates distributed across several regencies, including Purwakarta [7]. Policy-oriented scholarship likewise situates Bekasi–Karawang–Purwakarta as key industrial and logistics-adjacent areas on Jakarta's periphery that require robust supporting infrastructure to sustain interregional connectivity and economic function [8]. Empirically, the broader North Coast/Java corridor context also reflects rapid built-up expansion and land conversion pressures that can elevate traffic demand and axle-load exposure on connecting roads: remote-sensing evidence from West Java's north-coastal region reports net agricultural losses of approximately 1,850 ha/year (2013–2020) alongside built-up gains of approximately 2,030 ha/year over the same interval [4]. Major corridor infrastructure crossing or affecting West Java further reinforces the strategic role of Purwakarta in interregional movement (e.g., a 116 km toll-road segment operating since 2015 that connects regencies including Purwakarta within the West Java north-coastal system; and the wider Trans-Java network reported at $\sim$1,350 km) [6, 9, 10]. Purwakarta occupies a strategic position within the Jakarta–Bandung economic corridor and is traversed by the Cipularang Toll Road, making it an important gateway for passenger and freight movement between western and central Java [6, 8, 9]. Accordingly, the Ciganea–Cijantung Road Section (Purwakarta Regency, West Java) represents a local but strategically consequential link within this corridor system, where deterioration can plausibly impose user costs (delay, vehicle operating costs) and amplify public maintenance burdens given that road freight remains dominant nationally (e.g., goods movement assumptions of $\sim$76% by land mode in logistics modeling, and reported heavy reliance of national logistics on road transport) [11, 12]. In addition, operational road-class requirements are nontrivial in such corridors: Purwakarta's national-road context is described as meeting Class I standards, permitting vehicles $>$ 12 tons, underscoring the relevance of heavy-vehicle loading environments when considering deterioration risk and maintenance urgency [9].

Although scholarship on Java and West Java has strongly documented how transport infrastructure and corridor projects reshape spatial development, such as land-use change around major infrastructure and toll-road influences on settlement and built-up expansion, this evidence base is predominantly oriented toward regional urbanization processes and corridor restructuring, rather than toward operational, segment-scale pavement-condition prediction for local maintenance programming [4, 6, 7, 9]. Similarly, governance-focused studies emphasize that regional-road outcomes are shaped by decentralization and maintenance capacity, highlighting measurable service-level disparities between national and regional roads and the institutional need for sustained maintenance financing and monitoring [1, 2]. Despite these advances, an important gap remains. Existing studies clearly demonstrate the role of transport infrastructure in regional development [6, 9], yet they provide limited guidance on how corridor-level traffic dynamics can be translated into locally calibrated models for predicting pavement condition at the segment level [13, 14]. This limitation is particularly relevant for regional road agencies responsible for maintenance planning under constrained financial resources [1, 15, 16]. This gap provides a focused justification for a regression-based modeling framework tailored to local data and conditions, consistent with the demonstrated usefulness of regression approaches for quantifying infrastructure-related effects in West Java [6, 9], albeit in different application domains.

The relationship between vehicle composition and pavement deterioration depends on traffic volume, regulatory enforcement, and spatial contexts. While weigh-in-motion (WIM) systems ensure design compliance in some regions, vehicle overloading in developing areas accelerates deterioration beyond traffic counts alone. Urokov et al. [17] reported that trucks, representing only 18–25% of traffic, caused disproportionate Pavement Condition Index (PCI) deterioration driven by axle-load magnitude rather than frequency. Additionally, Bo et al. [18] demonstrated that drainage, pavement structure, and maintenance history substantially affect performance. Because regional economics, population distribution, and network efficiency shape traffic generation [19, 20], empirical vehicle-count models represent context-specific statistical relationships rather than universal functions, necessitating locally calibrated models over direct relationship transfers. Model selection must reflect data availability. Although machine-learning approaches achieve high predictive performance (R^2 = 0.86–0.96) using large databases [21–23], this study employs multiple linear regression (MLR). This method suits a corridor-scale dataset of 35 segments and three explanatory variables, providing coefficient interpretability crucial for engineering decision-making.

From a pavement mechanics perspective, pavement deterioration is governed by both traffic volume and axle-load magnitude. According to the fourth power law, pavement damage increases approximately with the fourth power of axle load, indicating that relatively small increases in axle load may produce disproportionately greater structural damage. Flexible pavements respond primarily to wheel loading, where heavier axle loads generate higher tensile strains within asphalt layers and greater compressive strains in the underlying pavement structure than lighter vehicles. This principle provides the engineering basis for analysing vehicle composition rather than traffic volume alone when evaluating pavement condition. Nevertheless, pavement deterioration is also influenced by pavement structure, environmental conditions, and maintenance history; therefore, statistical relationships should be interpreted within the context of local roadway characteristics [17, 24, 25].

Current approaches to modeling pavement deterioration typically aggregate traffic data into a single cumulative loading parameter, obscuring the differential impacts of vehicle classes. Rather than representing traffic loading using a single cumulative indicator, the present study develops an interpretable MLR model that separately evaluates the contribution of light, medium, and heavy vehicles to pavement condition. Focusing on the Ciganea–Cijantung Road Section in Purwakarta Regency, West Java Province, the proposed framework translates routinely collected field data into specific degradation coefficients for each vehicle type. By establishing this direct composition-deterioration relationship, the model provides an interpretable analytical framework for maintenance planning. Accordingly, this study examines the extent to which vehicle composition explains variations in the PCI along the Ciganea–Cijantung Road Section using a locally calibrated MLR model.

2 Methodology

2.1 Study Area and Research Design

2.1.1 Study area

This study was conducted on the Ciganea–Cijantung Road Section, Purwakarta Regency, West Java Province, Indonesia (Figure 1). The investigated corridor extends approximately 3.5 km, from STA 0+000 to STA 3+500, and forms part of the West Java provincial road network. The corridor extends from 6°35′09.03″ S, 107°26′00.22″ E at STA 3+500.

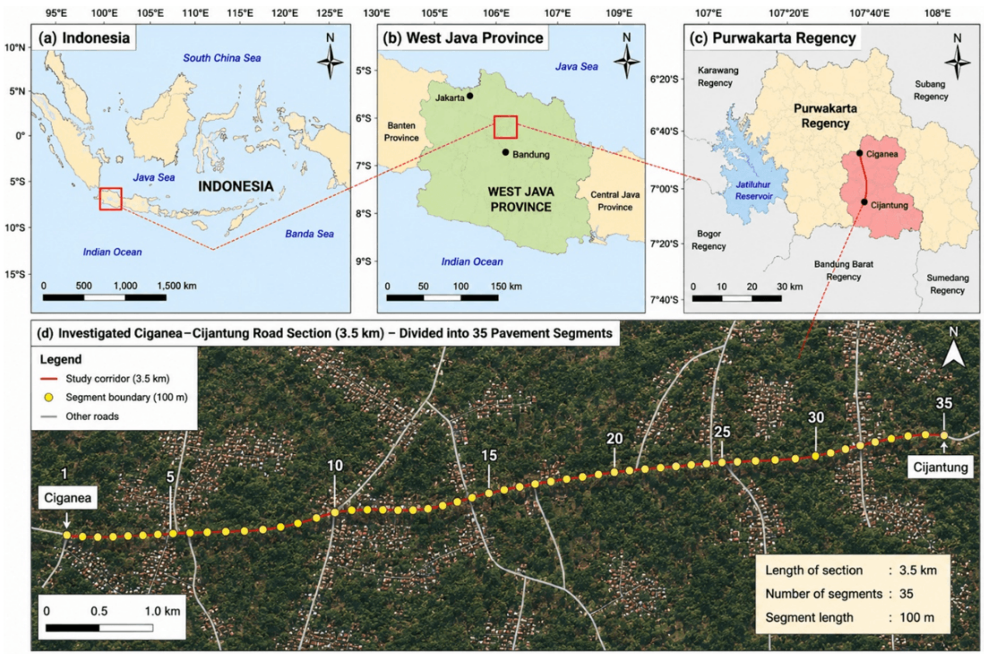

Figure 1. Location of the study area: (a) Indonesia; (b) West Java Province; (c) Purwakarta Regency; and (d) the Ciganea–Cijantung Road Section (STA 0+000–STA 3+500)

The Ciganea–Cijantung corridor was selected because it represents one of the principal provincial roads supporting regional mobility in Purwakarta Regency. The corridor accommodates continuous traffic movements generated by passenger vehicles, public transportation, commercial vehicles, and freight trucks travelling between Purwakarta and adjacent economic centers. The coexistence of high traffic demand and heterogeneous vehicle composition produces repeated traffic loading that is appropriate for examining the statistical relationship between vehicle categories and pavement deterioration. In addition, periodic pavement distress observed along this corridor provides a representative case for evaluating flexible pavement performance under mixed-traffic conditions.

Field data collection was carried out from 9 to 13 January 2026. Pavement distress inspections and traffic observations were conducted during the same survey period to ensure temporal consistency between pavement condition and traffic loading data. Daily observations were performed between 06:00 and 22:00 Western Indonesian Time (WIB) under comparable weather conditions, thereby reducing temporal discrepancies between the independent and dependent variables used in the statistical analysis. Figure 1 presents the geographical context of the study area. For clarity and international accessibility, the figure consists of four panels showing (a) the location of Indonesia, (b) West Java Province, (c) Purwakarta Regency, and (d) the investigated Ciganea–Cijantung Road Section, including the surveyed 3.5 km corridor.

2.2 Research Design

To represent the operational characteristics of the study corridor, this research adopted a quantitative field-based design comprising five sequential stages: road segmentation, pavement condition assessment, traffic survey, database preparation, and statistical modelling (Figure 2). The investigated corridor (STA 0+000–STA 3+500) was first divided into 35 homogeneous segments, each 100 m in length, which served as the analytical units throughout the study.

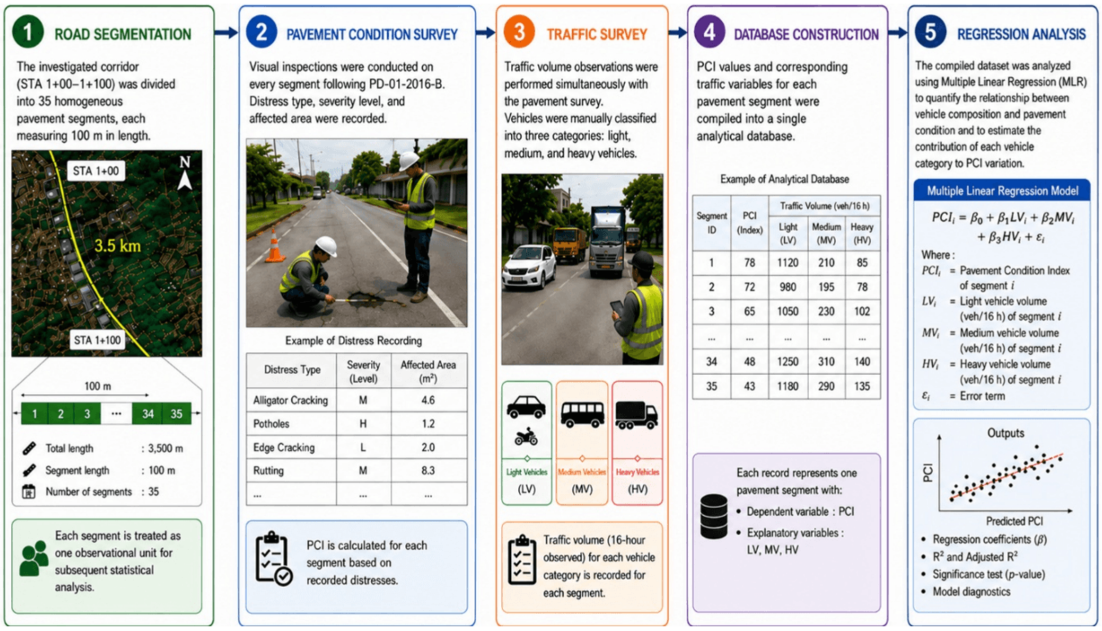

Figure 2. Research workflow for Pavement Condition Index (PCI) assessment of 35 pavement segments (100 m each) and traffic surveys at two control stations (STA 0+000 and STA 3+500)

Each segment underwent a visual pavement inspection following the Indonesian pavement condition guideline (PD-01-2016-B). The survey documented the type, severity, and extent of visible distress, allowing the PCI to be calculated for every segment. During the same survey period, manual traffic counts were conducted to classify vehicles into light, medium, and heavy categories. Conducting both surveys within the same observation window helped minimize temporal inconsistencies between the measured pavement condition and the recorded traffic characteristics.

After data collection, the PCI values and traffic observations were integrated into a single analytical dataset. In the regression analysis, PCI was specified as the dependent variable, whereas the three vehicle categories were treated as explanatory variables.

The relationship between traffic composition and pavement condition was subsequently examined using an Ordinary Least Squares (OLS)-MLR model (Figure 2). Within this framework, the intercept represents the expected PCI when the explanatory variables are zero, while each regression coefficient estimates the average change in PCI associated with a one-unit increase in a specific vehicle category, assuming the remaining variables remain constant. Although this linear formulation does not explicitly represent the physical mechanisms governing pavement deterioration, it provides an interpretable statistical framework for evaluating how variations in traffic composition are associated with observed pavement condition along the Ciganea–Cijantung corridor.

2.3 Data Collection

The study utilized both primary and secondary data to describe the physical condition and operational performance of the corridor. Primary data were obtained through field observations, including pavement distress surveys and traffic volume measurements. Secondary data, such as road classification, geometric characteristics, and inventory records, were sourced from relevant government agencies in Purwakarta Regency.

Pavement condition surveys covered all 35 segments using visual inspection methods. Each segment was evaluated by recording the type of distress, its severity level, and the affected area. The observed defects included rutting, potholes, cracking, and patching. These recorded parameters were used to calculate the PCI. During data processing, a systematic error in the initial dataset was identified and corrected: the distress density had been calculated using an erroneously reduced sample unit area, which artificially inflated the deduct values and decreased the preliminary mean PCI to approximately 50, whereas applying the correct 250 m^2 sample area yielded the accurate mean PCI of 61.89.

Manual traffic volume observations were conducted at the corridor boundaries (STA 0+000 and STA 3+500) concurrently with the PCI survey of 35 segments (100 m each). Because the 3.5 km corridor is continuous without major intersections or traffic generators, traffic composition is assumed consistent. Thus, the boundary volume data were applied as representative traffic exposure for all segments. While appropriate for this study, future research should verify this assumption using segment-level monitoring.

Traffic data were collected through manual vehicle counts conducted between 06:00 and 22:00 WIB (16-hour observed traffic volume). Vehicles were classified into light, medium, and heavy categories based on axle configuration and loading characteristics, following standard traffic engineering classification practices. Manual counting introduces limited observer-related variation; however, this method remains widely applied for corridor-scale traffic surveys in the absence of automated counting systems.

2.4 Pavement Condition Assessment Using Pavement Condition Index

Pavement condition for each sample unit was evaluated using the PCI method, adhering to the procedures specified in ASTM D6433 and the Indonesian pavement evaluation guideline (PD-01-2016-B). As a numerical metric, PCI quantifies surface condition on a scale from 0 (failed) to 100 (excellent) based on observed distress types, severity levels, and affected quantities. To facilitate this assessment, the investigated corridor was divided into 35 homogeneous 100-meter sample units. Given a pavement width of 2.5 meters, each unit yielded an inspection area of approximately 250 m^2, establishing the spatial basis for calculating distress density. Subsequently, Corrected Deduct Value (CDV) was derived utilizing established correction curves. The final PCI for each pavement segment was calculated using Eq. (1):

$$\mathrm{PCI} = 100 - \mathrm{CDV} \tag{1}$$

where, the resulting PCI values range from 0 to 100, with higher values signifying superior structural integrity. To interpret these numerical outcomes, the pavement segments were categorized according to the standard PCI rating adopted in this study (Table 1). These calculated PCI values were subsequently employed as the dependent variable in the MLR analysis to quantify their relationship against the selected traffic-related explanatory variables.

Table 1. Pavement Condition Index (PCI) rating adopted in this study

PCI	Pavement Condition
85–100	Excellent
70–84	Very good
55–69	Good
40–54	Fair
25–39	Poor
10–24	Very poor
0–9	Failed

Note: Adapted from Ref. [26].

2.5 Regression Model

The statistical relationship between traffic composition and pavement condition was analysed using an MLR model. In this model, the PCI served as the dependent variable, while the observed volumes of light, medium, and heavy vehicles functioned as independent variables. The mathematical form of the model is presented in Eq. (2).

$$\mathrm{PCI}_i = \beta_0 + \beta_1 \mathrm{LV}_i + \beta_2 \mathrm{MV}_i + \beta_3 \mathrm{HV}_i + \varepsilon_i \tag{2}$$

where, PCI_i = Pavement Condition Index for the segment i; β_0 is the intercept term; β_1, β_2, β_3 are the regression coefficients for the respective vehicle classes; and ε_i is the random error term. The variables incorporated into the regression model are summarized in Table 2.

The model describes statistical relationships without representing direct causation. Several variables that influence pavement deterioration, such as pavement layer thickness, structural capacity, subgrade resilient modulus, axle-load distribution, and material characteristics, were not available at the segment level and were not included in the analysis. Therefore, the regression coefficients reflect the relationship between traffic composition and PCI based on the observed data and do not represent the full mechanism of pavement deterioration.

Table 2. Variables used in the multiple linear regression (MLR) model

Variable	Unit	Coding	Description
PCI	Index (0–100)		Dependent variable (Pavement Condition Index)
LV	Vehicles/16 h	Continuous	Light vehicle traffic volume
MV	Vehicles/16 h	Continuous	Medium vehicle traffic volume
HV	Vehicles/16 h	Continuous	Heavy vehicle traffic volume

2.6 Statistical Analysis

Statistical analyses were performed using Stata software. The analytical dataset comprised 35 pavement segments, with the PCI specified as the dependent variable. Traffic volumes of light, medium, and heavy vehicles were included as explanatory variables. The relationship between traffic composition and pavement condition was analysed using an MLR model estimated by the OLS method (Figure 3).

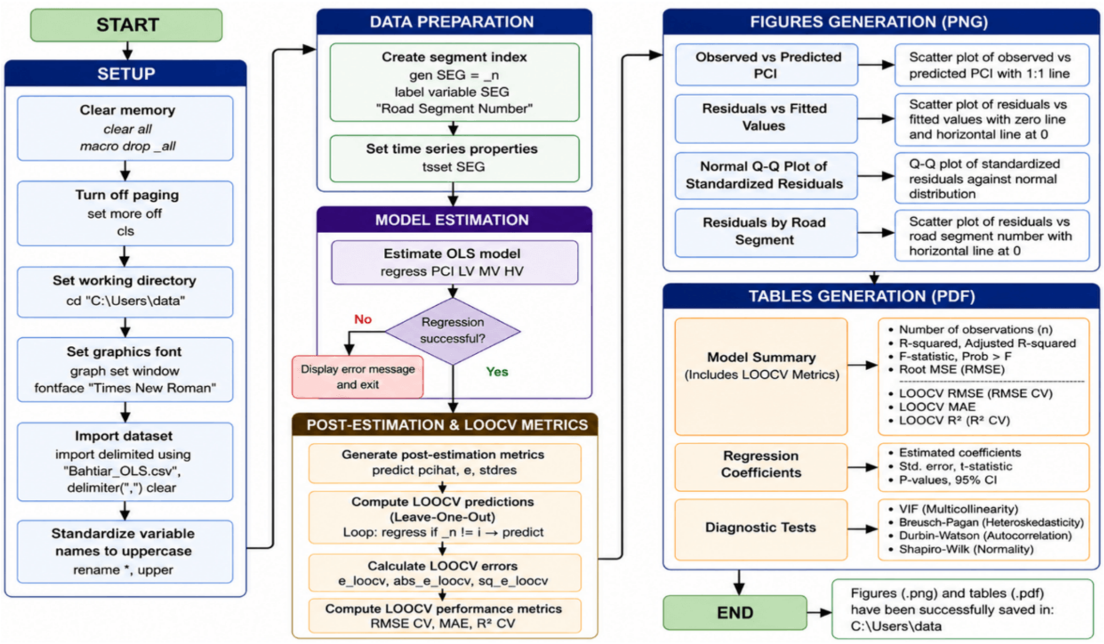

Figure 3. Workflow of the statistical analysis, including data preparation, OLS model estimation, diagnostic evaluation, and model validation

Note: OLS—Ordinary Least Squares; PCI—Pavement Condition Index; LV—light vehicle traffic volume; MV—medium vehicle traffic volume; HV—heavy vehicle traffic volume; CV—Cross-Validation; LOOCV—leave-one-out cross-validation; RMSE—Root Mean Square Error; MAE—Mean Absolute Error.

Figure 3 summarizes the statistical analysis workflow adopted in this study. Following data preparation, the regression model was estimated using OLS, after which predicted values and residuals were generated for diagnostic evaluation. Model assumptions were assessed by examining residual normality, multicollinearity, homoscedasticity, and residual independence. Residual normality was evaluated using graphical inspection and formal statistical tests, multicollinearity was assessed using the Variance Inflation Factor (VIF), homoscedasticity was examined using the Breusch–Pagan test, and residual independence was evaluated using the Durbin–Watson statistic.

Regression coefficients were interpreted together with their standard errors, 95% confidence intervals, and corresponding p-values using a significance level of $\alpha = 0.05$. Overall model performance was evaluated using the coefficient of determination (R^2), adjusted R^2, and the overall F-test. These procedures were intended to verify that the fitted regression model satisfied the principal assumptions of OLS while providing a statistically reliable representation of the relationship between vehicle composition and pavement condition.

3 Results and Discussion

3.1 Traffic Characteristics and Pavement Condition Overview

Field observations conducted across 35 consecutive pavement segments (STA 0+000–STA 3+500) revealed a distinctly heterogeneous pattern of pavement performance, characterized by alternating zones of deterioration and relatively intact surface conditions. This spatial variability indicates that pavement distress did not develop uniformly along the corridor but instead manifested in localized segments influenced by site-specific conditions. Among the observed distress types, rutting and potholes were the most dominant, reflecting the cumulative effects of repeated traffic loading and potential structural inadequacies in certain sections. Additional distress forms, including patching, longitudinal cracking, bleeding, raveling, and localized surface deformation, were also identified, although their occurrence was less extensive.

High-severity rutting was concentrated in several critical segments, specifically at STA 1+000–1+100, STA 1+600–1+900, STA 2+400–2+600, and STA 3+300–3+400. These locations exhibited pronounced wheel path depressions, suggesting sustained exposure to repetitive loading and possible subgrade or base layer weaknesses. In contrast, pothole formation was predominantly observed between STA 1+900 and STA 3+500, indicating progressive surface deterioration likely associated with moisture infiltration and material disintegration. Notably, several segments—including STA 1+100–1+200, STA 1+300–1+400, STA 2+300–2+400, and STA 2+700–2+800—showed minimal or no visible distress during the survey period. The coexistence of severely deteriorated and relatively intact segments within the same corridor underscores the influence of localized factors rather than uniform structural failure.

Representative examples of the observed pavement distress are presented in Figure 4. The spatial distribution of distress features reveals a clear concentration within wheel paths and near pavement edges, which are typically subjected to higher stress concentrations and environmental exposure. These areas frequently coincided with segments where roadside drainage systems were either absent, partially obstructed by vegetation, or inadequately maintained. Segments with compromised drainage conditions consistently exhibited more severe manifestations of rutting and pothole formation compared to those with functional drainage systems. Although drainage characteristics were not explicitly incorporated as variables in the regression analysis, the field observations strongly suggest that inadequate drainage contributed to accelerated deterioration by facilitating water infiltration and weakening pavement layers. This interaction between environmental conditions and traffic loading highlights the multifactorial nature of pavement performance.

Figure 4. Representative pavement distress documented during the Pavement Condition Index (PCI) survey along the Ciganea-Cijantung road section (STA 1+000–STA 3+500)

Traffic observations conducted over five survey days recorded a total of 76,062 vehicles, corresponding to an average 16-hour observed traffic volume of 15,212 vehicles (06:00–22:00 WIB). The traffic composition was dominated by light vehicles throughout the observation period, indicating that passenger transport constitutes the primary functional demand along the corridor. Despite this dominance, the presence of medium and heavy vehicles remains significant due to their disproportionate contribution to pavement loading and structural deterioration. A comparison between temporal traffic patterns shows that weekend traffic volume reached 39,274 vehicles, slightly exceeding weekday traffic of 36,788 vehicles. This relatively balanced distribution suggests that the corridor serves both routine commuter traffic and additional travel demand associated with economic, recreational, or inter-regional activities, thereby maintaining consistently high traffic intensity throughout the week.

The descriptive statistics of pavement condition and traffic variables are summarized in Table 3. The PCI values ranged from 51.84 to 71.88, with a mean value of 61.89 and a standard deviation of 6.07. Based on standard PCI classification criteria, the overall pavement condition can be categorized as good. However, the observed range indicates that this classification masks underlying variability in pavement performance across individual segments. Several segments exhibited PCI values approaching the lower threshold of the good category, suggesting that early-stage deterioration has already developed and may progress if not addressed through timely maintenance interventions. This variation highlights the importance of segment-level analysis rather than relying solely on corridor-wide averages.

Table 3. Descriptive statistics of pavement condition and traffic variables across the 35 surveyed segments

Variable	Mean	Min	Max	Standard Deviation (SD)
Pavement Condition Index (PCI)	61.89	51.84	71.88	6.07
Light vehicles (LV)	207.71	54	513	132.41
Medium vehicles (MV)	43.46	2	190	58.87
Heavy vehicles (HV)	30.40	0	88	27.53

Note: The values in Table 3 represent the daily average per road section, calculated from the total number of vehicles counted across all 35 sections during the 5-day (16-hour) period.

Traffic variables exhibited substantially greater dispersion compared to PCI values, indicating significant variability in traffic intensity and composition across the surveyed segments. Light vehicles recorded the highest mean volume at 207.71 vehicles per segment, accompanied by a large standard deviation of 132.41, reflecting uneven distribution of traffic demand along the corridor. Medium and heavy vehicles averaged 43.46 and 30.40 vehicles per segment, respectively, with standard deviations of 58.87 and 27.53. Although their absolute numbers are lower than those of light vehicles, the variability in medium and heavy vehicle volumes is particularly relevant due to their higher axle loads and greater potential to induce structural damage. The observed dispersion in traffic composition provides a meaningful basis for examining how different vehicle categories contribute to variations in pavement condition.

The surveyed corridor exhibited substantial segment-level variation in both pavement condition and traffic composition, despite an overall mean PCI corresponding to the good category. The PCI values ranged from 51.84 to 71.88, indicating that corridor-level averages do not fully capture local differences in pavement performance. Traffic volumes of light, medium, and heavy vehicles also varied considerably among segments, providing sufficient dispersion for model estimation. The subsequent analysis applies an MLR model to quantify the relationship between vehicle composition and the PCI and to estimate the contribution of each vehicle category to variations in pavement condition.

3.2 Pavement Distress Characteristics

Field observations identified rutting and potholes as the predominant pavement distress types along the surveyed corridor (Figure 4). Rutting was most extensive in Segment 25, affecting an area of 167.4 m^2, whereas potholes reached a maximum affected area of 42.0 m^2 in Segment 20. The concentration of these distress types indicates that pavement deterioration was not uniformly distributed but was confined to specific segments.

Rutting occurred primarily within wheel paths, where repeated traffic loading was concentrated. This observation is consistent with the established mechanism of permanent deformation in flexible pavements, in which repeated compressive loading progressively reduces the structural integrity of asphalt layers. Similar behaviour has been reported by Elias et al. [27], who showed that rut depth increases more rapidly when traffic loading exceeds the structural capacity of the pavement.

Potholes were concentrated predominantly between Segments 20 and 35, where field inspections also documented inadequate roadside drainage in several locations. Although drainage characteristics were not included as explanatory variables in the regression model, these observations indicate that moisture infiltration may have contributed to the progression of surface deterioration in affected segments. Comparable findings were reported by Al-Suleiman et al. [16], who demonstrated that inadequate drainage accelerates pavement deterioration by promoting moisture-related weakening of pavement layers. Collectively, these observations indicate that the observed distress pattern was associated with the combined influence of repeated traffic loading and localized environmental conditions.

3.3 Regression Model Performance

The overall performance of the proposed MLR model is summarized in Table 4, which was estimated using the OLS method based on observations from 35 pavement segments. In this model, the PCI was defined as the dependent variable, while traffic volumes of light, medium, and heavy vehicles were included as explanatory variables. The calibrated model produced a multiple correlation coefficient (R) of 0.891, indicating a strong linear relationship between observed and predicted PCI values. The coefficient of determination (R^2 = 0.794) showed that 79.4% of the variability in PCI could be explained by the included traffic variables, while the remaining 20.6% was attributed to other factors not captured in the model. The adjusted coefficient (Adjusted R^2 = 0.774) was only slightly lower than R^2, suggesting that the model maintained strong explanatory power without being overly influenced by the number of predictors. Furthermore, the regression model was statistically significant (F = 39.80, $p < 0.001$), indicating that the explanatory variables collectively were associated with variations in pavement condition.

Table 4. Model summary of the multiple linear regression (MLR) model

Parameter	Value
Regression method	Ordinary Least Squares (OLS)
Number of observations (n)	35
Number of predictors	3
Multiple correlation coefficient (R)	0.891
Coefficient of determination (R^2)	0.794
Adjusted R^2	0.774
Root Mean Square Error (RMSE)	2.888
Mean Absolute Error (MAE)	2.387
F-statistic	39.80
p-value (overall model)	<0.001
Log-likelihood	-84.661
Akaike Information Criterion (AIC)	4.00
Bayesian Information Criterion (BIC)	183.54
Leave-one-out cross-validation (LOOCV) RMSE	3.086
LOOCV MAE	2.706
LOOCV R^2	0.734

The model achieved a Root Mean Square Error (RMSE) of 2.888 PCI units, corresponding to approximately 6% of the observed PCI range (51.84–71.88), indicating acceptable prediction accuracy for engineering applications. The estimated log-likelihood (-84.661), along with AIC = 4.00 and BIC = 183.54, provides reference values for comparing alternative models. The remaining unexplained variability suggests that pavement condition is also influenced by factors not included in the model, such as structural characteristics, environmental conditions, and maintenance history.

The estimated regression coefficients are presented in Table 5, with an intercept of 69.612 ($p < 0.001$) representing the baseline PCI when all explanatory variables are zero. Although this condition is not observed in practice, it provides a reference for evaluating the influence of each vehicle category. All coefficients are negative, indicating that increased traffic volume is associated with reduced PCI. Light vehicles exhibit a coefficient of -0.0036 (p = 0.385), with a confidence interval that includes zero, indicating no statistically significant effect. This suggests that, despite their high volume, light vehicles do not independently explain variations in pavement condition due to their relatively low axle loads. In contrast, medium vehicles show a statistically significant coefficient of -0.0236 (p = 0.016), indicating a measurable contribution to pavement deterioration, approximately 6.6 times greater than that of light vehicles.

Heavy vehicles demonstrate the strongest effect, with a coefficient of -0.1955 ($p < 0.001$), corresponding to an average reduction of approximately 0.20 PCI units per additional vehicle. This effect is more than eight times greater than that of medium vehicles and substantially larger than that of light vehicles, supported by a narrow confidence interval and high statistical significance. The observed coefficient pattern is consistent with pavement engineering principles, where deterioration is governed by both traffic volume and axle-load magnitude. Vehicles with higher axle loads impose disproportionately greater structural damage, even at lower traffic volumes. These findings align with previous studies, including Elhadidy et al. [28] and Ibrahim et al. [29], which emphasize the importance of traffic-related variables and cumulative loading effects in explaining pavement condition.

Table 5. Estimated regression coefficients of the multiple linear regression (MLR) model

Predictor	**Coefficient (β)**	**Std. Error**	***t***	***p*-Value**	**95% Confidence Interval**
Constant	69.612	1.266	54.998	<0.001	67.030–72.193
Light vehicles (LV)	-0.0036	0.004	-0.881	0.385	-0.012–0.005
Medium vehicles (MV)	-0.0236	0.009	-2.560	0.016	-0.042–-0.005
Heavy vehicles (HV)	-0.1955	0.018	-10.594	<0.001	-0.233–-0.158

The diagnostic evaluation of the proposed MLR model is summarized in Table 6, with corresponding graphical assessments presented in Figure 5. These evaluations were conducted to verify compliance with the principal assumptions of OLS regression and to assess the reliability of the estimated coefficients. The multicollinearity assessment indicated no substantial linear dependence among explanatory variables, with VIF values of 1.22 (light vehicles), 1.20 (medium vehicles), and 1.05 (heavy vehicles), and a mean VIF of 1.16, all below the threshold of 5, indicating that coefficient estimates were not materially affected.

Table 6. Diagnostic evaluation of the proposed multiple linear regression (MLR) model

Diagnostic Test	**Statistic**	**Criterion**	**Interpretation**
Variance Inflation Factor (VIF)			
Light vehicles (LV)	1.22	<5	No multicollinearity
Medium vehicles (MV)	1.20	<5	No multicollinearity
Heavy vehicles (HV)	1.05	<5	No multicollinearity
Mean	1.16	<5	Acceptable
Breusch-Pagan test	LM = 0.580	p = 0.446	No evidence of heteroscedasticity
Durbin-Watson statistic	2.369	Compared with published dL and dU critical bounds (n = 35, k = 4)	Falls within the inconclusive region for negative autocorrelation (n = 35, k = 4); no strong evidence of residual dependence
Omnibus test	χ^2 = 5.201	p = 0.074	Residuals approximately normally distributed
Jarque-Bera test	JB = 2.948	p = 0.229	Normality not rejected
Shapiro-Wilk test	W = 0.921	p = 0.016	Mild departure from normality

Homoscedasticity, residual independence, and normality were evaluated using formal statistical tests and graphical diagnostics. The Breusch–Pagan test (LM = 0.580, p = 0.446) indicated no evidence of heteroscedasticity, suggesting that the residual variance remained approximately constant across the fitted values. The Durbin–Watson statistic was 2.369. Based on the published Durbin–Watson critical values for n = 35 and k = 4, this value falls within the inconclusive region for negative autocorrelation rather than indicating statistically significant residual dependence. Accordingly, no strong evidence of serial correlation was identified. However, because the observations represent consecutive road segments along a single roadway corridor, spatial dependence cannot be excluded. Pavement condition measurements obtained from adjacent segments frequently exhibit spatial autocorrelation, which may violate the independence assumption of OLS regression. Previous studies have recommended the use of spatial diagnostic tests or spatial regression models when analysing pavement condition data with potential spatial dependence [30, 31].

Residual normality was assessed using the Omnibus, Jarque–Bera, and Shapiro–Wilk tests. The Omnibus (χ^2 = 5.201, p = 0.074) and Jarque–Bera (JB = 2.948, p = 0.229) tests did not reject the null hypothesis of normality, whereas the Shapiro–Wilk test (W = 0.921, p = 0.016) indicated a slight departure from normality. This difference is consistent with the higher sensitivity of the Shapiro–Wilk test to minor deviations from normality in relatively small samples. Consequently, statistical tests should be interpreted together with graphical diagnostics rather than independently [32, 33]. The diagnostic plots presented in Figure 5 show close agreement between observed and predicted PCI values, no discernible pattern in the residual distribution, and only minor deviations from normality at the distribution tails.

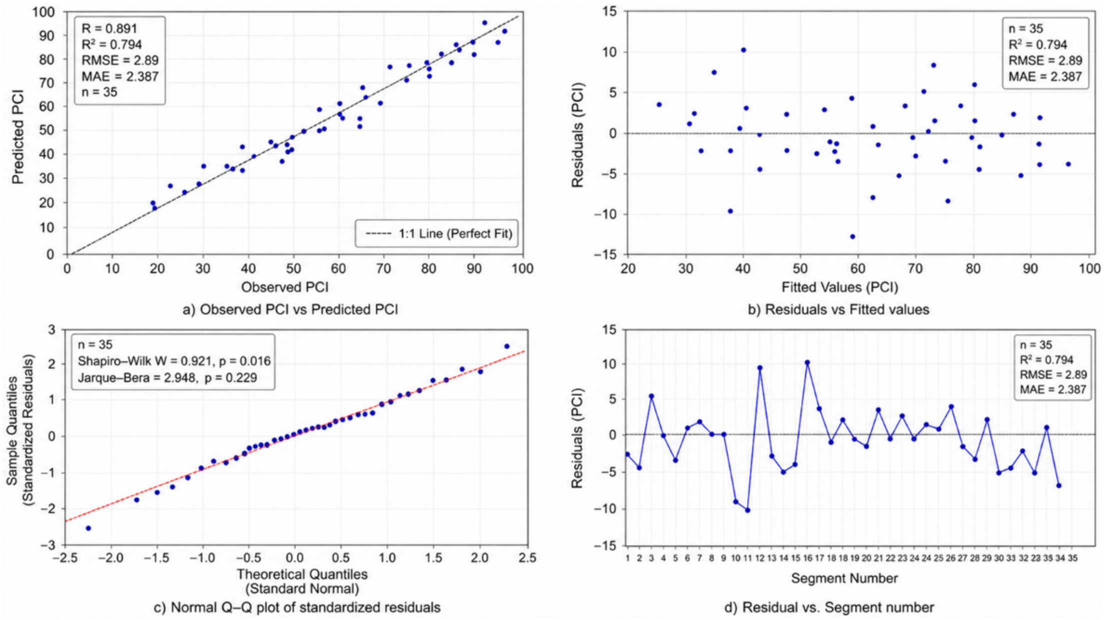

Figure 5. Regression diagnostic plots for the proposed multiple linear regression (MLR) model

Note: MLR—multiple linear regression; RMSE—Root Mean Square Error; MAE—Mean Absolute Error.

The predictive performance of the proposed model was further evaluated using Leave-One-Out Cross-Validation (LOOCV) based on the 35 pavement segments. The cross-validation produced an RMSE of 3.09 PCI units, an MAE of 2.71 PCI units, and a cross-validated coefficient of determination (R^2CV) of 0.73. These values are only slightly lower than the calibration performance (R^2 = 0.794), indicating that the model maintains satisfactory predictive accuracy when evaluated using unseen observations. The limited difference between the calibration and cross-validation metrics indicates that the model is unlikely to be substantially affected by overfitting despite the relatively small sample size. Similar findings have been reported in recent studies on PCI prediction and pavement deterioration modelling, in which comparable calibration and validation performance was interpreted as evidence of acceptable model generalizability [23, 34, 35].

3.4 Effect of Vehicle Composition on Pavement Condition Index

The relationship between vehicle composition and pavement condition was described by the MLR model presented in Eq. (3):

$$\mathrm{PCI} = 69.612 - 0.0036(\mathrm{LV}) - 0.0236(\mathrm{MV}) - 0.1955(\mathrm{HV}) \quad (3)$$

where, LV represents light vehicles, MV represents medium vehicles, and HV represents heavy vehicles. All regression coefficients were negative, indicating that increases in vehicle volume were associated with decreases in PCI after adjustment for the remaining explanatory variables. The intercept (69.612) represents the estimated PCI when the traffic volumes of all three vehicle categories are assumed to be zero. This condition is outside the observed range of the dataset; the intercept serves as a reference value to estimate the partial effect of each explanatory variable.

The observed coefficient pattern is consistent with the mechanical behaviour of flexible pavements. Vehicle classes imposing greater axle loads generate higher tensile strains within asphalt layers and greater compressive strains in the underlying pavement structure, thereby accelerating rutting, fatigue cracking, and permanent deformation under repeated traffic loading. Consequently, pavement deterioration is governed primarily by loading characteristics rather than vehicle frequency alone. Similar relationships between axle-load magnitude, vehicle–pavement interaction, and pavement deterioration have been reported in recent studies of flexible pavement performance [25, 36–38].

3.4.1 Light vehicles (LV)

Light vehicles produced a regression coefficient of -0.0036 (p = 0.385), indicating that their independent association with the PCI was not statistically significant at the 95% confidence level. After adjustment for medium- and heavy-vehicle traffic, variations in light-vehicle volume were not associated with measurable differences in pavement condition across the 35 surveyed segments. The 95% confidence interval included zero, indicating that the estimated effect could not be distinguished from random sampling variation.

Although light vehicles represented the dominant traffic category throughout the study corridor, their estimated coefficient was considerably smaller than those of medium and heavy vehicles. This result suggests that traffic frequency alone did not adequately explain segment-to-segment variation in PCI once differences in vehicle loading were incorporated into the regression model. The finding is consistent with pavement mechanics, where the structural response of flexible pavements depends primarily on wheel loads and the resulting stress–strain distribution rather than on vehicle counts alone. Passenger vehicles generally produce relatively small pavement responses because of their lower axle loads, whereas heavier commercial vehicles generate substantially greater tensile and compressive strains that accumulate into permanent pavement damage over repeated loading cycles [25, 37–39].

3.4.2 Medium vehicles (MV)

Medium vehicles produced a regression coefficient of -0.0236 (p = 0.016), indicating a statistically significant negative association with the PCI. After adjustment for the remaining predictors, each additional medium vehicle was associated with an average reduction of approximately 0.024 PCI units. Because the 95% confidence interval remained entirely below zero, the estimated relationship was statistically consistent across the observed data.

The coefficient magnitude exceeded that of light vehicles but remained substantially smaller than that of heavy vehicles, indicating an intermediate was associated with lower PCI values. This result is consistent with the loading characteristics of medium commercial vehicles, which impose higher axle loads than passenger vehicles while generally operating at greater frequencies than heavy trucks. Consequently, repeated loading from this vehicle class may contribute to cumulative pavement deterioration even when individual axle loads remain below those of heavy freight vehicles. Similar observations have been reported in recent pavement performance studies, which identified traffic composition, vehicle loading characteristics, and cumulative loading frequency as important determinants of pavement deterioration beyond total traffic volume alone [38, 40, 41].

3.4.3 Heavy vehicles (HV)

Heavy vehicles produced the largest regression coefficient (-0.1955) and the strongest statistical significance ($p <$ 0.001), indicating a consistent negative association with the PCI. After adjustment for light and medium vehicle volumes, each additional heavy vehicle was associated with an average reduction of approximately 0.20 PCI units. The confidence interval remained entirely below zero, indicating a stable and statistically reliable relationship across the observed pavement segments.

The magnitude of the estimated coefficient substantially exceeded that of the remaining traffic categories, indicating that heavy vehicles imposed the greatest deterioration effect within the calibrated model. Although heavy vehicles represented a relatively small proportion of the observed traffic, their higher axle loads generated considerably greater structural demand on the pavement system than passenger vehicles or medium commercial vehicles. This finding is consistent with recent pavement engineering studies demonstrating that pavement response is governed primarily by axle-load magnitude rather than vehicle frequency alone. Higher wheel loads increase tensile strain at the bottom of asphalt layers and compressive strain within the subgrade, thereby accelerating rutting, fatigue cracking, and cumulative structural deterioration under repeated loading cycles [24, 25, 36, 42].

3.5 Engineering Interpretation of Regression Results

The regression results demonstrated that the statistical contribution of each vehicle category differed substantially from its engineering significance. In the calibrated model, the estimated coefficients quantified the average change in PCI associated with variations in traffic volume after controlling for the remaining explanatory variables. These coefficients should not be interpreted as direct measures of structural damage because the model was developed from traffic counts rather than mechanistic pavement-response variables such as axle-load spectra, Equivalent Single Axle Loads (ESAL), pavement thickness, resilient modulus, or subgrade properties. Consequently, the estimated regression coefficients should be interpreted as empirical relationships calibrated from the observed field data rather than universal deterioration constants. Similar interpretations have been reported in recent pavement performance studies that distinguish statistical prediction models from mechanistic deterioration models [28, 41].

The analysis showed that heavy vehicles showed the strongest statistical association on PCI despite representing the smallest proportion of total traffic volume. The estimated coefficient for heavy vehicles was approximately 8.3 times greater than that of medium vehicles and more than 54 times greater than that of light vehicles. This large difference indicates that pavement deterioration was influenced primarily by traffic loading intensity rather than by traffic frequency alone. The result is consistent with the fundamental response of flexible pavements, where structural damage increases disproportionately with axle load because repeated high-stress loading accelerates permanent deformation, fatigue cracking, and cumulative structural deterioration [25, 36, 37].

By contrast, light vehicles constituted the dominant traffic class throughout the surveyed corridor but did not exhibit a statistically significant independent contribution after medium and heavy vehicles were incorporated into the regression model. This finding is consistent with pavement mechanics principles, wherein structural damage is governed primarily by axle-load magnitude rather than traffic frequency alone [25, 37, 38]. Instead, the regression model separated the effects of traffic quantity from traffic loading severity, demonstrating that the explanatory contribution of light vehicles diminished substantially when heavier vehicle classes were considered simultaneously. Accordingly, the influence of light vehicles should be interpreted as representing operational traffic demand rather than the principal source of structural pavement deterioration [23, 41].

Medium vehicles occupied an intermediate position within the calibrated model. Their regression coefficient remained statistically significant and negative, indicating that this vehicle category contributed measurably to reductions in PCI. Although the estimated deterioration rate was considerably lower than that associated with heavy vehicles, the relatively high operating frequency of medium commercial vehicles suggests that their cumulative contribution should not be overlooked in regional pavement management. Corridors supporting logistics distribution, public transportation, and commercial delivery services commonly experience sustained medium-vehicle traffic, which may accelerate deterioration even when heavy-truck volumes remain comparatively modest [38, 40].

Collectively, these findings suggest that pavement deterioration may not be adequately interpreted using traffic volume alone. Vehicle composition provides substantially greater explanatory value because it reflects differences in axle-loading characteristics among traffic classes. The regression model indicates that increases in heavy-vehicle traffic are associated with the largest reductions in pavement condition, whereas medium vehicles contribute a moderate but statistically significant effect, and light vehicles primarily represent overall traffic intensity. This distinction is particularly relevant for engineering decision-making because maintenance strategies based solely on total traffic volume may underestimate the structural consequences of relatively small increases in heavy commercial traffic [13, 43].

From an infrastructure management perspective, the calibrated model provides a practical framework for identifying the traffic characteristics most strongly associated with pavement deterioration at the corridor level. Nevertheless, the regression coefficients should not be interpreted as transferable deterioration factors for other road networks. Their magnitude reflects the combined influence of the local pavement structure, traffic composition, environmental conditions, and maintenance history observed along the Ciganea–Cijantung Road Section. Application of the model beyond the investigated corridor should therefore be preceded by local calibration using representative traffic and pavement-condition data. Future studies incorporating mechanistic traffic indicators, including ESAL, axle-load spectra, WIM measurements, and pavement structural properties, would provide a more comprehensive representation of deterioration processes and strengthen the engineering interpretation of regression-based pavement performance models [34, 35, 44].

3.6 Practical Implications for Pavement Maintenance

The regression analysis demonstrated that variations in pavement condition were associated with differences in vehicle composition across the surveyed corridor. Heavy vehicles exhibited the largest deterioration coefficient, indicating that increases in heavy-vehicle traffic were associated with greater reductions in the PCI than comparable increases in light or medium vehicles. This observation is consistent with pavement performance models that identify traffic composition as an important predictor of pavement deterioration [23, 41].

The descriptive analysis further showed that the investigated corridor remained within the good PCI category, with a mean PCI of 61.89, although considerable variation was observed among individual segments. Several segments exhibited PCI values approaching the lower limit of the good classification, indicating that localized deterioration had already developed despite the satisfactory corridor-wide average. Similar findings have been reported in network-level pavement studies, where average condition indices often mask localized distress requiring early intervention [13, 43]. This pattern highlights the limitation of relying exclusively on network-level condition indicators, as average PCI values may conceal segments requiring earlier intervention. Consequently, maintenance prioritization should be established at the segment level rather than solely on corridor-wide averages.

The regression coefficients provide additional guidance for maintenance decision-making. Segments experiencing relatively high heavy-vehicle traffic should receive greater attention during periodic condition assessments because the estimated deterioration rate associated with heavy vehicles substantially exceeded those of the remaining traffic categories. Likewise, corridors carrying sustained volumes of medium commercial vehicles should not be overlooked, as the regression results indicated that this vehicle class also contributed significantly to reductions in PCI. Previous research has emphasized that medium commercial vehicles, due to their frequency and moderate axle loads, can cumulatively accelerate pavement deterioration [41]. In contrast, although light vehicles dominated overall traffic volume, their independent contribution was not statistically significant after accounting for heavier vehicle classes. This finding indicates that maintenance priorities should be determined using traffic composition rather than traffic volume alone.

The field survey also identified localized concentrations of rutting and potholes in sections where roadside drainage was absent or inadequately maintained. Although drainage variables were not explicitly incorporated into the regression model, these observations suggest that routine drainage maintenance should accompany pavement preservation activities. The influence of moisture infiltration on pavement deterioration has been widely documented, particularly in flexible pavements where water weakens the subgrade and accelerates distress development [13, 44]. Preventing water infiltration through timely cleaning of drainage channels, shoulder maintenance, and localized surface repairs is likely to reduce the progression of moisture-related deterioration and extend pavement service life, particularly in segments already exhibiting early signs of distress.

From an asset management perspective, the proposed MLR model provides a practical decision-support tool because it requires only routinely collected traffic data and PCI measurements. The model enables road agencies to identify segments where changes in traffic composition are associated with increased deterioration risk, thereby supporting more effective allocation of maintenance resources. This approach aligns with recent developments in pavement management systems that emphasize data-driven prioritization and cost-effective maintenance planning under limited budgets [13, 44]. It is particularly applicable to regional road networks where detailed mechanistic evaluations are constrained by limited budgets, equipment availability, or traffic-loading measurements.

The calibrated model should nevertheless be interpreted within the scope of the available data. The estimated coefficients quantify empirical relationships observed along the Ciganea–Cijantung Road Section and do not explicitly account for pavement structural capacity, axle-load spectra, material characteristics, climatic exposure, or maintenance history. Consequently, the model is most appropriate as a screening and prioritization tool rather than a substitute for detailed pavement structural evaluation. Future pavement management systems would benefit from integrating traffic composition with mechanistic indicators such as ESAL, WIM measurements, pavement structural properties, and environmental variables to improve both predictive accuracy and engineering interpretability, as recommended in recent pavement performance modeling studies [23, 44].

4 Conclusions

This study developed an MLR model to quantify the relationship between vehicle composition and the PCI along the Ciganea–Cijantung Road Section. The calibrated model showed strong explanatory power (R^2 = 0.794; Adjusted R^2 = 0.774), with diagnostic evaluations confirming the absence of problematic multicollinearity and heteroscedasticity. Although the corridor maintained a good average PCI (61.89), substantial segment-level variation was observed. Field assessments identified rutting and potholes as predominant distresses, localized primarily in segments with inadequate roadside drainage and intensive traffic loading. These findings suggest that corridor-wide average PCI values may be insufficient for detecting localized deterioration, necessitating segment-level evaluation.

Regression analysis indicated that different vehicle categories were differently associated with pavement condition. Heavy vehicles exhibited the largest negative coefficient, followed by medium vehicles, whereas light vehicles lacked statistical significance after controlling for heavier classes. These results suggest that traffic composition provides greater explanatory value for pavement deterioration compared to aggregate traffic volume alone. The additional LOOCV analysis (RMSE = 3.09, MAE = 2.71, and R^2CV = 0.73) further demonstrates that the proposed model retains acceptable predictive performance beyond the calibration dataset, although validation using larger datasets from different road corridors remains desirable.

The proposed model functions as a practical, data-driven screening tool for regional road agencies to prioritize maintenance based on traffic loading profiles, particularly where mechanistic data are unavailable. However, because the empirical coefficients do not capture structural capacity, axle-load spectra, material properties, or maintenance history, the model's transferability is inherently constrained to the investigated corridor. Future research should integrate mechanistic indicators—including ESAL, WIM data, pavement structural capacity, and environmental variables—to enhance the physical interpretability and predictive accuracy of pavement performance models.

Author Contributions

Conceptualization, Bahtiar; methodology, Bahtiar and T.A.A.; software, Joni and M.R.K.; validation, Bahtiar and T.A.A.; data curation, D.P., Falderika, and M.R.K.; writing—original draft preparation, Bahtiar and Joni; writing—review and editing, Bahtiar; visualization, Joni; supervision, Bahtiar. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Declaration on the Use of Generative AI and AI-assisted Technologies

The authors declare that generative artificial intelligence (AI) and AI-assisted technologies were used in the preparation of this manuscript, primarily to support language refinement, grammar correction, and the organization of ideas. No data, results, or references were fabricated, and all intellectual contributions, interpretations, and conclusions were made by the authors. The authors remain fully responsible for the accuracy, originality, and integrity of the work, and for ensuring compliance with ethical and publishing standards. Generative AI tools were not listed as authors, and their role was limited to assisting with clarity and readability of the text.

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Nomenclature

PCI	Pavement Condition Index
LV	light vehicle traffic volume, vehicles/16 h
MV	medium vehicle traffic volume, vehicles/16 h
HV	heavy vehicle traffic volume, vehicles/16 h
CV	Cross-Validation
R	multiple correlation coefficient
R^2	coefficient of determination
Adjusted R^2	adjusted coefficient of determination
RMSE	Root Mean Square Error
LOOCV	leave-one-out cross-validation
OLS	Ordinary Least Squares
MLR	multiple linear regression
VIF	Variance Inflation Factor
DW	Durbin-Watson statistic
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
F	F-statistic of the regression model
p	probability value (statistical significance)
n	number of observations
β_i	regression coefficient for predictor i, PCI/(vehicle/16 h)
β_0	regression intercept
ε	random error term

Subscripts

i	road segment index