

Research Paper

Socio-Environmental Evaluation of Overload Truck: Carbon Emissions, Carbon Tax, and Policy Intention Perspectives

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Abstract

The issue of global warming and the increasing concentration of carbon dioxide (CO₂) represents a significant environmental challenge, with the transportation sector contributing approximately 23% of global greenhouse gas emissions. One of the crucial problems is the operation of Over-Dimension Over-Load (ODOL) trucks, which generate serious negative environmental and social impacts. This study conducts a socio-environmental evaluation of ODOL trucks from the perspectives of carbon emissions and carbon tax, and further analyzes the acceptance of the Zero ODOL and Carbon Tax policies in Indonesia. The technical evaluation involves simulates fuel consumption, CO₂ emissions, and carbon tax burdens based on ODOL truck travel data. Meanwhile, the social evaluation is conducted through a survey of two respondent groups, namely truck drivers (97 respondents) and the general public (214 respondents), using a questionnaire that integrates constructs from the Health Belief Model (HBM), risk perception, user cost, law enforcement knowledge (LEK), and the Policy Acceptance Model (PAM). The technical findings indicate that ODOL trucks have higher fuel consumption, CO₂ emissions, and carbon tax burdens compared to non-ODOL trucks. From the social perspective, acceptance of the Zero ODOL policy is influenced by different determinants across the two groups. For drivers, policy acceptance is highly sensitive to economic-based instruments such as carbon tax and knowledge of sanctions. In contrast, the general public is more driven by safety perception, traffic order, and the social impacts of road disturbances. These findings emphasize the importance of tailored policy implementation strategies, where economic incentive-based approaches are more effective for drivers, while safety- and public order-based approaches are more resonant for the public.

Keywords: Over-Dimension Over-Load (ODOL) trucks; Carbon emissions; Carbon tax; Zero ODOL policy; Policy acceptance

1. Introduction

Freight transportation decarbonization has become one of the most critical global challenges in achieving sustainable development goals and reducing greenhouse gas (GHG) emissions [1]. The issue of global warming caused by increasing concentrations of carbon dioxide (CO₂) has intensified international attention toward the transportation sector, which contributes

approximately 23% of total global greenhouse gas emissions and represents one of the largest sources of CO₂ emissions worldwide [2], [3], [4]. In Europe, the transportation sector accounted for approximately 27% of total greenhouse gas emissions in 2015, making it the second-largest emitting sector [5]. Similarly, freight transportation activities in the United States play a crucial role in supporting economic growth



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while simultaneously contributing significantly to environmental degradation and emissions [6].

Despite various technological and policy initiatives, freight transport remains particularly difficult to decarbonize due to the continuous growth of logistics demand, increasing freight mobility, and strong dependence on road transportation systems [7]. This challenge is even more pronounced in low and middle-income countries (LMICs), where rapid urbanization, expanding freight activity, infrastructure limitations, weak enforcement systems, and fragmented logistics operations complicate the implementation of sustainable freight policies [8]. Previous studies on freight decarbonization highlight that governance constraints, behavioral resistance, and operational pressures remain major barriers in transitioning toward sustainable freight systems, particularly in emerging economies. Furthermore, decarbonization policies in freight transportation often face social and operational resistance because environmental objectives may conflict with economic efficiency, logistics competitiveness, and business survival [8].

In the Southeast Asian context, Indonesia is one of the major contributors to CO₂ emissions and is ranked among the countries with the highest carbon emission levels globally, partly influenced by intensive logistics and freight transportation activities [9]. Freight transportation systems generally consist of five major modes, namely road, rail, water, air, and pipeline transportation [10]. Among these modes, road transportation dominated by trucking remains the primary mode for freight distribution due to its operational flexibility and accessibility. However, road freight transportation is also recognized as one of the largest contributors to greenhouse gas emissions compared to other freight transport modes.

One manifestation of unsustainable freight practices commonly found in emerging economies is the persistence of Over-Dimension Over-Load (ODOL) trucks (see Figure 1). Overload (OL) refers to cargo exceeding the legally permitted load limit of trucks, which varies depending on truck type and axle configuration [10]. Meanwhile, over-dimension (OD) refers to vehicles whose length, width, or height exceed established regulatory standards [11]. Thus,

ODOL vehicles are trucks operating beyond the allowable standards of both dimensions and load capacity [12], [13]. The persistence of ODOL practices is often driven by economic considerations, as freight operators perceive overloaded operations as a strategy to reduce transportation costs, minimize operational expenses, increase logistics efficiency, and reduce delivery frequency (Bayramoğlu). This condition reflects a broader policy dilemma between economic efficiency and environmental sustainability within freight transportation systems.

The ODOL phenomenon is not only experienced in developing countries but has also become a governance concern in several developed and rapidly industrializing countries. In Abu Dhabi, approximately 61% of trucks monitored through highway sensors and toll roads were identified as violating legal load regulations, with violations increasing during winter seasons [11]. In Brazil, approximately 28.9% of trucks were reported to operate under overloaded conditions, particularly during nighttime periods to avoid strict enforcement [14]. Similarly, Malaysia reported that the percentage of overloaded and over-dimension trucks reached nearly 60% [15]. These findings indicate that ODOL practices represent not merely technical violations, but broader freight governance and compliance challenges influenced by economic incentives, monitoring limitations, and weak enforcement systems.

From an environmental perspective, ODOL trucks generate substantial externalities that under-



Figure 1. ODOL truck

mine freight decarbonization efforts. Overloaded vehicles accelerate pavement deterioration and significantly reduce road service life [11], [12]. Similar conditions have been reported in Colombia, where ODOL operations contributed to severe road damage across several transportation corridors [16]. In Indonesia, research utilizing Weight-in-Motion (WIM) data in Eastern Sumatra revealed that approximately 60% of freight vehicles were categorized as ODOL, contributing to accelerated pavement deterioration and infrastructure degradation [13].

Figure 2 illustrates the clear difference between the axle configuration of a standard vehicle (left) and an ODOL vehicle (right). Under normal conditions, a truck has an approximate length of 6.5 m and a height of 2.5 m, with front and rear axle loads of 45,000 N each. This relatively balanced load distribution remains within pavement design limits, allowing the stress on the road structure to be tolerated. In contrast, under ODOL conditions, vehicle dimensions increase to approximately 9 m in length and 3 m in height, accompanied by axle loads rising to 90,000 N on both the front and rear axles. The doubling of axle loads significantly increases pavement stress and potentially accelerates cracking (Figure 3) and the reduction of road service life. Therefore, ODOL configurations not only increase structural pressure on road infrastructure but also elevate the long-term risk of pavement deterioration [12], [17], [18].

In addition to structural pavement deterioration, overloaded axle configurations may indirectly increase fuel consumption and transport-related carbon emissions due to higher rolling resistance, rougher pavement conditions, and reduced traffic efficiency. Poor pavement

conditions caused by excessive axle loads can increase vehicle operating resistance, leading to greater energy consumption and higher greenhouse gas emissions across freight transportation systems. The European Commission [19] estimated that overloaded trucks may produce up to 20% higher greenhouse gas emissions than standard-load vehicles. Similarly, Frey *et al.* [20] found that fully loaded diesel tandem trucks generated approximately 44% higher CO₂ emissions compared to unloaded conditions, while Song *et al.* [21] reported increases in NO_x emissions ranging from 18% to 41% under loaded operating conditions. These findings indicate that ODOL practices not only accelerate infrastructure deterioration but also undermine freight transport decarbonization efforts by increasing energy consumption and carbon emissions.

Beyond environmental impacts, ODOL operations also create serious social and public safety concerns. In many developing countries, overloaded trucks are associated with increased accident severity, braking failures, reduced vehicle stability, and road safety risks [12], [22]. In mainland China, ODOL trucks have remained one of the major contributors to freight-related traffic accidents over the past three decades [22]. In Indonesia, traffic accidents caused approximately 22,500 fatalities in 2020, with overloaded and over-dimension vehicles recognized as important contributing factors due to braking system failures and poor vehicle dynamics [23]. Similar findings were reported in Thailand and Australia, where overloaded trucks substantially increased the likelihood and severity of fatal road accidents [12], [24]. These safety risks not only generate substantial social costs, but may also influence

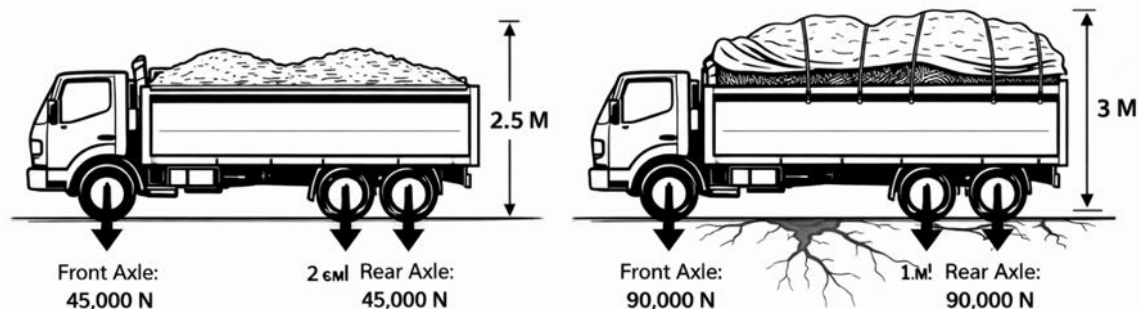


Figure 2. Illustration of normal and overload axle configuration



Figure 3. Potentially road cracking

public risk perception and support toward freight control policies such as Zero ODOL implementation.

In Indonesia, ODOL regulations are governed through Law No. 22 of 2009 concerning Road Traffic and Transportation, Government Regulation No. 55 of 2015 concerning Vehicles, and Minister of Transportation Regulation No. 33 of 2018 concerning Vehicle Type Testing. The Indonesian government has also intensified

ODOL enforcement through the implementation of the Zero ODOL policy aimed at reducing overloaded freight operations, improving traffic safety, and minimizing road deterioration [23]. Nevertheless, implementation of the Zero ODOL policy continues to face considerable resistance from freight operators and industry stakeholders, as reflected in several demonstrations rejecting the regulation (Figure 4). This condition suggests that the success of freight decarbonization and compliance policies depends not only on technical regulations and law enforcement mechanisms, but also on policy legitimacy and behavioral acceptance among affected stakeholders.

From a behavioral perspective, previous studies demonstrate that ODOL practices are strongly influenced by psychosocial, economic, and operational factors. Chen *et al.* [25] found that pressure from freight operators and suppliers often compels truck drivers to engage in overloading practices. Other studies identified transportation type, operational conditions, and economic motivations as dominant factors encouraging overloaded freight operations [26]. Ahmed and Kumar [11] further showed that profit maximization remains one of the strongest motivations behind overloading behavior among freight operators. In addition, previous research applying the Theory of Planned Behavior (TPB), the Health Belief Model (HBM), risk perception, and law enforcement knowledge frameworks



Figure 4. Demonstration rejecting the zero ODOL regulation

demonstrated that limited awareness of regulations and low perception of risk significantly increase the tendency toward overloading behavior [13], [27].

1.1. Identified Gaps and Research Novelty

Although previous studies have extensively examined ODOL from technical, operational, enforcement, and driver behavior perspectives, limited attention has been given to the broader issue of social legitimacy and behavioral acceptance of ODOL control policies within the context of freight transport decarbonization and environmental governance, particularly in LMICs. Existing studies predominantly focus on infrastructure damage [14], [28], [29], [30], accident severity [22], [31], [32], or freight operator compliance [13], [33], while the perspectives of the general public as recipients of environmental and social externalities remain underexplored. Moreover, limited studies position ODOL control policies as socio-environmental instruments aimed at reducing freight externalities, similar to other freight decarbonization policies such as emission regulations, low-emission zones, and carbon pricing mechanisms.

Therefore, this study contributes to the literature in several ways. First, it positions ODOL control policies within the broader discourse of freight transportation decarbonization and environmental governance in emerging economies. Second, this study integrates psychosocial perspectives, including the Health Belief Model (HBM), risk perception, and user cost considerations, to explain behavioral acceptance toward freight compliance policies. Third, this study examines policy legitimacy not only from the perspective drivers, but also from the general public as recipients of the environmental and social impacts caused by ODOL practices. Finally, this study provides empirical evidence from Indonesia as a representative LMIC context facing freight sustainability, governance, and enforcement challenges in transitioning toward more sustainable freight transportation systems.

2. Material and Methods

2.1. Material

2.1.1. Health belief model

The Health Belief Model (HBM) is used to understand and predict individual behavior

based on their perceptions of health and associated risks [34]. HBM has been applied to explain health-related behavior, with main components including perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cues to action, and self-efficacy, which are associated with safe driving behavior [35]. The results showed that cues to action, such as reminders from police officers, were the strongest predictors of safe driving behavior among taxi drivers, while perceived barriers, such as poor road conditions and limited facilities, had a negative effect.

Previous studies demonstrated that perceived severity, perceived barriers, and cues to action significantly influence transportation-related behavioral decisions. For example, Tengecha *et al.* [36] found that perceived accident severity strongly influenced transportation choices among rural schoolchildren, while Melaku *et al.* [37] showed that drivers who perceived greater safety benefits were more likely to avoid risky driving behavior. In the context of freight transportation, HBM is relevant for explaining why drivers and affected communities may accept or reject ODOL control policies depending on their perception of accident risks, enforcement consequences, operational burdens, and expected benefits. Widyanti *et al.* [13] applied HBM, the Theory of Planned Behavior (TPB), and sanction variables to examine overloaded truck operations in Indonesia and found that perceptions of severity, perceived barriers, cues to action, and sanctions significantly influenced drivers' intentions to operate ODOL trucks. These findings indicate that compliance with freight transportation policies is not determined solely by regulations and enforcement, but also by psychosocial perceptions regarding risks, costs, and policy consequences.

2.1.2. Perceived of risk

Perceived risk refers to an individual's perception of the level of danger or negative consequences that may arise from a particular behavior or condition [38]. In transportation systems, risk perception has been recognized as an important predictor of driving behavior, traffic violations, and transportation mode choices [39], [40]. Previous studies showed that low awareness of accident risks and traffic violations tends to increase risky driving behavior among transportation operators [39].

Within freight transportation systems, risk perception is particularly relevant in explaining overloading behavior and compliance decisions among truck drivers. Baikejuli and Shi [27] incorporated risk perception into the TPB framework to examine overloading behavior among commercial truck drivers and found that higher risk perception regarding accidents and infrastructure damage was associated with lower intentions to overload vehicles. Conversely, drivers with limited awareness of the dangers and consequences of overloading were more likely to engage in ODOL practices. These findings suggest that environmental and safety awareness may influence behavioral acceptance toward freight control policies and decarbonization-related regulations.

2.1.3. Road user cost (RUC)

Road User Cost (RUC) refers to the estimated economic costs borne by road users due to disruptions, delays, or additional expenses incurred while using roads, particularly in the context of construction, maintenance, or other traffic disturbances [41]. RUC consists of several components, including (a) travel delay cost/value of time resulting from traffic disruptions that cause congestion and route diversion, (b) vehicle operating cost, which includes fuel consumption, maintenance costs, tires, and other expenses related to vehicle usage on the road, (c) accident costs, referring to costs associated with accidents that may occur during traffic disturbances, (d) emission costs related to increased vehicle emissions due to poor traffic conditions, and (e) impacts of nearby projects, referring to external effects such as noise, business losses, and inconvenience to surrounding communities [41], [42].

In freight transportation, overloaded trucks contribute significantly to these external costs by accelerating pavement deterioration, increasing congestion, worsening road safety conditions, and generating higher transport-related emissions. Previous studies highlighted that road user costs are closely related not only to economic efficiency but also to social and environmental sustainability [43], [44], [45], [46]. Agyekum *et al.* [45] emphasized that transportation sustainability should integrate economic, environmental, and social dimensions, including indirect costs

associated with congestion, pollution, and reduced quality of life. In the context of ODOL operations, these findings indicate that overloaded truck practices generate broader socio-environmental externalities affecting not only freight operators but also the general public as road users and recipients of environmental impacts.

2.1.4. Law enforcement knowledge

Law Enforcement Knowledge (LEK) in this study refers to the extent to which respondents understand the existence of regulations, legal provisions, and sanctions related to violations [27]. The study by Zahra and Brilliant [47] examined how students' knowledge of traffic regulations influences their awareness and safe driving practices. This issue is particularly relevant in freight transportation systems, where truck drivers often operate under economic pressure while possessing limited understanding of transportation regulations and safety standards [31], [48].

In the context of ODOL practices, limited law enforcement knowledge may reduce drivers' awareness regarding the legal, environmental, and social consequences of overloaded operations. As a result, insufficient regulatory understanding may contribute to the persistence of overloading behavior despite the existence of enforcement policies and sanctions. Therefore, law enforcement knowledge plays an important role in shaping compliance behavior and policy acceptance toward freight sustainability regulations.

2.1.5. Policy acceptance model

The Policy Acceptance Model (PAM) extends the Technology Acceptance Model (TAM) by incorporating social and demographic factors to explain public acceptance of policies [49]. Previous studies emphasized that policy acceptance is influenced not only by perceived effectiveness, but also by trust, perceived fairness, ease of implementation, and broader social contexts [50]. In transportation studies, PAM has been applied to examine acceptance of environmentally oriented transportation policies, including electric vehicle adoption, mobility restrictions, and greenhouse gas reduction strategies [51], [52], [53].

Within the context of freight transportation decarbonization, policy acceptance becomes particularly important because environmental regulations often create economic and operational pressures for transport operators. Policies aimed at reducing freight externalities, such as ODOL control measures, emission regulations, carbon pricing, and operational restrictions, may face resistance if stakeholders perceive them as economically burdensome or socially unfair. Consequently, the effectiveness of freight sustainability policies depends not only on technical enforcement mechanisms but also on behavioral acceptance and perceived legitimacy among affected stakeholders.

2.1.6. Zero ODOL

The “Zero ODOL” (Over-Dimension Over-Load) program, launched by the Ministry of Transportation of the Republic of Indonesia through the Directorate General of Land Transportation. The policy aims to improve road safety, reduce pavement deterioration, and minimize the negative externalities generated by overloaded freight operations. Since its introduction, the policy has been supported through regulatory frameworks, enforcement systems, vehicle inspections, and electronic monitoring mechanisms. However, implementation of the Zero ODOL policy continues to face substantial challenges, including resistance from freight operators, economic pressures within logistics systems, and limitations in monitoring and enforcement capacity. This condition reflects broader governance challenges commonly experienced in emerging economies, where freight sustainability objectives frequently conflict with operational efficiency and logistics competitiveness. Therefore, understanding the social legitimacy and behavioral acceptance of Zero ODOL policies becomes essential for improving policy effectiveness and long-term freight sustainability transitions.

2.1.7. Carbon tax

Carbon tax is one of the Carbon Economic Value (Nilai Ekonomi Karbon/NEK) instruments imposed on carbon emissions that generate negative environmental impacts, with the objective of shifting economic actors' behavior toward low-carbon green activities, encouraging

environmentally friendly innovation and investment, and supporting the achievement of greenhouse gas emission reduction targets [54]. Its legal basis is regulated under Law No. 7 of 2021 concerning Harmonization of Tax Regulations (Article 13) and Presidential Regulation No. 98 of 2021 concerning the Implementation of Carbon Economic Value (Article 58).

The carbon tax rate is set at a minimum of IDR 30.00 per kilogram of carbon dioxide equivalent (CO₂e) and will be evaluated periodically, determined to be equal to or higher than the carbon price in the carbon market. Initial implementation of the carbon tax began on 1 April 2022, specifically targeting entities engaged in coal-fired power plants (CFPP), under a cap-and-tax scheme. Although the implementation of carbon tax policies in Indonesia currently focuses on the power generation sector, the transportation sector remains one of the priority sectors for future emission reduction strategies. In freight transportation systems, carbon pricing and freight control policies may function as socio-environmental instruments intended to reduce emissions, infrastructure damage, congestion, and accident risks associated with unsustainable freight practices.

However, previous studies indicate that the effectiveness of environmental policy instruments strongly depends on social legitimacy, perceived fairness, and behavioral acceptance among affected stakeholders. Therefore, understanding public and driver acceptance toward freight sustainability policies becomes increasingly important in supporting freight transportation decarbonization efforts in emerging economies.

2.2. Methods

2.2.1. Emission model

Various CO₂ emission analysis models have been widely used and developed in previous studies. The decomposition model approach functions to break down the relative contribution of various factors to changes in emissions, identifying the influence of energy intensity, transportation structure, and economic activity on emission increases [55]. Although effective for macro-level analysis, this model has limitations in representing vehicle operational dynamics in detail.

At the operational level, traffic-based emission models are used to capture the influence of traffic

conditions on vehicle emissions. Grote *et al.* [56] developed several variants of models based on average speed and traffic situations, while Bharadwaj *et al.* [57] showed that peak-hour congestion significantly contributes to emission increases. This approach is considered more realistic in representing actual road conditions; however, it requires detailed traffic data and relatively complex computational processes.

Another commonly used approach is mathematical modeling to predict emissions based on fuel consumption. Zhuang *et al.* [58] applied a similar quantitative approach to evaluate fleet emission trends. Darmian *et al.* [59] modeled emission optimization in waste collection activities. Yousefloo *et al.* [60] used a Mixed Integer Linear Programming (MILP) model to analyze emissions generated by heavy vehicles. Jasmine *et al.* [61] integrated vehicle routing results using a Genetic Algorithm into a mathematical model to compare emissions between overloaded and non-overloaded trucks. Mathematical models are suitable for quantitative simulations due to their precise numerical outputs. However, sensitivity to input data quality remains one of their main limitations.

This study adopts the mathematical model from Jasmine *et al.* [61], as it involves similar vehicle characteristics, namely Over-Dimension Over-Load (ODOL) trucks. The data used include travel distance D_{i-j} [60], [62], [63], and fuel consumption F_c (Jasmine; Akhtar; Mick; Qiao), where fuel consumption for ODOL vehicles is defined as $F_c = 1$ for $D_{i-j} \geq 4$ km, while for non-ODOL vehicles $F_c = 1$ for $D_{i-j} \geq 6$ km, or ODOL fuel consumption F_c is 50–70% higher per km (Torres-falcón). The mathematical model is as follows:

$$F_c = \sum_{v=1}^V \sum_{i=0}^N \sum_{j=0}^N \frac{D_{i-j}}{F_{c_{ijv}}} + 5 \quad (1)$$

$$E_{CO_2} = \left(\sum_{v=1}^V \sum_{i=0}^N \sum_{j=0}^N F_c \right) * EM_f \quad (2)$$

$$TC_x = E_{CO_2} * C_x \quad (3)$$

where, Eq. (1) explains truck fuel consumption, in which each trip starts from and returns to depot 0 ($i=0, j=0$), V represents the vehicle, and since the vehicles examined in this study are homogeneous (using CDD trucks), its value is 1. Eq. (2) converts the result of Equation (1) into emission simulates using the diesel emission factor EM_f referring to the IPCC value of 74.1 tons CO_2/TJ , equivalent to

approximately 2.64 kg CO_2 per liter of diesel fuel [64]. Eq. (3) is used to simulate the indicative estimates of carbon tax in accordance with the applicable regulation, namely IDR 30,00/ E_{CO_2} .

Based on Figure 1, The vehicle type used in this study was represented by a Cold Diesel Double (CDD) truck, which is commonly utilized in freight transportation operations in Indonesia. Under normal operating conditions, the vehicle typically has dimensions of approximately 4.2–4.5 m in length, 1.7–2.0 m in width, and 1.6–2.0 m in height. However, under ODOL conditions, the vehicle height may increase significantly to approximately 3.5–4.0 m due to excessive loading and over-dimension practices.

In terms of body type, the vehicle was classified as a Cold Diesel Double standard truck commonly used for medium-scale freight distribution. The normal cargo capacity of the vehicle ranges from approximately 10–12 CBM, while ODOL practices may increase the cargo volume to approximately 17–19 CBM or more.

The operating speed of non-ODOL vehicles was assumed to be approximately 60 km/h under normal traffic conditions. In contrast, ODOL vehicles tend to operate at lower speeds, approximately 40 km/h, due to the increased vehicle load and stability limitations. From an aerodynamic perspective, ODOL vehicles generally do not possess optimized aerodynamic characteristics. Excessive cargo dimensions and irregular loading configurations may increase aerodynamic drag and vehicle instability, particularly under crosswind conditions, potentially affecting vehicle balance, fuel consumption, and operational safety.

As illustrative data in this study, travel data adopted from Jasmine *et al.* [61] which examined overloaded truck operations in wood waste collection and transportation processes, are used. The dataset was selected because the vehicle characteristics indicate load and dimension conditions exceeding established standards. Therefore, this dataset is considered representative in describing the Over-Dimension Over-Load (ODOL) vehicle phenomenon in Indonesia, particularly in the context of truck-based freight operations.

The use of secondary data was also motivated by the limited availability of detailed operational and emission-related primary data for ODOL vehicles in Indonesia. Collecting real-time

operational data from overloaded freight vehicles remains challenging due to limited monitoring systems, inconsistent enforcement practices, and difficulties in accessing freight operator operational records. Consequently, the adopted dataset provides a practical basis for exploring the potential operational and environmental implications of ODOL practices.

In this study, the simulation does not aim to fully generalize all freight transportation conditions in Indonesia, but rather functions as an exploratory and illustrative model to demonstrate how ODOL operational characteristics may influence transportation performance, road impacts, and emission-related externalities within freight transportation systems.

2.2.2. Social model

In addition to technical and environmental evaluation, this study also analyzes the social dimension in the form of policy acceptance toward the handling of Over-Dimension Over-Load (ODOL) vehicles. This analysis is important because the success of transportation policy implementation is not only determined by technical effectiveness, but also by the level of acceptance among affected stakeholders.

2.2.3. Survey

2.2.3.1. Respondents

This study employed a purposive sampling approach to select respondents considered relevant to the research context. The survey targeted two main respondent groups, namely freight truck drivers and members of the public who were familiar with freight transportation activities and ODOL-related traffic conditions.

Driver respondents were required to meet several inclusion criteria, including: (1) actively working as freight vehicle drivers, (2) having at least one year of driving experience in logistics or goods transportation operations, and (3) being familiar with ODOL practices or freight transportation routes in Indonesia. Public respondents were selected from the general public based on several criteria, including: (1) being at least 17 years old, (2) having a minimum educational background of senior high school (SMA) or equivalent, (3) being active road users, and (4) conducting travel activities on public roads at least once per week. These criteria were applied to ensure that respondents possessed

sufficient exposure and understanding regarding road traffic conditions, freight transportation activities, and ODOL-related issues.

The survey was conducted in Jepara, Central Java, Indonesia. Jepara is widely recognized as one of Indonesia's major wood industry and furniture production centers, characterized by extensive timber distribution and freight transportation activities. The high intensity of logistics movements and freight truck operations in this region makes it relevant for examining ODOL-related transportation issues, emissions, and policy acceptance. Meanwhile, data collection was carried out using both direct paper-based questionnaires and online questionnaires distributed through Google Forms.

The combined approach was intended to improve respondent accessibility and participation across different respondent groups. The truck drivers, totaling 97 individuals who voluntarily completed the questionnaire, were selected because they act as direct operators in freight transportation. Meanwhile, the general public, totaling 214 individuals, represents parties indirectly affected by safety risks, road damage, and environmental impacts resulting from ODOL practices. By involving both groups, the analysis is expected to provide a more comprehensive understanding of the dynamics of policy acceptance.

2.2.3.2. Questionnaire

To identify the determinants of policy acceptance, this study integrates several behavioral constructs, namely the Health Belief Model (HBM), perceived risk, user cost, law enforcement knowledge (LEK), and the Policy Acceptance Model (PAM) (Table 1), then the item of questionnaire explained in Appendix. This framework is used to analyze how risk perception, perceived benefits, cost burden, and understanding of law enforcement influence the level of acceptance of the Zero ODOL and carbon tax policies among both respondent groups—drivers and the public—using a Likert scale (1 = strongly disagree – 5 = strongly agree).

2.2.3.3. SEM-PLS Model and Hypothesis

This study employs Structural Equation Modeling–Partial Least Squares (SEM-PLS) to analyze the relationships among latent constructs in the research model. SEM-PLS was selected in

Table 1. Variable operationalization

Variables	Operational Definition	Indicators
Health Belief Model [34]	Respondents' perceptions regarding the risks, severity, benefits, and barriers associated with ODOL truck operations and Zero ODOL policy implementation.	• Perceived Severity (PS) • Perceived Benefits (PB) • Perceived Barriers (PR) • Cues to Action (CA)
Perceived of Risk [38]	Respondents' perceptions regarding the potential negative consequences arising from ODOL truck operations, including accident risk, infrastructure damage, environmental pollution, and safety threats.	• Perceived Behavioral Control (PC) • Voluntariness of Risk (VR) • Control over Risk (CR) • Common-Dread (CD) • Chronic-Catastrophic (CC)
Road User Cost [42]	Respondents' perceptions regarding the economic and social costs generated by ODOL operations, including increased travel time, vehicle operating costs, and environmental externalities affecting road users and surrounding communities.	• Time Delay Cost (TDC) • Vehicle Operating Cost (VOC) • Emission Cost (EC)
Law Enforcement Knowledge [27]	Respondents' understanding of traffic regulations, ODOL-related legal provisions, sanctions, and enforcement mechanisms associated with overloaded freight transportation.	• Regulation Knowledge (RK) • Sanction Knowledge (SK)
Public Acceptance Model [49]	Respondents' acceptance toward the Zero ODOL policy and related freight transportation regulations.	• Zero ODOL (ZO) • Carbon Tax (CT)

this study because it is more suitable for exploratory research, non-normal data distributions, relatively small sample sizes, and complex models involving multiple latent constructs [65], [66]. In contrast, Covariance-Based Structural Equation Modeling (CB-SEM) is generally more appropriate for confirmatory studies aimed at testing well-established theories and evaluating overall model fit using statistical fit indices [67]. In this study, the data were measured using ordinal-scale responses, the sample size was relatively limited, and the primary objective was to predict and explore the relationships among psychosocial and policy acceptance constructs related to Zero ODOL

implementation. Therefore, PLS-SEM was considered more appropriate and effective for achieving the objectives of this study, with the model visualization presented as follows.

Based on Figure 5, the research hypotheses are formulated as follows:

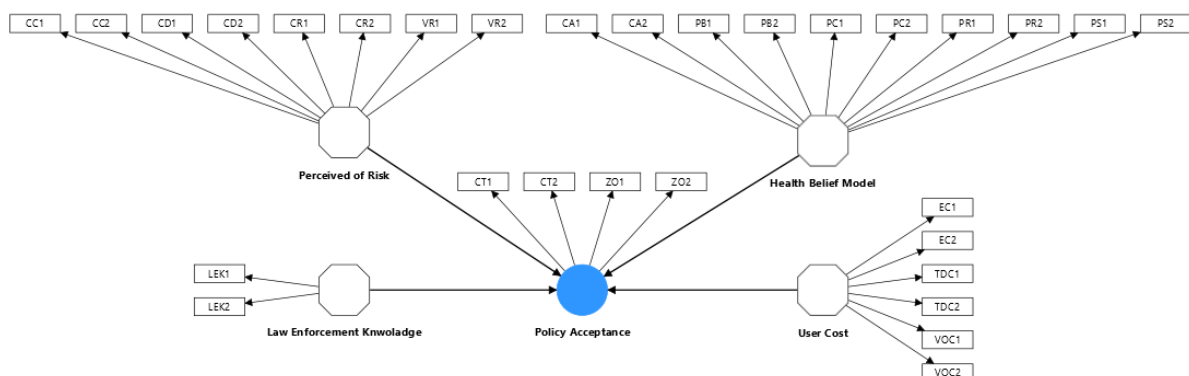
Hypotheses for Truck Drivers

H1 = Health Belief Model has a positive effect on Policy Acceptance.

H2 = Perceived Risk has a positive effect on Policy Acceptance.

H3 = User Cost has a negative effect on Policy Acceptance.

H4 = Law Enforcement Knowledge has a positive effect on Policy Acceptance.

**Figure 5.** SEM model

Hypotheses for the Public

H5 = Health Belief Model has a positive effect on Policy Acceptance.

H6 = Perceived Risk has a positive effect on Policy Acceptance.

H7 = User Cost has a negative effect on Policy Acceptance.

H8 = Law Enforcement Knowledge has a positive effect on Policy Acceptance.

3. Results and Discussion

3.1. Emission and Carbon Tax

This study begins by estimating the carbon emissions generated by freight vehicles as a basis for determining the carbon tax amount. Emission simulation are conducted based on vehicle fuel consumption and standard emission factors, resulting in an estimation of total CO₂ emissions generated from the operational activities of ODOL and non-ODOL trucks. Table 2 presents the O-D matrix data adopted from Jasmine *et al.* [61]. The existing route is T_0 0-1-2-3-4-5-6-0 with a total distance $D_{(i-j)} = 19.25$ km (ODOL), and the new routes generated from the Genetic Algorithm (GA) optimization model are divided into two routes, namely v_1 0-4-2-1-3-0 and v_2 0-5-6-0, with a total distance of 20.45 km.

Furthermore, Table 3 presents the simulations results of total fuel consumption, total carbon emissions generated, and the carbon tax burden, including a sensitivity analysis of carbon tax rates, which serves as the basis for the subsequent social analysis to examine policy implications.

Based on the mathematical model in Eq. (1), the fuel consumption values obtained are F_c 9.8 L for ODOL trucks with total travel distance of 19.25 km, and 9.09 L for non-ODOL trucks with travel distance of 20.45 km. The calculation adopted simplified fuel efficiency assumptions to reflect the operational differences between ODOL and non-ODOL vehicles, with ODOL trucks assumed to consume approximately 1 liter of fuel per 4 km and non-ODOL trucks approximately 1 liter per 6 km. Using $EM_f = 2.64$ kg/CO₂ in Eq. (2), the estimated carbon emissions are 25.905 kg CO₂ for ODOL trucks and 23.9976 kg CO₂ for non-ODOL trucks. Carbon tax simulates were then conducted using sensitivity analysis with three rate scenarios: a low scenario (50% of the standard rate) at IDR 15.00, a moderate scenario (100%) at IDR 30.00, and a high scenario (150%) at IDR 75.00. The results indicate that ODOL trucks generate a higher carbon tax burden compared to non-ODOL trucks, consistent with their higher fuel consumption and emission levels.

Although the carbon tax per trip is relatively small, this finding has important implications. In the context of freight operations with high trip frequency, the accumulated carbon costs have the potential to significantly increase total operational costs in the long term.

3.2. Social

Demographic analysis was conducted to describe respondent characteristics based on their stance toward the policy, categorized as pro, moderate, and contra. In addition, a chi-square

Table 2. Origin-desination matrix (km) adopted by Jasmine *et al.* [61]

	Depo (0)	1	2	3	4	5	6
Depo (0)	0	4.4	4.1	3.8	1.6	1	5.4
1	4.4	0	0.3	0.65	2.7	3.4	4.8
2	4.1	0.3	0	0.55	2.4	3	5.2
3	3.8	0.65	0.55	0	2.3	2.8	4.1
4	1.6	2.7	2.4	2.3	0	1	5.7
5	1	3.4	3	2.8	1	0	5.3
6	5.4	4.8	5.2	4.1	5.7	5.3	0

Table 3. Result of emission measurement

Description	ODOL	Non-ODOL
Route	0-1-2-3-4-5-6-0	0-4-2-1-3-0, 0-5-6-0
Distance (km)	19.25	20.45
Fuel Consumption (l/km)	9.8125	9.09
CO ₂ Emission (kg/CO ₂)	25.905	23.9976
Carbon Tax – Low (50%) (IDR)	IDR 388.58	IDR 359.96
Carbon Tax – Moderate (100%) (IDR)	IDR 777.15	IDR 719.93
Carbon Tax – High (150%) (IDR)	IDR 1,942.88	IDR 1,799.82

test was used to identify significant differences among groups.

3.2.1. Result of demographic (drivers)

Table 4 illustrates the characteristics of the 97 driver respondents, divided into three categories: pro, moderate, and contra.

Age - The chi-square test indicates that age is significantly associated with respondents' attitudes ($\chi^2 = 25.165$; $p < 0.001$). This finding is consistent with Moe *et al.* [52], who reported that opposition to sustainable transport policies was dominated by older respondents. However, this result differs from Baikejuli & Shi [27] and Widyanti *et al.* [13], who found that age did not significantly influence ODOL driving behavior ($p = 0.85$ and $p = 0.55$, respectively).

Status - A significant difference was found based on employment status. Chen *et al.* [26], [68], reported that individual operators have nearly twice the probability of engaging in overloading compared to company-employed drivers. This finding aligns with Ahmed & Kumar [11], who showed that drivers working for medium and large companies tend to be more supportive of overloading regulations. Conversely, Ilham *et al.* [69], found that company drivers, due to lower fixed salaries compared to independent drivers, may be more likely to engage in overloading to supplement their income.

Driving Experience - Driving experience shows a non-significant chi-square result. This finding is in line with Widyanti *et al.* [13] who reported that possession of a driving license—used as a proxy for experience—did not significantly influence the intention to engage in

overloading ($p = 0.319$). However, Ahmed and Kumar [11], found that companies operating for less than 10 years were more likely to accept overloading regulations compared to those operating for more than 12 years.

Trip Frequency - Trip frequency shows a significant association and is consistent with Ahmed & Kumar [11], Chen *et al.* [26], Baikejuli and Shi [27], who found that drivers covering longer distances tend to have higher frequencies of overloading. In contrast, Widyanti *et al.* [13] reported that average travel distance did not significantly influence overloading intention ($p > 0.001$).

3.2.2. Result of demographic (publics)

Table 5 presents the demographic characteristics of public respondents. In the Pro category, the gender composition is relatively balanced between females (50.7%) and males (49.3%), and this characteristic is not significant with a p-value of 0.025. In terms of age, the Pro group is dominated by respondents aged <20 years (28.9%) and 20–30 years (28.3%). Although gender among public respondents does not significantly influence policy acceptance, the finding is consistent with Moe *et al.* [52], who reported that opposition to policy was dominated by males. This group tends to express stronger concerns regarding policy clarity, effectiveness, and fairness. Overall, gender shows a weak effect, similar to primary transport mode ($p = 0.013$) and age ($p = 0.037$). This contrasts with Ahmed and Kumar [11], who found that age had a strong influence on policy rejection. The education level in this category is predominantly Diploma/Bachelor's

Table 4. Drivers demographic

	Pro		Moderate		Contra		Chi-square	p-value
	n	%	n	%	n	%		
Age								
<30 years	9	38	13	36	-	-	25.165	0.000
30-40 years	11	46	15	42	11	31		
> 40 years	6	25	8	22	24	69		
Status								
Company Drivers	2	92	13	36	-	-	46.312	0.000
Individu Drivers	4	17	23	64	35	100		
Experiences								
< 3 years	3	13	5	14	-	-	6.991	0.319
> 3 years	3	96	31	86	35	100		
Travel Frequency								
< 3 trips/week	9	38	28	78	-	-	28.170	0.000
> 3 trips/week	7	71	8	22	35	100		

Table 5. Publics demographic

	Pro		Moderate		Contra		Chi-Square	p-value
	n	%	n	%	n	%		
Gender								
Woman	77	50.7	14	28.6	3	23.1	7.192	0.025
Man	75	49.3	35	71.4	8	61.5		
Age								
< 20 years	44	28.9	-	-	-	-	7.870	0.037
20-30 years	43	28.3	12	24.5	5	38.5		
30-40 years	31	20.4	27	55.1	3	23.1		
> 40 years	34	22.4	10	20.4	5	38.5		
Education								
High School	24	15.8	28	57.1	6	46.2	5.114	0.084
Diploma/Undergraduate	121	79.6	21	42.9	7	53.8		
Postgraduate	7	4.6	-	-	-	-		
Employment Status								
Students	15	9.9	3	6.1	-	-	33.176	0.000
Business Owner	9	5.9	24	49.0	6	46.2		
Private sector								
employee/state-owned	116	76.3	10	20.4	3	23.1		
employee/civil servant								
Housewife	5	3.3	7	14.3	2	15.4		
Not working/retired	7	4.6	5	10.2	2	15.4		
Primary Transportation Modes								
Pedestrians	4	2.6	11	22.4	1	7.7	9.013	0.013
Motorcycles	113	74.3	31	63.3	5	38.5		
Cars	35	23.0	7	14.3	2	15.4		
Frequency of Main Road Use								
1-2 times/week	2	1.3	3	6.1	3	23.1	38.529	0.000
3-5 times/week	31	20.4	8	16.3	4	30.8		
Every day	119	78.3	38	77.6	6	46.2		
Activity Location								
Rural Area	2	1.3	22	44.9	4	30.8	45.824	0.000
Urban Area	9	5.9	21	42.9	4	30.8		
Industrial Area	141	92.8	6	12.2	5	38.5		

degree (79.6%), with the majority employed as private employees/SOEs/civil servants (76.3%), and this characteristic is statistically significant ($\chi^2 = 33.176$; $p < 0.001$). Most Pro respondents use motorcycles as their primary mode of transportation (74.3%), use main roads daily (78.3%), and conduct activities in industrial areas (92.8%). These findings indicate that younger individuals, with higher education, working in the formal sector, and having high mobility intensity in industrial areas tend to respond positively to the existing policy.

Meanwhile, the Moderate and Contra categories show different patterns. In both categories, male respondents are more dominant, accounting for 71.4% (Moderate) and 61.5% (Contra), respectively. The Moderate group is largely within the 30–40-year age range (55.1%) and has a high school education background

(57.1%), with a considerable proportion of self-employed respondents (49.0%). The Contra group is relatively more dispersed in age, particularly within the 20–30-year and >40-year ranges (38.5% each), and many are also self-employed (46.2%). Compared to the Pro group, Moderate and Contra respondents show more variation in road usage frequency and are more likely to reside in rural and urban areas outside industrial zones. Overall, non-formal employment status, more mature age, and activity locations outside industrial areas tend to be associated with more moderate or opposing attitudes.

The most influential characteristics affecting differences in policy acceptance among the public are activity center, frequency of main road usage, and employment status (all $p < 0.001$). The pro group is highly dominated by respondents who conduct activities in industrial areas (92.8%), use

main roads daily (78.3%), and are employed as private/BUMN/civil servants (76.3%). In contrast, the moderate and contra groups are more likely to come from non-industrial areas, show more varied road usage patterns, and are dominated by self-employed individuals. These findings indicate that the intensity of interaction with road infrastructure and the occupational context are strongly associated with policy acceptance levels.

3.2.3. Measurement and structural model

Figure 6 presents the structural model for driver respondents, while Figure 7 shows the model for public respondents. Both models were evaluated at the measurement model stage by testing internal consistency reliability, convergent validity, and discriminant validity, referring to Hair *et al.* [65].

Figure 6 and Figure 7 display the outer loading values of each questionnaire item and the β (path coef.), values, which are summarized in Table 6. In Table 6 and Table 7, all constructs have undergone an elimination process of several questionnaire

items, retaining only indicators with good measurement quality. The evaluation results show that all retained items have outer loading values above 0.7, meeting the cut-off recommended by Hair *et al.* [66]. This indicates that the questionnaire indicators demonstrate adequate indicator reliability in reflecting the measured constructs. Furthermore, the Composite Reliability (CR) and Cronbach's Alpha (CA) values for all constructs are greater than 0.7, which is the minimum threshold recommended by Hair *et al.* [65], indicating good internal consistency of the model.

Convergent validity was assessed to examine whether indicators intended to measure the same construct are strongly correlated, as indicated by the Average Variance Extracted (AVE) value [70]. The AVE values for each construct exceed 0.5, the minimum threshold suggested by Hair *et al.* [66], thus confirming convergent validity. Discriminant validity testing using the HTMT criterion shows that all ratio values are below the threshold of 0.85 for strict discriminant validity

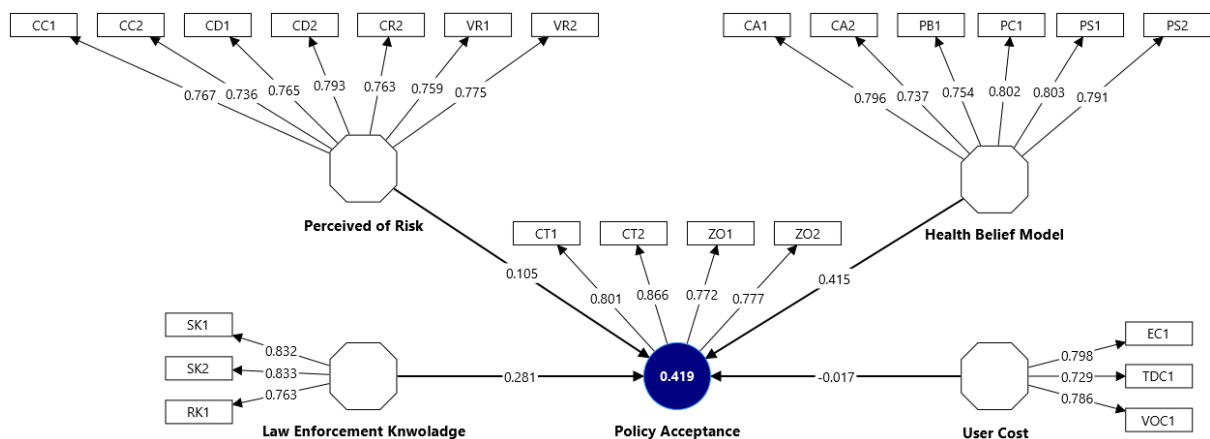


Figure 6. Structural model for driver respondents

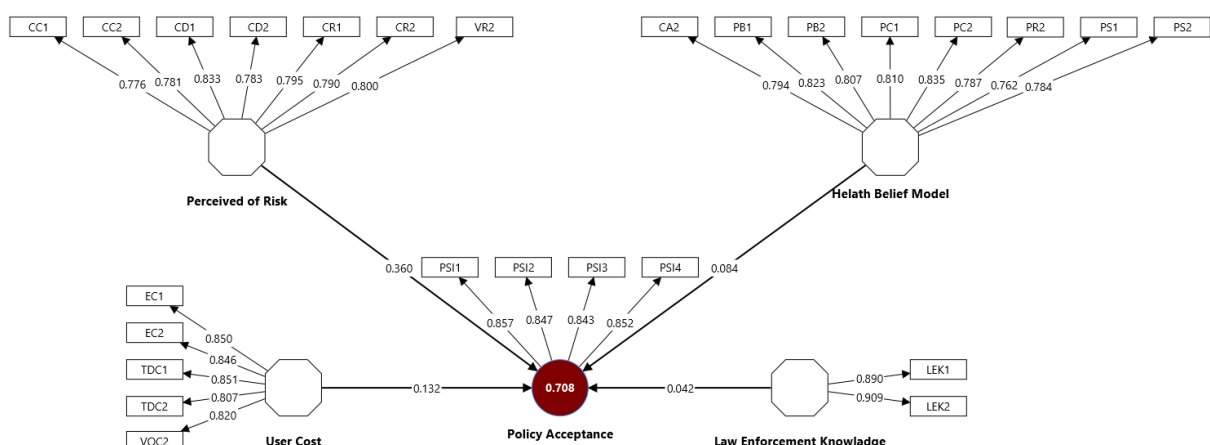


Figure 7. Structural model for public respondents

Table 6. Measurement model of construct

Variable	Construct	Outer Loading	AVE	CR	Con. α	VIF
HBM	PS1	0.803	0.610	0.904	0.872	2.236
	PS2	0.791				2.553
	PB1	0.754				2.702
	CA1	0.796				2.746
	CA2	0.737				2.957
	PC1	0.802				2.766
Perceived of Risk	VR1	0.759	0.586	0.908	0.883	2.419
	VR2	0.775				2.626
	CR2	0.763				2.039
	CD1	0.765				1.982
	CD2	0.793				2.346
	CC1	0.767				2.110
User Cost	CC2	0.736	0.595	0.815	0.721	2.874
	TDC1	0.729				2.829
	VOC1	0.786				2.631
	EC1	0.798				2.259
	RK1	0.763				2.728
	SK1	0.832				3.051
LEK	SK2	0.833	0.656	0.851	0.745	3.073
	ZO1	0.772				2.712
	ZO2	0.777				2.689
PAM	CT1	0.801	0.648	0.880	0.818	2.581
	CT2	0.866				2.066

and 0.90 for liberal discriminant validity [65]. Variance Inflation Factor (VIF) analysis was conducted to assess potential multicollinearity among indicators in the measurement model. The results showed that all VIF values are below the recommended threshold value of 5.0 [66]. This indicates that multicollinearity was not a concern in this study and that the indicators did not exhibit excessive correlation or redundancy. Therefore, it can be concluded that the constructs in this research model are empirically distinct, and the measurement model satisfies the required reliability and validity criteria.

Table 8 presents the results of discriminant validity testing using the Heterotrait–Monotrait Ratio (HTMT). The HTMT values for the driver group range from 0.405 to 0.663, while for the public group they range from 0.523 to 0.845. All values are below the threshold of 0.85 for severe discriminant validity and 0.90 for liberal discriminant validity [71], indicating that discriminant validity among constructs has been achieved. The lowest HTMT value is observed in the relationship between User Cost and Policy Acceptance in the driver group (0.405), while the highest value is found in the relationship between Policy Acceptance and Perceived Risk in the public group (0.845).

3.2.4. Evaluation inner model (R^2 , Q^2 , β)

R-Square - R^2 is used to examine the extent to which independent variables explain the endogenous variable (Policy Acceptance). Based on the criteria referenced in Hair *et al.* [66], an R^2 value > 0.75 indicates substantial predictive power, $R^2 > 0.50$ indicates moderate predictive power, and $R^2 < 0.25$ indicates weak predictive power.

The R^2 values in **Table 9** show that the independent variables in the model explain 41.9% of the variance in Policy Acceptance for the driver group, which falls into the moderate category. Meanwhile, for the public group, the R^2 value of 0.708 indicates strong explanatory power. These findings indicate that the research model explains policy acceptance more effectively among the public (0.708) than among drivers (0.419). Widyanti *et al.* [13] reported similar findings, where the HBM and Sanction model explained only 20.8% of driver behavior, which was lower compared to truck owners with an explanatory power of 58%.

Q-square - To evaluate the predictive capability of the structural model, this study employs Q^2 predict analysis. The Q^2 value is used to assess the extent to which the model has predictive relevance for the endogenous construct.

Table 7. Measurement model of public respondent

Variable	Construct	Outer Loading	AVE	CR	Con. α	VIF
HBM	PS1	0.762	0.641	0.920	0.920	2.138
	PS2	0.784				2.621
	PB1	0.823				1.530
	PB2	0.807				2.542
	CA2	0.794				2.163
	PC1	0.810				1.762
	PC2	0.835				1.850
Perceived of Risk	VR2	0.800	0.631	0.903	0.902	2.023
	CR1	0.795				1.735
	CR2	0.790				2.335
	CD1	0.833				2.431
	CD2	0.783				1.728
	CC1	0.776				1.791
	CC2	0.781				1.395
User Cost	TDC1	0.851	0.697	0.893	0.891	1.351
	TDC2	0.807				1.984
	VOC1	0.820				1.772
	EC1	0.850				1.575
	EC2	0.846				1.735
LEK	RK1	0.890	0.809	0.769	0.764	1.875
	SK1	0.909				2.072
PAM	ZO1	0.857	0.723	0.873	0.872	2.993
	ZO2	0.847				2.872
	CT1	0.843				2.138
	CT2	0.852				2.621

Table 8. Heterotrait-monotrait ratio (HTMT) result

Parameters	Truck Drivers	Publics
Law Enforcement Knowledge <-> Health Belief Model	0.449	0.535
Perceived of Risk <-> Health Belief Model	0.513	0.619
Perceived of Risk <-> Law Enforcement Knowledge	0.413	0.570
Policy Acceptance <-> Health Belief Model	0.663	0.740
Policy Acceptance <-> Law Enforcement Knowledge	0.581	0.660
Policy Acceptance <-> Perceived of Risk	0.467	0.845
User Cost <-> Health Belief Model	0.449	0.651
User Cost <-> Law Enforcement Knowledge	0.470	0.523
User Cost <-> Perceived of Risk	0.596	0.608
User Cost <-> Policy Acceptance	0.405	0.762

Table 9. Determinant coefficient of models

Parameters	R-square	R-square adjusted
Policy Acceptance (Truck Drivers)	0.419	0.394
Policy Acceptance (Publics)	0.708	0.702

A model is considered to have good predictive ability if the Q^2 value is greater than zero [66].

Based on the Q^2 predict analysis results, the structural model in this study demonstrates good predictive capability, as all Q^2 values are above the zero threshold, indicating predictive relevance. In the driver group, the constructs CT1 ($Q^2 = 0.240$) and CT2 ($Q^2 = 0.294$) show moderate to strong predictive ability, while ZO1 ($Q^2 = 0.167$) and ZO2 ($Q^2 = 0.197$) are at a moderate level. In contrast, in

the public group, all constructs demonstrate strong predictive capability, namely CT1 ($Q^2 = 0.530$), CT2 ($Q^2 = 0.476$), ZO1 ($Q^2 = 0.456$), and ZO2 ($Q^2 = 0.539$). Overall, these findings indicate that the model has higher predictive relevance for public respondents compared to driver respondents (Table 10).

Path Coefficient (β) - To examine the relationships among variables in the structural model, path coefficient analysis was conducted.

The β parameter is used to describe the direction and magnitude of the effect, while the level of significance is determined by the t-statistic value > 1.96 for a two-tailed test and a p-value < 0.05 [72], [73].

The path coefficient analysis shows that in the truck driver group, the Health Belief Model has a significant positive effect on Policy Acceptance ($\beta = 0.415$; $t = 4.562$; $p < 0.001$). In addition, Law Enforcement Knowledge also has a significant positive effect ($\beta = 0.281$; $t = 3.254$; $p = 0.001$). In contrast, Perceived Risk does not show a significant effect on Policy Acceptance ($\beta = 0.105$; $t = 1.075$; $p = 0.140$). The User Cost variable has a negative but statistically significant coefficient ($\beta = -0.017$; $t = 2.588$; $p = 0.028$), although the magnitude of the effect is very small; therefore, H2 is rejected.

In the public group, all exogenous variables show significant effects on Policy Acceptance. The Health Belief Model ($\beta = 0.211$; $t = 4.325$; $p < 0.001$) and Law Enforcement Knowledge ($\beta = 0.131$; $t = 3.160$; $p = 0.002$) have significant positive effects. Perceived Risk is the strongest predictor ($\beta = 0.428$; $t = 9.059$; $p < 0.001$). Meanwhile, User Cost has a significant negative effect on Policy Acceptance ($\beta = -0.260$; $t = 5.199$; $p < 0.001$); thus, all hypotheses (H5–H8) are accepted (Table 11).

4. Discussion

The phenomenon of ODOL trucks in Indonesia remains an unresolved issue. ODOL vehicles on toll roads in Indonesia are frequently encountered on weekdays (45.09%) and in the morning (38.40%) [13]. The presence of ODOL trucks on highways reduces pavement service life and causes road damage. This finding is consistent with the study by Jasmine *et al.* [61] which reports road deterioration caused by ODOL trucks in wood waste collection activities. It is also in line with studies by Kharvi *et al.* [74], Pinkaew *et al.* [12], Permana *et al.* [23], which state that ODOL trucks increase maintenance costs due to road damage.

Various efforts have been implemented to reduce the presence of ODOL trucks in several countries, such as the use of Weigh-in-Motion (WIM) systems in Brazil [14], Rusia [75], Abu Dhabi [11], France [76], China [26], and others. To support the Zero ODOL policy, the Indonesian government has implemented Electronic Traffic Law Enforcement (ETLE) and Weigh-in-Motion (WIM) technologies, which have currently been installed on seven toll road sections [23], [77]. The Zero ODOL policy has faced resistance from ODOL truck drivers in various regions. Similarly,

Table 10. Blindfolding analysis results

Q ² predict		
Constructs	Truck Drivers	Publics
CT1	0.240	0.530
CT2	0.294	0.476
ZO1	0.167	0.456
ZO2	0.197	0.539

Table 11. Path relations

Truck Drivers						
Parameters	Path Coef.	St. Dev	T-stat	P values	Sig.	Hypotesis
Health Belief Model -> Policy Acceptance	0.415	0.091	4.562	0.000	***	Supported H1
Perceived of Risk -> Policy Acceptance	0.105	0.097	1.075	0.140	NS	Not-Supported H1
User Cost -> Policy Acceptance	-0.017	0.086	2.588	0.028	**	Supported H3
Law Enforcement Knowledge -> Policy Acceptance	0.281	0.086	3.254	0.001	***	Supported H4
Publics						
Health Belief Model -> Policy Acceptance	0.211	0.049	4.325	0.000	***	Supported H5
Perceived of Risk -> Policy Acceptance	0.428	0.047	9.059	0.000	***	Supported H6
User Cost -> Policy Acceptance	-0.260	0.050	2.004	0.02	**	Supported H7
Law Enforcement Knowledge -> Policy Acceptance	0.131	0.041	3.160	0.002	***	Supported H8

the implementation of freight transport policies, whether public or private, continues to face numerous challenges, particularly in terms of policy acceptance among drivers [11], [52].

The findings demonstrate that ODOL trucks generate higher fuel consumption, CO₂ emissions, and carbon tax burdens compared to non-ODOL trucks, despite operating on relatively shorter travel distances. Based on the simulation results, ODOL trucks produced 25.905 kg CO₂, while non-ODOL trucks generated 23.9976 kg CO₂. Similarly, fuel consumption under ODOL conditions reached 9.81 L, exceeding non-ODOL operations at 9.09 L. These findings indicate that overloaded freight operations reduce transportation energy efficiency and increase environmental externalities within freight transportation systems [11], [12], [14], [78].

Mechanistically, ODOL operations increase total vehicle weight and axle loads, which subsequently increase rolling resistance, engine workload, and fuel demand during freight operations. Excessive loading conditions may also worsen pavement conditions and increase aerodynamic drag due to irregular cargo dimensions and unstable vehicle configurations. Consequently, vehicles require greater energy consumption to maintain movement, leading to higher fuel consumption and carbon emissions. This finding is consistent with previous studies reporting that overloaded trucks contribute significantly to infrastructure deterioration, fuel inefficiency, and transport-related emissions [12], [17], [20], [79].

In addition to environmental impacts, ODOL operations generate broader freight externalities, including pavement deterioration, congestion, increased maintenance costs, and road safety risks. These findings reinforce the argument that ODOL practices represent not merely operational violations, but also socio-environmental governance challenges that undermine freight transport decarbonization efforts, particularly in emerging economies such as Indonesia.

4.1. Structural Equation Model

Among truck drivers, policy acceptance is primarily influenced by the Health Belief Model ($\beta = 0.415$; $p < 0.01$; H1 supported) and Law Enforcement Knowledge, while perceived risk

does not significantly affect policy acceptance ($\beta = 0.105$; $p > 0.01$; H2 not supported). In contrast, within the public group, perceived risk emerges as the strongest predictor of policy acceptance ($\beta = 0.415$; $p < 0.01$; H6 supported). These differences indicate that drivers and the public interpret freight sustainability policies through different experiential and socio-economic lenses.

Drivers tend to evaluate ODOL policies through operational and economic perspectives, emphasizing transport costs, sanctions, operational feasibility, and livelihood implications. This finding indicates that although drivers may be aware of the risks, such awareness is not sufficiently strong to alter their policy acceptance attitudes. In line with this, Baikejuli & Shi [27], found that drivers tend to ignore risks in pursuit of economic benefits. In this group, the carbon tax construct emerged as the strongest indicator influencing policy acceptance, confirming that economic-based instruments are highly salient among freight operators directly involved in transportation activities. This finding aligns with studies showing that freight drivers frequently prioritize economic survival and operational continuity over environmental considerations [11], [26], [27].

The findings reveal that the carbon tax construct emerged as the strongest indicator influencing policy acceptance among drivers, with an outer loading value of 0.866. Although the carbon tax burden per trip appears relatively small, drivers perceive the policy as a direct economic pressure because freight transportation activities are closely associated with trip frequency, operational margins, fuel expenditure, and income stability. This finding reflects the concept of cost salience, where individuals tend to respond more strongly to immediate and visible economic costs than to long-term environmental benefits. Consequently, carbon taxation is not primarily interpreted by drivers as an environmental mitigation strategy, but rather as an additional operational burden that may reduce profitability and threaten livelihood stability.

In Indonesia, carbon tax implementation has not yet been maximized due to political elites' awareness of corruption-related challenges [80], and because it is not yet considered an urgent priority for certain sectors [81]. However, carbon tax implementation has been shown to reduce

carbon emissions by up to 0.13% in Nordic countries and 1.2% in Canada [82]. This finding is supported by Ahmad *et al.* [11], who reported that environmental taxes have a strong negative effect on CO₂ emissions in the transportation sector, with a probability of emission reduction of up to 45%.

Conversely, within the general public group, the Zero ODOL construct emerged as the strongest factor influencing policy acceptance. This finding indicates that the public is more driven by perceptions of safety, traffic order, and the social impacts of road disruption. For the general public, ODOL enforcement policies are perceived as direct public protection measures, making them more likely to receive support. This difference in pattern confirms that policy implementation strategies need to be tailored to the characteristics of each target group, where economic incentive-based approaches are more effective for drivers [11], [12], [13], [27], while safety- and public-order-based approaches are more resonant for the general public [78], [83].

The dominance of perceived risk within the public group further reinforces this interpretation. The common-dread dimension emerged as the strongest perceived risk construct with a high outer loading value of 0.833, indicating that fear and concern when interacting with ODOL trucks represent the most salient public perception. This finding is consistent with Ono *et al.* [84] and Mustafa *et al.* [85], who identified dread as an important factor shaping policy acceptance. The result also aligns with demographic patterns observed in this study, where women constituted a large proportion of respondents within the pro-policy group. Previous studies by Gnerre *et al.* [86] similarly reported that women tend to exhibit higher levels of transport-related risk perception.

Moreover, the significant negative effect of User Cost in both groups confirms that an increase in perceived costs tends to reduce the level of policy acceptance. This finding is consistent with Izadi *et al.* [44] who reported that user cost has a significant negative effect in cost modeling and cost-factor analysis in road freight transportation. This result is further supported by Karakurt and Gokasar [87], who identified a conflict between user costs and operational costs that affects policy effectiveness. Baghestani *et al.* [88] also revealed that increased perceived costs reduce individuals' intentions to choose sustainable transportation.

The sanction knowledge construct emerged as the strongest factor within the Law Enforcement Knowledge (LEK) variable. This indicates that respondents are more sensitive to direct and strict consequences [13], [26], [27], making knowledge of sanctions the most influential factor affecting policy acceptance. In their study, Pinkaew *et al.* [12] recommended the implementation of an overload permit fee system as a potential policy option to improve regulatory compliance and promote sustainable transport management practices.

5. Implication

This study provides several important implications, both practical and theoretical, in addressing the issue of over-dimension over-load (ODOL) trucks and carbon emissions from the transportation sector.

5.1. Practical Implications

Governance policy: The findings indicate that freight sustainability policies should not rely solely on punitive enforcement approaches. Although technologies such as Electronic Traffic Law Enforcement (ETLE) and Weigh-in-Motion (WIM) systems may strengthen regulatory monitoring, enforcement alone is insufficient to ensure long-term policy acceptance among truck drivers. Since drivers are highly sensitive to operational costs and economic pressures, policy implementation should also incorporate economic transition mechanisms, including operational incentives, gradual compliance schemes, fuel-efficiency programs, fleet modernization assistance, and fairer cost-sharing arrangements among freight stakeholders [11], [12], [13], [27].

Communication and Socialization Strategies: Policy acceptance was found to vary significantly among truck drivers based on age, employment status (individual owner-operators versus company drivers), and trip frequency. The group opposing the policy was predominantly composed of older drivers and individual owner-operators [11], [26], indicating the need for targeted communication and educational strategies. Socialization programs should be more intensive for these groups and adopt a more narrative approach [89] emphasizing regulatory understanding, accident risks, road damage, and

the long-term benefits for safety and the environment.

5.2. Theoretical Implications

Theoretically, this study extends the application of the Health Belief Model (HBM) and perceived risk frameworks into the context of freight transportation governance and ODOL regulation. Previous HBM studies have largely focused on health behavior, traffic safety, and individual behavioral intention [13], [26]. However, this study demonstrates that HBM constructs also play an important role in explaining policy acceptance within freight transportation systems, particularly among truck drivers exposed to operational and regulatory pressures.

This study demonstrates the existence of divergent acceptance structures between truck drivers and the general public. Among drivers, policy acceptance is primarily influenced by operational-economic considerations and enforcement awareness, while among the public, perceived risk and socio-environmental concerns become dominant factors. This finding contributes to freight governance literature by showing that different stakeholder groups respond differently to sustainability policies depending on their operational exposure, perceived externalities, and socio-economic position.

This study proposes a socio-technical acceptance perspective by integrating technical emission simulation, carbon burden estimation, behavioral acceptance analysis, and freight governance considerations into a single analytical framework. This integration contributes to the growing discussion regarding sustainable freight transportation and transportation decarbonization in low- and middle-income countries (LMICs), where environmental objectives frequently intersect with operational efficiency pressures and socio-economic vulnerability.

6. Conclusion, Limitations and Future Research

6.1. Conclusion

The issue of over-dimension over-load (ODOL) trucks represents a significant challenge

in Indonesia's transportation sector, which is a major contributor to global CO₂ emissions. Although the Zero ODOL policy has been introduced since 2017 to address this problem, its implementation continues to face resistance from drivers and industry actors [11], [23], [69]. This study evaluates ODOL truck operations from technical, environmental, economic, and behavioral perspectives within the context of freight transportation sustainability in Indonesia. The findings indicate that ODOL trucks generate higher fuel consumption, CO₂ emissions, and carbon tax burdens compared to non-ODOL freight operations. These results confirm that overloaded freight practices contribute not only to infrastructure deterioration but also to environmental externalities that may undermine freight transport decarbonization efforts.

From the behavioral perspective, this study reveals the existence of divergent policy acceptance structures between truck drivers and the general public. Truck drivers tend to evaluate Zero ODOL and carbon-related policies through economic and operational considerations, including operational costs and sanctions. Meanwhile, the general public demonstrates stronger support toward Zero ODOL policies due to concerns regarding road damage, traffic safety, congestion, environmental pollution, and public road order. Perceived risk was found to significantly influence policy acceptance among the public but not among drivers, indicating that economic pressure and operational normalization may reduce the influence of safety-related perceptions in freight operations (consistent with [11], [27], [90]).

These findings suggest that freight sustainability policies should not rely on uniform governance approaches. Drivers and the general public respond to different policy narratives and incentive structures. Therefore, policy implementation strategies should combine enforcement mechanisms with economic transition support [12], [91], fairness considerations, and differentiated communication approaches tailored to stakeholder characteristics.

Theoretically, this study contributes to the freight governance literature by integrating technical emission analysis, economic burden evaluation, and psychosocial acceptance frameworks into a socio-technical perspective of

freight sustainability policy acceptance. The study also extends the application of the Health Belief Model and perceived risk frameworks into the context of freight transportation governance in emerging economies.

6.2. Limitations

Nevertheless, this study has several limitations.

- a. Data Scope: The study still adopts data from Jasmine *et al.* [61] which are limited to trips with relatively short frequency. Although considered representative, the specific characteristics of these transport types and routes may not fully reflect the diversity of ODOL truck operations across different types of goods and regions in Indonesia. Variations in truck types, road conditions, and driving patterns may influence emission and fuel consumption outcomes.
- b. Sample Size and Representation: this study only involved truck drivers and the general public as respondents. Cargo owners, freight operators, and logistics decision-makers were not included in the analysis.
- c. Emission Model: The emission model employed simplified assumptions regarding fuel efficiency and did not incorporate several operational variables such as vehicle weight variation, road gradient, traffic speed fluctuations, engine technology, aerodynamic conditions, and real-time driving behavior.

6.3. Future Research

Future research directions include:

- a. In-depth Study of Carbon Tax Implementation. Given drivers' sensitivity to carbon tax and its effectiveness in reducing emissions in other countries, future research may focus on feasibility studies, optimal rate determination, and implementation mechanisms of carbon tax in Indonesia's transportation sector.
- b. Expansion of Respondent Scope. This study involved drivers and the general public. Future research may expand the respondent including cargo owners, freight companies, logistics planners, and supply-chain decision-makers, to obtain a more comprehensive understanding of policy dynamics.
- c. Emission Model. More advanced mechanistic emission models incorporating vehicle weight,

road gradient, traffic speed, engine characteristics, and driving behavior are also recommended to better capture actual freight transportation conditions.

- d. Use of Real-Time Data. Future research may utilize real-time data based on CCTV [13] and Weight in Motion [76] to provide actual operational data on ODOL trucks in Indonesia.

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Author's Declaration

Authors' contributions and responsibilities

The authors made substantial contributions to the conception and design of the study. The authors took responsibility for data analysis, interpretation and discussion of results. The authors read and approved the final manuscript.

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Availability of data and materials

All data are available from the authors.

Competing interests

The authors declare no competing interest.

Generative AI statement

During the preparation of this manuscript, the authors used Claude and ChatGPT (GPT-5) to assist with literature review, literature categorization, and the identification of research gaps. All AI-assisted output was subsequently reviewed, verified, and, where necessary, edited by the authors, who take full responsibility for the final content of the manuscript.

Additional information

No additional information from the authors.

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Appendix

The appendix contains the questionnaire items used in the study, divided into two groups (drivers and general public), where each question has the same meaning but is phrased differently.

Drivers		
Variable	Construct	Item
HBM	PS1	High emissions from freight vehicles can have serious impacts on the environment and future quality of life.
	PS2	Emission reduction policies are important because pollution from transportation can affect public health.
	PB1	Emission reduction through vehicle operational regulation can help mitigate environmental impacts.
	PB2	Emission-related policies can encourage the use of more efficient transportation.
	PR1	The implementation of a carbon emission tax may increase the operational costs of my transport activities.
	PR2	Operational adjustments to reduce emissions may be challenging in my work.
	CA1	Information about the impact of carbon emissions makes me more likely to consider more fuel-efficient driving practices.
	CA2	Information or regulations related to emissions may influence the way I work.
	PC1	I feel capable of reducing fuel consumption through more efficient driving practices.
	PC2	I feel able to adjust my work practices in response to emission reduction efforts.
	VR1	Driving a vehicle with excessive load involves certain safety risks.
	VR2	Driving an ODOL truck is a risk I choose as part of my job.
	CR1	I feel capable of controlling risks when driving an ODOL truck.
Perc. of Risk	CR1	My driving experience makes me confident in facing ODOL-related risks.
	CD1	The risks of driving an ODOL truck have become normal to me.
	CD2	I am not overly afraid of the risks when carrying excessive loads.
	CC1	ODOL-related accidents may be rare but can have very fatal consequences.
	CC2	Accidents caused by ODOL can result in serious consequences for drivers.
	TDC1	Regulations related to ODOL may increase my travel or delivery time.
RUC	TDC2	Traffic conditions influenced by ODOL vehicles often cause delays in my trips.
	VOC1	Driving a truck with excessive load increases vehicle operational costs.
	VOC2	Road damage caused by heavy vehicles increases my vehicle maintenance costs.
	EC1	Vehicles with excessive loads can generate higher emissions.
LEK	EC2	I am aware of the carbon tax policy in the transportation sector.
	RK1	I am aware of the Zero ODOL regulation.
	RK2	I understand the permitted vehicle load and dimension limits.
	SK1	I am aware of the sanctions and legal consequences for ODOL violations.
PAM	ZO1	I intend to comply with vehicle load and dimension regulations.
	ZO2	I am willing to support the Zero ODOL policy.
	CT1	I am willing to accept a carbon tax policy if it aims to reduce emissions from the transportation sector.
	CT2	I will attempt to operate vehicles in a more fuel-efficient manner if a carbon tax policy is implemented.