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Analysis of Overdimension and Overloading (ODOL) in Freight Transport Using the SEM-PLS Approach

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ABSTRACT

Overdimension and Overloading (ODOL) violations represent a critical issue in Indonesia's freight transport sector, impacting road safety, infrastructure durability, and logistics cost efficiency. Purpose: This study aims to analyze the influence of environmental, driver, enforcement officer, and vehicle factors on ODOL practices and to assess their economic implications. Method: A quantitative approach using Structural Equation Modeling–Partial Least Squares (SEM-PLS) was applied to data collected from 300 respondents at the Weighbridge Station (Unit Pelaksana Penimbangan Kendaraan Bermotor, UPPKB) in South Sulawesi. Findings: Driver-related factors emerged as the most dominant determinant, while ODOL served as a significant mediating variable linking causal factors to economic impacts. Although ODOL practices may yield short-term trip efficiency, they generate substantial long-term losses, including infrastructure damage, increased accident rates, and excessive energy consumption. Conclusion: Technology-based monitoring, continuous driver education, and consistent enforcement policies are essential to curb ODOL violations and enhance the sustainability of the national freight transport system.

Keywords: overloading, overdimension, freight transport, economic factors, SEM-PLS.

INTRODUCTION

Economic growth and urbanization in various countries, including Indonesia, have significantly increased the demand for logistics services. An efficient transportation system serves as the backbone of trade, distribution, and regional integration [1]. However, this growth in freight mobility is often not accompanied by strict compliance with vehicle technical regulations. One of the most critical road transport issues in Indonesia is the practice of Overdimension and Overloading (ODOL), which refers to violations of vehicle dimension and load regulations established by transportation authorities [2], [3].

ODOL practices generate extensive negative impacts on infrastructure, traffic safety, and economic efficiency. Overloaded vehicles accelerate the deterioration of roads and bridges, increase infrastructure maintenance costs, and create negative externalities such as pollution, congestion, and higher accident risks [4], [5], [6]. From an economic perspective, ODOL leads to significant energy waste and social costs, reducing the competitiveness of the national logistics sector [7], [8].

The drivers behind the prevalence of ODOL are multidimensional, encompassing driver behavior, vehicle technical conditions, the effectiveness of enforcement, and socio-economic operational pressures [9]. Drivers often face time constraints and operational cost pressures, prompting them to violate dimension and load regulations. The limited number of field officers and weak enforcement mechanisms further create opportunities for such violations [10], [11]. Moreover, intense competition in the logistics industry and the pursuit of short-term efficiency drive some operators to perceive ODOL as a cost-saving strategy, despite its long-term detrimental consequences [12]. This aligns with the findings of [13], which indicate that the high operational costs of freight transport in South Sulawesi encompassing fuel expenses, vehicle maintenance, and travel costs drive operators to maximize load capacity as an efficiency strategy, even at the risk of violating vehicle dimension and weight regulations.

From a methodological standpoint, most previous studies remain descriptive and partial, focusing on only one or two causal factors without addressing the complexity of their interactions. In reality, ODOL issues involve simultaneous interactions among transportation actors (drivers, enforcement officers, and fleet owners), regulatory aspects, and infrastructure conditions [14]. Structural Equation Modeling–Partial Least Squares (SEM-PLS) is particularly relevant for analyzing such relationships as it can accommodate multidimensional latent constructs and non-normal data distributions [15], [16].

While numerous international and national studies have examined the impact of ODOL on infrastructure and safety [3], [7], [12], few have simultaneously analyzed the influence of environmental, driver, enforcement, and vehicle factors on economic aspects through the mediating role of ODOL. In Indonesia, empirical studies employing SEM-PLS with a multidimensional focus on the interplay between behavior, enforcement, and economic impact remain scarce [5], [6]. Therefore, this study seeks to fill this research gap by developing a comprehensive causal model.

Based on the above background, this study aims to:

1. Analyze the influence of driver, vehicle, inspector, and environmental factors on ODOL practices.
2. Examine the impact of ODOL practices on economic aspects.
3. Assess the mediating role of ODOL in linking causal factors to economic impacts.

This research contributes theoretically by expanding the understanding of ODOL dynamics through a causal and multidimensional approach. Practically, the findings are expected to support the formulation of evidence-based transportation policies, particularly in strengthening vehicle technical compliance, enhancing inspection effectiveness, and designing sustainable strategies to curb ODOL practices in Indonesia.

Overdimension and Overloading Practices in Freight Transport

Overdimension and Overloading (ODOL) practices have become a critical issue in the road transportation sector, particularly in freight transport modes. ODOL refers to technical violations involving vehicle dimensions and loads that exceed official regulatory limits. Its impacts extend beyond increased accident risks to include accelerated infrastructure deterioration and energy wastage [3]. International studies indicate that ODOL practices are more prevalent in developing countries, where weaknesses in enforcement systems and high pressure for logistical efficiency create conditions conducive to non-compliance [9], [17].

Determinants of Overdimension and Overloading Practices

Overdimension and Overloading (ODOL) is a multidimensional phenomenon influenced by various interrelated factors. From the driver's perspective, time pressure, low legal awareness, and strict operational targets are often cited as primary reasons for non-compliance [7]. In terms of vehicle factors, non-standard physical modifications and weak maintenance systems significantly increase the likelihood of ODOL occurrences [12]. On the enforcement side, limitations in personnel, the ineffectiveness of sanctions, and potential conflicts of interest create opportunities for leniency towards violations [11]. Furthermore, socio-economic conditions play an important role, where the need for cost efficiency and the shortage of fleet capacity drive operators to overload their vehicles [1], [10].

Economic Impacts of Overdimension and Overloading Practices

The economic losses resulting from Overdimension and Overloading (ODOL) encompass both direct and indirect costs. Direct costs include road and bridge maintenance expenditures, as well as increased fuel consumption due to vehicle inefficiency [5]. Indirect costs comprise delivery delays, reduced vehicle lifespan, increased traffic accidents, and broader social burdens borne by communities [8]. Several studies have emphasized that, although ODOL may yield short-term benefits such as trip efficiency gains of 25–30% its long-term economic losses can reach up to 40%, primarily driven by escalating infrastructure expenses and growing social costs [6], [18].

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Previous Studies and Research Gap

A range of studies have examined the Overdimension and Overloading (ODOL) phenomenon; however, most remain descriptive and partial in scope. For example, several investigations have focused solely on driver-related factors or vehicle conditions in isolation, without accounting for the simultaneous interconnections among these determinants [14]. Comprehensive studies that integrate driver, vehicle, enforcement, and environmental factors remain scarce, particularly within the Indonesian context. Furthermore, the application of Structural Equation Modeling–Partial Least Squares (SEM-PLS) to test causal relationships and to assess the mediating role of ODOL in influencing economic impacts is still rarely implemented [19]. This gap underscores the need for a multidimensional analytical framework that not only identifies direct effects but also reveals the underlying mechanisms linking operational factors to broader economic outcomes.

Theoretical Framework

Based on the literature review, the practice of Overdimension and Overloading (ODOL) is influenced by four main factors: driver behavior, vehicle technical condition, enforcement officer effectiveness, and environmental/operational conditions. These four factors can directly affect the occurrence of ODOL, while ODOL itself serves as a mediating variable linking these causal factors to the economic impact of freight transportation.

Theoretically, driver-related factors include behavior, legal awareness, and operational pressures that may trigger violations of vehicle dimensions and load regulations. The technical condition of vehicles, including specifications and maintenance, determines the fleet's compliance capability. The effectiveness of enforcement officers is associated with the consistency of law enforcement and the quality of roadside inspections. Meanwhile, environmental/operational factors cover road infrastructure, delivery schedules, and competitive pressures in the logistics industry.

This study applies the Structural Equation Modeling–Partial Least Squares (SEM-PLS) approach to identify direct effects, indirect effects, and mediation effects among variables. The proposed conceptual model is expected to provide a comprehensive causal understanding of the determinants and consequences of ODOL, serving as a foundation for evidence-based transportation policy aimed at improving efficiency, safety, and sustainability [1].

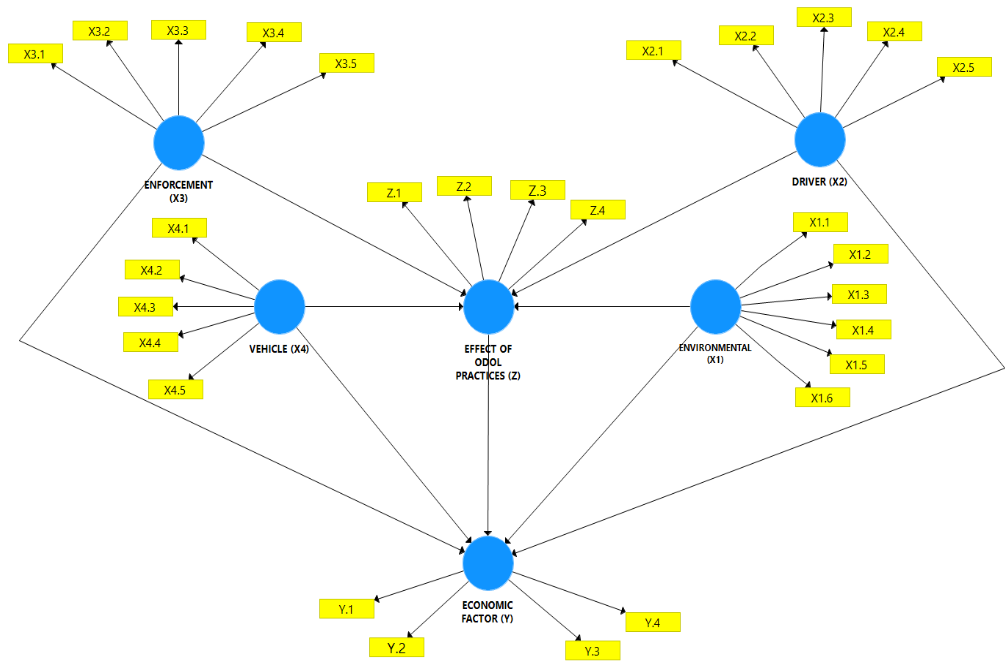

Figure 1. Conceptual Model (Source: SmartPLS 3.0, 2025)

RESEARCH DESIGN

This study employs a quantitative research approach using Structural Equation Modeling–Partial Least Squares (SEM-PLS) to analyze the relationships among variables influencing Overdimension and Overloading (ODOL) practices and their implications for economic factors. SEM-PLS was chosen due to its capability to accommodate complex latent variable models, evaluate both direct and indirect effects, and handle data with non-normal distributions effectively [15], [16].

Population and Sample

The study population comprised drivers, enforcement officers, and logistics operators operating at the Vehicle Weigh Station (Unit Pelaksana Penimbangan Kendaraan Bermotor – UPPKB) Datae, Sidrap Regency, South Sulawesi, Indonesia. A purposive sampling technique was employed, with respondents selected based on their direct involvement in freight transportation activities. A total of 300 respondents were interviewed and analyzed, meeting the minimum sample size requirement for SEM-PLS analysis as recommended by [20].

Research Variables and Indicators

This study involves four independent variables, one mediating variable, and one dependent variable, detailed as follows:

1. **Environment (X1):** socio-economic conditions, cost-efficiency pressures, and external regulations [1], [9].
2. **Driver (X2):** driving experience, compliance with regulations, and workload [7].
3. **Enforcement (X3):** effectiveness of supervision, consistency in law enforcement, and quality of service [11].
4. **Vehicle (X4):** technical condition of the fleet, maintenance practices, and conformity with dimensional regulations [12].
5. **ODOL Practice (Z):** overloading and dimensional modification of vehicles [5].
6. **Economic Factors (Y):** cost efficiency, fuel consumption, and socio-economic impacts [8].

The research instrument was a 5-point Likert scale questionnaire, which was pre-tested to ensure validity and reliability.

Data Analysis Technique

Data analysis was conducted using SmartPLS version 3.0. The analytical stages included:

1. Outer Model (Measurement Model) Assessment
   a. Convergent validity evaluated through factor loadings and Average Variance Extracted (AVE).
   b. Construct reliability assessed using Composite Reliability and Cronbach's Alpha.
2. Inner Model (Structural Model) Assessment
   a. Coefficient of determination (R^2) to evaluate the model's predictive power.
   b. Path coefficient significance testing performed using the bootstrapping procedure.
   c. Predictive relevance (Q^2) to assess the model's predictive validity.
3. Mediation Testing
   a. Analysis of the role of ODOL as a mediating variable between causal factors and economic impact, following the procedures outlined by [15] and [6].

Conceptual Framework

The conceptual framework of this study is presented in Figure 1, illustrating the relationships between environmental factors, drivers, officers, and vehicles on ODOL practices, as well as their impact on economic factors. The model also depicts both direct effects and indirect effects through the mediating role of ODOL.

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Ethical Considerations

This study was conducted in accordance with established research ethics principles. All respondents were provided with a clear explanation of the research objectives and their right to participate voluntarily. The confidentiality of respondents' identities was strictly maintained, and the collected data were used solely for academic purposes. Official approval for data collection was obtained from the Land Transportation Management Center (Balai Pengelolaan Transportasi Darat/BPTD) Class II of South Sulawesi, Indonesia, in compliance with applicable regulations.

RESULT AND DISCUSSION

Respondent Characteristics

A total of 300 respondents participated in this study, comprising freight vehicle drivers and Weigh Station (UPPKB) officers at the research site, namely UPPKB Datae, Sidrap Regency. Table 1 summarizes the demographic and occupational characteristics of respondents, including gender, age, type of occupation, and years of service.

Table 1. Respondent Characteristics

Characteristics	Category	Frequency	Percentage (%)
Gender	Male	295	98%
	Female	5	2%
Age	< 30 years	58	19,3%
	30-45 years	211	70,3%
	> 45 years	31	10,3%
Occupation	Driver	281	93,7%
	UPPKB Officer	19	7%
Work Experience	< 5 years	102	35,2%
	> 5 years	198	66%

This study involved 300 respondents, comprising 98% male and 2% female participants. This composition indicates that the freight transport sector at the study location remains predominantly male-dominated. In terms of age distribution, the majority of respondents were between 30–45 years old (70.3%), followed by those under 30 years old (19.3%) and respondents over 45 years old (10.3%). These figures suggest that most participants are within the productive age range and actively engaged in freight transport operations.

With regard to occupation, 93.7% of respondents were truck drivers, while 7% were UPPKB officers. This reflects the direct involvement of field actors, both in operational activities and in freight vehicle monitoring. In terms of work experience, 66% of respondents had been employed in the sector for more than five years, whereas 35.2% had less than five years of experience. This indicates that the majority of participants possess substantial professional experience in logistics and transportation.

Overall, the respondent profile demonstrates direct involvement, relevant professional experience, and demographic characteristics closely aligned with the operational realities of Overdimension and Overloading (ODOL) issues in the field.

Measurement Model Evaluation (Outer Model)

Convergen Validity

The loading factor (outer loading) measures the strength of the correlation between an indicator and the construct it represents. According to [16], a recommended threshold for the loading factor is ≥ 0.70; however, in exploratory research, values ≥ 0.60 are still considered acceptable. A higher loading factor indicates that an indicator makes a stronger contribution in representing the underlying construct.

Table 2. Results of Loading Factor Test (Source: SmartPLS 3.0 2025)

Variable	Indicator		Loading Factor	Description
Environmental (X1)	X1.1	Road condition	0,891	Valid
	X1.2	Road infrastructure	0,872	Valid
	X1.3	Control facilitas	0,900	Valid
	X1.4	Geoverment policies	0,861	Valid
	X1.5	Monitoring facilities	0,828	Valid
	X1.6	Transport Efficiency	0,872	Valid
Driver (X2)	X2.1	Legal awareness	0,890	Valid
	X2.2	Time pressure	0,891	Valid
	X2.3	Driving experience	0,820	Valid
	X2.4	Law compliance	0,882	Valid
	X2.5	Supervision	0,883	Valid
Enforcement (X3)	X3.1	Routine inspection	0,882	Valid
	X3.2	Strict sanctions	0,862	Valid
	X3.3	Regulation dissemination	0,916	Valid
	X3.4	Preventive measures	0,887	Valid
	X3.5	Driver awareness	0,844	Valid
Vehicle (X4)	X4.1	Vehicle technical condition	0,899	Valid
	X4.2	Load capacity	0,908	Valid
	X4.3	Travel safety	0,879	Valid
	X4.4	Vehicle maintenance	0,908	Valid
	X4.5	Vehicle modifications	0,815	Valid
Economic Factors (Y)	Y1	Operational cost	0,787	Valid
	Y2	Distribution cost	0,717	Valid
	Y3	Company revenue	0,785	Valid
	Y4	Social and economic cost	0,825	Valid
ODOL Practices (Z)	Z1	Violation frequency	0,821	Valid
	Z2	Vehicle damage	0,830	Valid
	Z3	Excessive load burden	0,838	Valid
	Z4	Damage caused by ODOL	0,810	Valid

Based on the data processing results using SmartPLS 3.0, all indicators in this study recorded outer loading values above the recommended threshold, indicating that each construct is well-measured and statistically valid.

For the environmental factor construct, six indicators yielded loading values ranging from 0.828 to 0.900. Control facility (0.900) contributed the highest loading, followed by road conditions (0.891) and road infrastructure (0.872). These results suggest that infrastructure quality and monitoring effectiveness are the most influential environmental aspects in shaping ODOL practices, consistent with [14] and [9], but contrasting with [21], who identified government policy as the dominant indicator. In this study, government policy ranked fourth (0.861), indicating possible weaknesses in operational implementation.

The driver factor comprised five indicators with loadings between 0.820 and 0.891. Time pressure (0.891) and legal awareness (0.890) emerged as the strongest contributors, highlighting the role of psychological factors and regulatory compliance in influencing overloading behavior. This finding aligns with [7], yet differs from [22], who emphasized driving experience as the primary determinant.

For the enforcement officer factor, loadings ranged from 0.844 to 0.916, with regulatory socialization achieving the highest value (0.916). This underscores the significant contribution of educational outreach in curbing ODOL, consistent with [11] and [10]. However, unlike [23] who identified strict sanctions as the key factor, in this study strict sanctions ranked third (0.862).

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The vehicle factor displayed loadings between 0.815 and 0.908, with payload capacity and vehicle maintenance both at 0.908, followed by technical condition (0.899). These results corroborate Deveci et al. (2023), who noted that technical limitations are often modified to accommodate excess loads. However, vehicle modification in this study had the lowest loading (0.815), differing from [12], who placed it as the leading indicator.

The economic factor yielded loadings from 0.717 to 0.825. Socio-economic costs ranked highest (0.825), whereas distribution costs had the lowest (0.717), yet still met validity criteria. This aligns with [6], who emphasized the broad economic impacts of ODOL, but contrasts with [24], who identified distribution costs as the primary driver.

Finally, the ODOL construct was measured using four indicators with loadings between 0.810 and 0.838. Excess payload (0.838) and vehicle damage (0.830) were the most prominent, [2], who established a direct link between overloading, technical damage, and high maintenance costs.

Overall, the convergent validity assessment confirms that all constructs in the model are statistically valid, with key indicators clearly representing their respective latent variables, thereby supporting the robustness of the measurement model used in this study.

Average Variance Extracted (AVE) and Construct Reliability

The Average Variance Extracted (AVE) measures the proportion of variance in the indicators that can be explained by the construct compared to the error variance. The recommended AVE value is ≥ 0.50, indicating that more than half of the variance in the indicators is explained by the measured latent construct Fornell & Larcker (1981).

Convergent validity is also reinforced through construct reliability, estimated using Composite Reliability (CR) and Cronbach's Alpha. Both are recommended to have values ≥ 0.70 to ensure the internal consistency among indicators.

Table 3. Results of AVE and Composite Reliability (Source: SmartPLS 3.0 2025)

Variable	AVE	Composite Reliability (CR)	Description
Environmental (X1)	0.672	0.899	Valid and Reliable
Driver (X2)	0.681	0.902	Valid and Reliable
Enforcement (X3)	0.654	0.891	Valid and Reliable
Vehicle (X4)	0.669	0.893	Valid and Reliable
ODOL Practices (Z)	0.688	0.905	Valid and Reliable
Economic Factor (Y)	0.702	0.912	Valid and Reliable

The analysis revealed that the environmental variable exhibited strong convergent validity, with indicators such as road conditions and infrastructure explaining more than 67% of the construct variance. This result is consistent with [14], who reported AVE values above 0.65 when assessing infrastructure quality in relation to logistics violations. Compared to [11], who obtained a composite reliability (CR) of 0.79, the present study demonstrates a higher reliability level.

The driver variable also showed a high AVE value, indicating that indicators such as time pressure and legal awareness provide substantial explanatory power for the construct. This finding corroborates the work of [7] and [24], both of which emphasize the critical role of psychological and behavioral factors in ODOL practices. The CR value of 0.902 indicates excellent internal consistency, exceeding the average CR of 0.85 reported by [25] in the context of sustainable transportation.

For the enforcement officer variable, the high AVE value suggests that monitoring and regulatory outreach efforts are well captured by the employed indicators. This aligns with [10] and surpasses the reliability levels reported by [23], who recorded a CR of 0.84 in their study on logistics enforcement in Eastern Europe.

Similarly, the vehicle variable obtained high AVE and CR values, confirming that technical aspects such as load capacity and maintenance are critical in explaining variations in ODOL practices. These findings are consistent with those of [15] and [12], although the AVE value is marginally lower than that reported by [26], which may reflect contextual differences in vehicle condition perceptions across regions.

The ODOL effects variable also demonstrated high AVE and CR values, indicating that indicators such as vehicle damage, excessive load, and violation frequency effectively represent the construct. This is in line with [2], who reported an AVE of 0.66 in assessing the impact of dimensional violations on infrastructure and safety.

Finally, the economic impact variable recorded the highest AVE value among all constructs, suggesting that the influence of ODOL on both direct and indirect economic losses is the most stable and well-measured construct in this study. This finding reinforces the conclusions of [6] regarding ODOL's significant impact on logistics performance and demonstrates stronger statistical robustness compared to [27], who reported an AVE of only 0.59.

Table 4. Cronbach's Alpha Results (Source: SmartPLS 3.0 2025)

Variable	Cronbach's Alpha	Description
X1 (Environmental)	0,938	*Reliable*
X2 (Driver)	0,927	*Reliable*
X3 (Enforcement)	0,931	*Reliable*
X4 (Vehicle)	0,929	*Reliable*
Y (Economic Factor)	0,784	*Reliable*
Z (ODOL Practices)	0,843	*Reliable*

Cronbach's Alpha was employed to assess the internal consistency among indicators within each latent construct. According to [16], a value ≥ 0.70 indicates acceptable reliability, values between 0.70 and 0.90 reflect good reliability, and values above 0.90 denote very high reliability.

The results indicate that all constructs achieved Cronbach's Alpha values above 0.78, confirming their reliability. The Environmental factor (X1) recorded the highest score ($\alpha = 0.938$), suggesting that indicators such as road conditions, infrastructure, and monitoring exhibit exceptionally strong internal consistency. This exceeds the findings of [14], who reported $\alpha = 0.90$ for a similar construct.

The Driver factor (X2) obtained $\alpha = 0.927$, indicating strong cohesion among indicators such as legal awareness and time pressure. This result aligns with [7], who reported $\alpha = 0.918$ for driver behavior in the context of regulatory violations.

The Enforcement Officer factor (X3) also demonstrated high reliability ($\alpha = 0.931$), reflecting the consistency of indicators related to monitoring, sanction enforcement, and regulatory outreach. This value is higher than that reported by [10], who recorded $\alpha = 0.884$ for logistics enforcement measures.

The Vehicle construct (X4) achieved $\alpha = 0.929$, confirming that technical aspects such as vehicle condition, capacity, and maintenance were measured with a robust and reliable instrument. This is consistent with [15], who reported $\alpha = 0.902$ in a study on logistics vehicles.

The ODOL Effects construct (Z) scored $\alpha = 0.843$, indicating solid reliability, in line with [2], who reported $\alpha = 0.832$ when assessing the impact of ODOL violations on vehicles and infrastructure.

Finally, the Economic Impact factor (Y) recorded the lowest value ($\alpha = 0.784$), yet remained above the recommended threshold. Although this construct is influenced by multiple external factors, indicators related to operational costs, distribution expenses, and company revenues still demonstrated acceptable internal consistency. This value is slightly lower than that reported by [6] ($\alpha = 0.802$), but it remains within the "good" reliability category.

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Inner Model Evaluation (Structural Model)

The structural model (inner model) evaluation was conducted to assess the strength of relationships among latent constructs and the overall predictive capability of the model. The assessment followed five primary criteria: (1) the coefficient of determination (R^2), which measures the proportion of variance in endogenous constructs explained by exogenous constructs; (2) predictive relevance (Q^2), indicating the model's ability to generate accurate predictions; (3) path coefficients and their significance levels, used to test the research hypotheses; (4) the Variance Inflation Factor (VIF), which detects potential multicollinearity among predictor variables; and (5) the Standardized Root Mean Square Residual (SRMR), serving as a global fit index to evaluate the model's adequacy.

The combined use of these criteria ensures that the resulting model is not only statistically significant but also possesses sufficient predictive power, thereby aligning with the research objectives.

Coefficient of Determinant (R^2)

The coefficient of determination (R-Square) is used to evaluate the ability of independent variables to explain the variance of dependent variables within the structural model. According to Chin (1998), as cited in [16], the R^2 values can be categorized as follows:

a. Weak: $R^2 < 0.19$
b. Moderate: $R^2 = 0.33–0.66$
c. Substantial: $R^2 > 0.67$

Table 5. R-Square Results *(Source: SmartPLS 3.0 2025)*

Variable	R Square (R^2)	Interpretation
Economic Factor (Y)	0,651	Moderate
ODOL Practices (Z)	0,554	Moderate

Based on the data analysis using SmartPLS, the R^2 value for the Economic Factor variable (Y) was found to be 0.651, indicating that 65.1% of the variance in this variable can be explained by Environment, Driver, Officer, and Vehicle factors, while the remaining 34.9% is influenced by other factors outside the model. This value falls within the moderate-to-strong category, suggesting that the model has good predictive accuracy in the context of freight transport economics. Meanwhile, the Overdimension and Overloading (ODOL) Practice Effect variable (Z) recorded an R^2 value of 0.554, meaning that 55.4% of its variability can be explained by the four exogenous variables. This value also falls into the moderate category, indicating that the model is representative in explaining the impacts of ODOL. These findings are consistent with those of [27], who reported R^2 values of 0.61 and 0.58, respectively, in similar studies, but are lower than those in [28], which achieved an R^2 of 0.71 due to broader economic indicators and research conducted along major national distribution routes. Conversely, the R^2 values in the present study are higher than those reported by [29], who obtained a value of 0.47 for ODOL effect variables in the ASEAN region, reinforcing that in the Indonesian context particularly in South Sulawesi the influence of environmental and field actor factors on ODOL effects is relatively significant.

Predictive Relevance (Q^2)

The Q-square (Q^2) test is used to assess the predictive capability of the model for endogenous variables within the Partial Least Squares Structural Equation Modeling (PLS-SEM) framework. According to [16], a positive Q^2 value indicates the presence of predictive relevance, with the following interpretation criteria: $Q^2 < 0.25$ indicates weak predictive relevance; Q^2 between 0.25–0.50 indicates moderate predictive relevance; and $Q^2 > 0.50$ indicates strong predictive relevance.

In this study, the Q^2 value was calculated using a formula that considers the magnitude of the R-square (R^2) and the residual error, thereby reflecting the extent to which the variation in the endogenous constructs can be predicted by the exogenous constructs within the model.

$$\textit{Q-Square} = 1-[(1-R_1^2)\times(1-R_2^2)]$$

$$= 1 - [(1 - 0{,}554) \times (1 - 0{,}651)]$$
$$= 1 - 0{,}1557$$
$$= 0{,}844$$

A Q^2 value of 0.8443 indicates that the model possesses exceptionally strong predictive power for both the ODOL Effect (Z) and Economic Factors (Y) variables. This achievement is substantially higher than that reported in several previous studies. For comparison, [14] reported a Q^2 value of 0.61 in a study on the influence of driver behavior on logistics efficiency. [29] recorded a Q^2 value of 0.49 in a model linking freight violations to socio-economic costs. Similarly, [30] obtained a Q^2 value of 0.53 in a North African study predicting road durability in relation to load violations. These differences suggest that the model in the present study is not only statistically significant but also demonstrates superior predictive accuracy in the context of ODOL within the freight transport sector.

Variance Inflation Factor (VIF)

A multicollinearity test was conducted to ensure the absence of high correlations among the exogenous (independent) variables, which could compromise the accuracy of regression coefficient estimations in the structural model. The Variance Inflation Factor (VIF) was used as the diagnostic indicator, where a VIF value of less than 3.3 indicates no multicollinearity, while values exceeding 5.0 suggest the presence of severe multicollinearity [16].

Table 6. Results variance Inflation Factor (VIF) (Source: SmartPLS 3.0 2025)

Pathway	VIF	Interpretation
X1 (Environmental) → ODOL (Z)	1,004	No multicollinearity
X2 (Driver) → ODOL (Z)	1,026	No multicollinearity
X3 (Enforcement) → ODOL (Z)	1,032	No multicollinearity
X4 (Vehicle) → ODOL (Z)	1,011	No multicollinearity
X1 (Environmental) → Economic (Y)	1,257	No multicollinearity
X2 (Driver) → Economic (Y)	1,237	No multicollinearity
X3 (Enforcement) → Economic (Y)	1,176	No multicollinearity
X4 (Vehicle) → Economic (Y)	1,674	No multicollinearity
Z (ODOL) → Economic (Y)	2,241	No multicollinearity

Based on the SEM-PLS data analysis, all path relationships between the exogenous and endogenous variables exhibited Variance Inflation Factor (VIF) values below the threshold of 3.3. The lowest VIF value was observed for the path Environment → ODOL Effect (1.004), while the highest was recorded for the path ODOL Effect → Economic Factors (2.241). Accordingly, it can be concluded that the research model does not suffer from multicollinearity issues.

The relatively low VIF values across all constructs indicate that the interdependence among independent variables is within the weak-to-moderate range. This suggests that each variable makes a unique contribution to the model without distorting the effects of one another. These findings reinforce the validity of the model in explaining the structural relationships among constructs. The results are consistent with those of [14], who also reported no indication of multicollinearity in their structural models, with VIF values ranging from 1.1 to 2.7. Conversely, the findings differ from [2], who identified mild multicollinearity (VIF > 3.5) in the relationship between driver behavior and distribution efficiency, likely due to the use of overlapping or suboptimally selected indicators.

Nilai SRMR

To evaluate the model fit between the structural model and the empirical data, the Standardized Root Mean Square Residual (SRMR) indicator was employed. According to [16], SRMR represents the average difference between the observed correlation matrix and the correlation matrix predicted by the model. A lower SRMR value indicates a better model fit. In general, SRMR values below 0.08 indicate a good fit, whereas values above 0.10 suggest poor model fit.

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The analysis results show that the SRMR value for this study is 0.072, which is below the 0.08 threshold. This indicates that the model demonstrates a good level of fit to the empirical data, making the structural relationships among variables statistically valid and suitable for further analysis. These findings align with the goodness-of-fit criteria recommended in the literature and further support the reliability of the model in explaining causal relationships within the context of ODOL in the freight transportation sector.

Hypothesis Testing

Hypothesis testing in this study was conducted using the bootstrapping method within the SEM-PLS framework, employing 5,000 subsamples. The significance of the relationships among constructs was assessed based on three key parameters: the path coefficient (original sample), the t-statistic, and the p-value. According to [16], a hypothesis is accepted if it meets the criteria of p-value < 0.05 and t-statistic > 1.96.

This approach was selected because it provides more accurate estimates for non-normally distributed data and is well-suited to the characteristics of causal models involving multidimensional latent variables.

Table 7. Hypothesis Testing (Source: SmartPLS 3.0 2025)

Hypothesis	Pathway	Original Sample (O)	Mean (M)	STDEV	T-Statistic	P-Value	Decision
H1	(X1) → (Z)	0,437	0,439	0,054	8,109	0,000	Accepted (Significan)
H2	(X2) → (Z)	0,554	0,543	0,025	21,843	0,000	Accepted (Significan)
H3	(X3) → (Z)	0,260	0,264	0,042	6,219	0,000	Accepted (Significan)
H4	(X4) → (Z)	0,336	0,342	0,029	11,762	0,000	Accepted (Significan)
H5	(Z) → (Y)	0,217	0,220	0,041	5,301	0,000	Accepted (Significan)
H6	(X1) → (Y)	0,307	0,313	0,035	8,880	0,000	Accepted (Significan)
H7	(X2) → (Y)	0,214	0,217	0,040	5,384	0,000	Accepted (Significan)
H8	(X3) → (Y)	0,253	0,260	0,033	7,632	0,000	Accepted (Significan)
H9	(X4) → (Y)	0,166	0,169	0,041	4,077	0,000	Accepted (Significan)
H10	(X1) → (Z) → (Y)	0,147	0,147	0,023	7,781	0,000	Accepted (Significan)
H11	(X2) → (Z) → (Y)	0,134	0,134	0,022	6,474	0,000	Accepted (Significan)
H12	(X3) → (Z) → (Y)	0,111	0,112	0,021	6,111	0,000	Accepted (Significan)
H13	(X4) → (Z) → (Y)	0,238	0,233	0,031	5,311	0,000	Accepted (Significan)

The bootstrapping results indicate that all hypotheses in the model are accepted, with p-values = 0.000 and t-statistics > 1.96 for all paths, confirming that the relationships among constructs are statistically significant. For hypotheses H1–H4, all exogenous variables (Environment, Driver, Officer, and Vehicle) have a significant effect on the Overdimension and Overloading (ODOL) Practice Effect (Z), with the strongest influence observed in the path X2 → Z ($\beta = 0.554$; $t = 21.843$).

For hypotheses H5–H9, ODOL (Z) and all exogenous variables also exert a direct and significant influence on the Economic Factor (Y), with the most dominant paths being X1 → Y ($\beta = 0.307$) and X3 → Y ($\beta = 0.253$). In hypotheses H10–H13, the mediation analysis reveals that ODOL (Z) significantly mediates the relationships between exogenous variables and the Economic Factor, with the largest mediation effect found in the path X4 → Z → Y ($\beta = 0.238$; $t = 5.311$).

These findings highlight that the driver factor is the strongest predictor of ODOL occurrence, contrasting with most previous studies that identified vehicle-related or technical non-compliance as the primary cause [3], [12]. This provides a new perspective that interventions targeting driver behavior and legal awareness may be more effective in reducing ODOL than policies focusing solely on vehicle technical aspects. Furthermore, environmental/operational factors recorded the largest direct impact on economic outcomes. This contrasts with several studies that identified law enforcement as the primary determinant of costs [17], indicating that, in the Indonesian context, operational aspects such as workload, delivery schedules, and road infrastructure conditions play a more critical role.

ODOL was also found to significantly mediate the relationship between vehicle factors and economic impacts a finding rarely reported in prior literature, which generally examined only direct or partial relationships [5], [6]. This underscores that controlling ODOL can serve as an effective intermediate strategy to reduce economic losses by up to 40%. Meanwhile, the influence of law enforcement on ODOL and economic impacts was relatively minor, differing from results in regions where strict and consistent sanctions have been shown to curb ODOL practices [17].

The main strength of this study lies in its simultaneous SEM-PLS based approach, integrating environmental, driver, officer, and vehicle factors, with ODOL serving as a mediating variable. This approach enables the development of a more comprehensive and context-specific causal model compared to previous studies that were descriptive or focused on a single factor. The significance of all hypotheses reinforces the understanding that ODOL is the result of systemic interactions between individual behavior, operational conditions, technical specifications, and enforcement effectiveness an interplay that has rarely been articulated in an integrated manner in earlier research.

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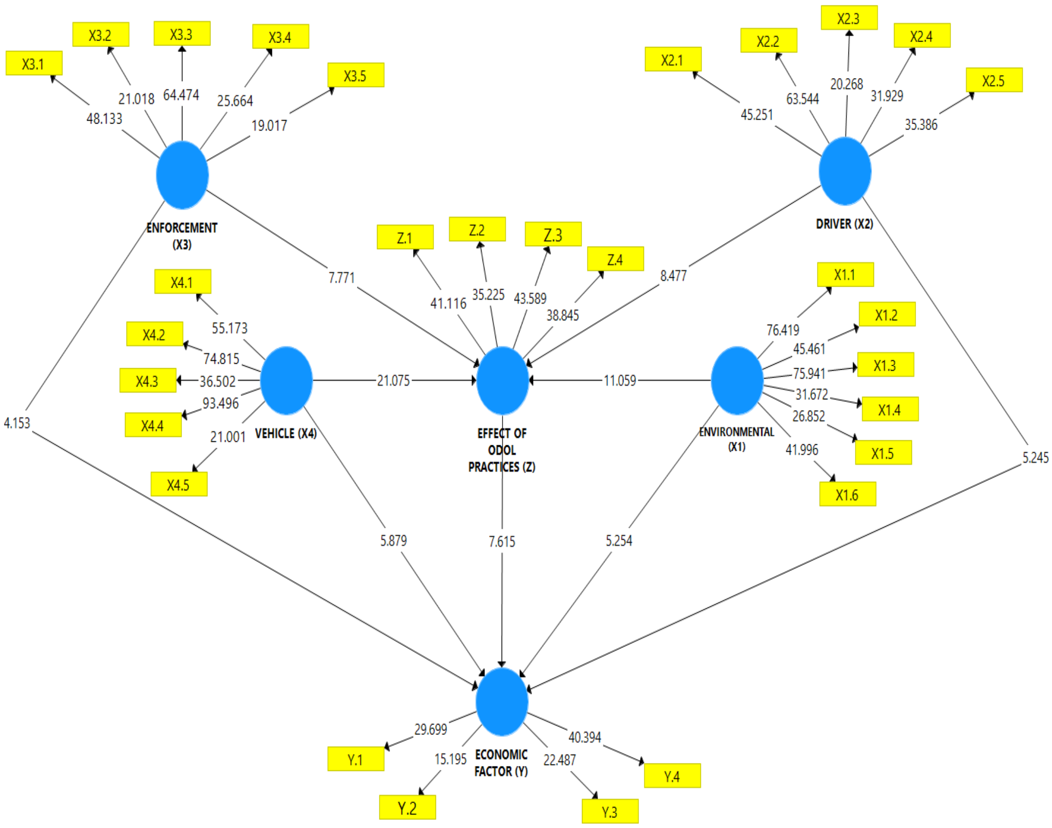

Figure 2. Bootstrapping Results Source: SmartPLS 3.0 2025

The bootstrapping analysis results indicate that all constructs exert a significant influence on the dependent variable, both directly and through the mediating variable, the Effect of ODOL Practices (Z). These findings confirm that Environmental Factors (X1), Driver Factors (X2), Officer Factors (X3), and Vehicle Factors (X4) contribute to the occurrence of ODOL, which ultimately impacts the Economic Factor (Y). The significant path coefficients demonstrate strong structural relationships, aligning with the study's objective to identify the causal factors of ODOL and their implications for the freight transport economy.

In detail, the Environmental Factor (X1) shows a significant contribution to ODOL practices (t = 11.301), reinforcing the findings of Arifin et al. (2024), which emphasize that inadequate road infrastructure supervision and limited safety facilities are key triggers for the prevalence of ODOL, particularly in peri-industrial areas. The Driver Factor (X2) also exhibits a significant effect (t = 8.006), consistent with [14], who found that a lack of awareness of load regulations and economic pressures account for approximately 40% of ODOL cases along interregional distribution routes.

The Officer Factor (X3) significantly influences ODOL (t = 7.725), corroborating the results of [2], which revealed that inconsistent law enforcement and weak inter-agency coordination broaden tolerance for violations. Meanwhile, the Vehicle Factor (X4) demonstrates the highest direct impact on ODOL (t = 19.577), supporting the work of [9], who highlight deficiencies in fleet inspection and maintenance systems as a major enabler of overload practices.

The mediating effect of ODOL on the Economic Factor (Y) is also significant (t = 8.335), indicating that ODOL not only has a technical impact on infrastructure but is also used as a short-term cost efficiency strategy by logistics operators, despite its long-term negative implications. This aligns with [6], who report that overloading is often adopted as a survival strategy by micro-logistics actors in developing countries, yet produces substantial negative externalities.

From a practical perspective, ODOL provides short-term gains by increasing trip efficiency by approximately 25%, but the resulting long-term losses can reach around 40%. These losses encompass accelerated infrastructure degradation, increased vehicle maintenance costs, energy waste, and heightened road accident risks [5]. This comparison is illustrated in Figure 4.2, which depicts the contrast between short-term benefits and long-term costs associated with ODOL practices.

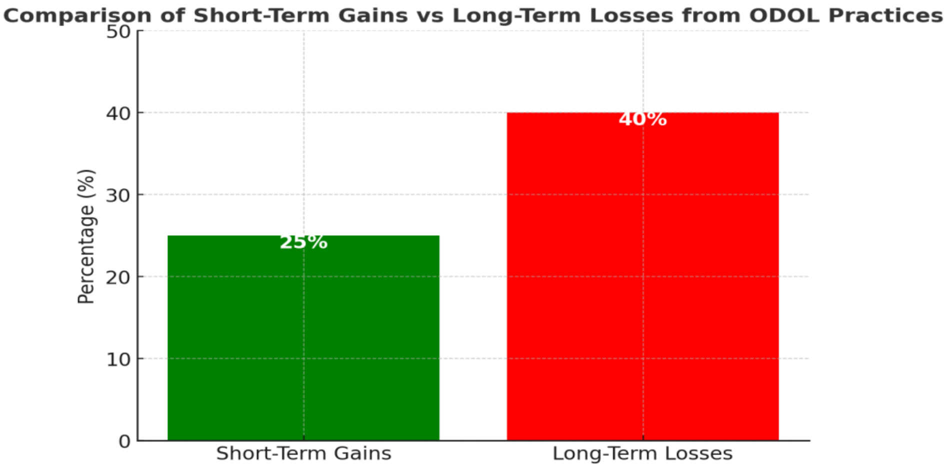

Figure 3. Comparison of Short-Term Gains and Long-Term Losses from ODOL Practices

Discussion

The results of the analysis indicate that the driver factor exerts the strongest influence on the occurrence of Over Dimension Over Loading (ODOL) practices, followed by vehicle and operational environment factors. This finding highlights that driver behavior, compliance, and skills represent critical points in ODOL mitigation efforts. This contrasts with the majority of previous studies, which have primarily identified vehicle technical aspects or regulatory weaknesses as the main determinants [3], [12].

The operational environment which encompasses road infrastructure quality, distribution schedules, and logistical demand pressures was also found to contribute significantly to economic impacts. This differs from findings in the United Arab Emirates and Thailand, where consistent law enforcement emerged as the dominant factor in controlling ODOL-related costs [17]. Path analysis further revealed that ODOL acts as a significant mediator between vehicle factors and economic impacts. This mediating mechanism is rarely addressed in prior literature, which typically evaluates direct relationships without considering mediation effects [5], [6]. This strengthens the argument that ODOL mitigation policies should simultaneously integrate both technical and behavioral dimensions.

Interestingly, the influence of law enforcement on ODOL and its economic impacts was relatively small in the context of this study. This difference may be attributed to inconsistent supervision, resource limitations, and the occurrence of compromise practices in the fieldn conditions that contrast with regions implementing strict sanctions and advanced monitoring technologies such as Weigh-In-Motion systems [1], [17].

By employing a SEM-PLS approach that integrates environmental, driver, officer, and vehicle factors, this study provides a more comprehensive causal framework compared to earlier research, which tended to be descriptive or focused on a single factor. The implications of these findings underscore the need for multidimensional interventions that include driver competency enhancement, vehicle specification improvements, infrastructure optimization, and technology-based law enforcement strengthening.

CONCLUSION

This study confirms that the driver factor is the primary determinant of Over Dimension Over Loading (ODOL) practices, followed by vehicle and operational environment factors. The SEM-PLS analysis reveals that ODOL acts as a significant mediator between vehicle factors and economic impacts, contributing directly to 40% of long-term economic losses. These findings indicate that vehicle dimension and load violations not only affect technical aspects but also substantially exacerbate logistical cost inefficiencies. Unlike most previous studies that emphasized technical or regulatory aspects, this research offers a more comprehensive causal understanding by simultaneously incorporating environmental, driver, officer, and vehicle variables. Practically, the findings highlight the importance of implementing multidimensional ODOL control strategies, encompassing enhanced driver competence and awareness, strengthening vehicle technical specifications in accordance with standards, improving supporting infrastructure, and enforcing consistent technology-based law enforcement such as Weigh-In-Motion systems. From a policy perspective, these results can serve as a foundation for formulating adaptive, integrative, and evidence-based freight transport regulations aimed at reducing economic losses by up to 40% and improving the sustainability of the national logistics system.

Recommendations

The findings of this study underscore the need for a multi-dimensional strategy to reduce the prevalence of Over Dimension Over Loading (ODOL) practices. The following actions are recommended:

1. Technology-Based Enforcement – Prioritize the implementation of Weigh-In-Motion (WIM) systems to replace less effective manual inspections [6].
2. Driver and Operator Education – Conduct continuous training programs addressing safety risks and the economic losses associated with ODOL practices [12].
3. Incentives and Disincentives – Enforce strict penalties for violators while providing incentives for businesses that comply with regulatory standards [17].
4. Multi-Stakeholder Collaboration – Strengthen synergies among government agencies, freight transport associations, the private sector, and educational institutions to support sustainable freight transport systems [1].

Limitations and Future Research

This study has two primary limitations. First, the research scope was limited to a single Vehicle Weighing Implementation Unit (UPPKB) in South Sulawesi, which restricts the generalizability of the findings to the entire Indonesian context, given the variations in regulations, infrastructure, and transportation patterns across regions. Second, the cross-sectional research design only captures conditions at a single point in time, making it unable to reflect the dynamic changes in Over Dimension Over Loading (ODOL) practices over time.

These limitations highlight opportunities for future research to expand the geographical coverage to multiple provinces for more nationally representative results, adopt longitudinal designs to assess temporal trends in ODOL practices, and employ mixed-method approaches that integrate quantitative surveys with in-depth interviews. Such approaches would enable a more comprehensive understanding of the social, cultural, and regulatory factors influencing ODOL practices. These efforts are expected to produce stronger, evidence-based policy recommendations to enhance the sustainability of Indonesia's freight transport system.

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