

## The Impact of Urban Traffic Congestion on the Operational Costs of Logistics Transportation in Bogor City

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**ABSTRACT:** Urban traffic congestion is a major challenge for logistics efficiency, particularly in rapidly growing cities like Bogor, Indonesia. This study aims to quantify the impact of traffic congestion on logistics operational costs by analyzing congestion levels and cost components in urban freight transport. A quantitative approach was used, involving 50 logistics fleet respondents from Bogor. Primary data were collected through structured questionnaires measuring daily congestion duration, travel time, average speed, fuel consumption, driver wages, and vehicle maintenance costs. Statistical analysis was conducted using simple linear regression. The results reveal that logistics vehicles experience approximately 95 minutes of congestion daily, with travel speeds reduced to 13.5 km/h. The study finds a strong, positive, and statistically significant relationship between congestion and logistics costs (regression coefficient = 0.674,  $p < 0.001$ ), with congestion explaining 45.5% of cost variation. Increased fuel consumption, labor costs, and maintenance expenses are the main contributors to operational inefficiencies. These findings underscore how urban congestion increases the cost to serve and diminishes logistics reliability. The study suggests that policymakers adopt adaptive strategies such as smart routing, freight dedicated lanes, and urban consolidation centers. It also calls for greater integration of logistics planning in urban transport systems to enhance resilience and sustainability. These findings contribute to the growing discourse on urban freight efficiency in Southeast Asian cities.

**Keywords:** Urban Logistics, Traffic Congestion, Operational Cost, Urban Freight Efficiency, Indonesia Logistics Planning.



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## INTRODUCTION

Urban traffic congestion has become one of the most pressing challenges facing cities within the Jakarta metropolitan area (Jabodetabek), including Bogor City. Rapid urbanization has driven significant population growth, placing unprecedented pressure on existing infrastructure. Bogor,

strategically located within this conurbation, experiences high vehicular density that regularly exceeds road capacity. Studies indicate that traffic congestion in Jabodetabek is among the worst in Southeast Asia, with far reaching consequences for daily commuting, urban air quality, and economic productivity (Buyukeren & Hiramatsu, 2015; Mukti & Prambudia, 2018). The need for effective transportation policy has grown urgent, as congestion increasingly hinders logistics activities crucial to maintaining the flow of goods within and beyond city borders.

As Bogor's population continues to rise, transport demand grows across both personal and commercial sectors. This growth has been accompanied by an expansion of motorized vehicles, creating congestion driven not only by commuters but also by freight vehicles essential to supply chains. Without effective interventions, this dual burden threatens to undermine public mobility and logistics performance, thereby weakening overall urban resilience (Meirinawati et al., 2021).

One of the core concerns emerging from this context is the substantial economic burden traffic congestion places on urban logistics. Timely delivery and cost efficiency two fundamental pillars of logistics performance are compromised in congested environments. Prolonged delays, unreliable travel times, and fuel inefficiencies contribute to elevated operational costs. Vichiensan et al. (2021) argue that lost productivity alone due to traffic delays represents a significant economic drain, while Buyukeren & Hiramatsu (2015) emphasize how these effects ripple through the broader economy by elevating supply chain expenses and reducing business competitiveness.

To address such multifaceted issues, policymakers in numerous global cities have implemented congestion mitigation strategies targeting logistics optimization. Examples include congestion pricing schemes, designated urban freight corridors, and the expansion of public transit networks. These approaches not only reduce private vehicle dependency but also enhance the operational environment for logistics providers (Albalade & Fageda, 2019). The integration of multimodal transport systems has proven particularly valuable in cities like Beijing and Singapore, where efficient freight movement coexists with reduced urban congestion (Buyukeren & Hiramatsu, 2015).

Beyond economic and policy implications, traffic congestion also presents a substantial environmental concern. Increased idling times and slow moving traffic directly elevate greenhouse gas emissions and fuel consumption, undermining sustainability goals. The environmental footprint of urban freight activities grows in tandem with congestion, highlighting the urgent need for low carbon logistics innovations. Škultéty et al. (2021) find that in high density cities, logistics vehicles contribute disproportionately to air pollution due to stop and go driving patterns. Thus, effective congestion management is pivotal not only for economic efficiency but also for environmental stewardship.

In this context, the experience of Bogor City, although less documented than Jakarta, offers valuable insight into secondary urban centers within the Jabodetabek region. Rakhmatullah et al. (2024) and others have pointed out that cities like Bogor face unique challenges tied to their geography and integration with metropolitan Jakarta. Comparative assessments reveal that cities with well-developed public transportation networks exhibit greater resilience to congestion related

disruptions, a lesson that can inform logistics strategy development in Bogor (Mukti & Prambudia, 2018).

This research aims to quantify the impact of traffic congestion on logistics operational costs in Bogor. Specifically, it examines variations in fuel consumption, driver wages, and vehicle maintenance in relation to congestion indicators such as travel time, average vehicle speed, and daily delay duration. By focusing on Bogor a mid-sized city with unique challenges compared to Jakarta this study contributes new empirical evidence that has been largely absent from the literature. The findings not only enrich academic understanding of urban freight in secondary cities but also provide actionable insights for policymakers and practitioners seeking to design adaptive, sustainable logistics strategies.

## METHOD

This study employed a quantitative associative research design aimed at analyzing the relationship between urban traffic congestion (independent variable) and logistics transportation operational costs (dependent variable) in Bogor City. A quantitative approach was selected to enable systematic statistical analysis and provide empirical support for policy recommendations. Regression analysis, a common method in urban transport studies, was used to quantify the strength and nature of the correlation between congestion metrics and cost variables (Aprilia, 2024; Michelle & Susilo, 2021).

The research was conducted in Bogor City, West Java, a key urban node within the Jabodetabek region characterized by high traffic density and active logistics operations. The city was selected due to its strategic role in regional logistics and its known congestion challenges. The study was implemented from January to February 2024, a period that reflects typical urban activity and logistics demand.

The study population included logistics transportation service providers operating in Bogor. A purposive sampling method was employed, targeting operators that: (1) have been active for at least one year, (2) maintain routine vehicle operational records, and (3) were willing to participate. A total of 50 logistics fleet units were sampled. While purposive sampling enabled focused data collection, its non-random nature was mitigated through demographic and operational diversity considerations (Muazam et al., 2024).

Primary data were gathered through structured questionnaires administered to fleet managers and drivers. Questions covered:

- Average daily congestion duration (minutes),
- Travel time per kilometer (minutes/km),
- Daily fuel consumption (liters),
- Fuel cost per day (IDR),
- Driver wage per hour (IDR),
- Overtime cost due to congestion (IDR/day),

- Vehicle maintenance cost (IDR/month).

Secondary data were obtained from local transportation authorities and logistics firms, offering contextual and comparative insights. The use of structured instruments ensured data uniformity and reliability.

Independent Variable (X): Urban congestion, measured via indicators including average daily congestion duration, vehicle speed, and travel time per kilometer.

Dependent Variable (Y): Logistics transportation operational costs, comprising fuel expenses, driver wages (including overtime), and vehicle maintenance costs.

Data analysis involved descriptive statistics and simple linear regression to examine the relationship between congestion and logistics costs. Instrument validity and reliability were tested using SPSS, along with standard assumption checks (normality, heteroscedasticity) to ensure model robustness (Uzawa et al., 2024)

The research complied with ethical standards, ensuring informed consent, participant anonymity, and confidentiality throughout the data collection process.

While simple linear regression effectively established a baseline understanding of variable relationships, it does not capture multivariate influences. Future studies could apply multiple regression models to integrate additional explanatory factors, thereby enhancing the robustness of logistics cost analyses (ÖNÜR & KOZIKOĞLU, 2020).

## RESULT AND DISCUSSION

The results of this study are presented in four sub sections that align with the research framework: respondent characteristics, traffic congestion level, logistics operational costs, and regression analysis. The results are supported by descriptive statistics and inferential testing, as well as interpretations grounded in relevant literature.

### Characteristics of Respondents

This research involved 50 logistics fleet respondents operating in Bogor City. Table 1 presents the demographic and operational profile of the respondents.

**Table 1. Characteristics of Respondents**

| Characteristic  | Category             | Frequency | Percentage (%) |
|-----------------|----------------------|-----------|----------------|
| Gender          | Male                 | 45        | 90%            |
|                 | Female               | 5         | 10%            |
| Age             | < 30 years           | 12        | 24%            |
|                 | 30–40 years          | 26        | 52%            |
|                 | > 40 years           | 12        | 24%            |
| Type of Vehicle | Small truck (pickup) | 30        | 60%            |
|                 | Medium truck         | 15        | 30%            |
|                 | Large truck          | 5         | 10%            |

Source primary data 2024

A total of 50 logistics fleet respondents participated in the study (Table 1). Most were male (90%), within the 30–40 age group (52%), and operated small trucks (60%). These characteristics align with the urban logistics profile in Indonesia, where the workforce is predominantly male and small vehicles are preferred for maneuverability in congested streets.

These findings are consistent with the logistics workforce trends in urban Indonesia, which remains male dominated due to structural and cultural norms (Levy et al., 2010). The age distribution indicates that logistics drivers are generally within productive age, which enhances adaptability and technological familiarity, particularly among the younger cohort (Kii et al., 2021). The predominance of light duty vehicles reflects a strategic adaptation to urban congestion, as smaller vehicles offer better maneuverability in narrow, traffic prone streets (Yu-hui et al., 2020).

### **Traffic Congestion Level**

The study quantified urban traffic congestion using three core indicators: daily congestion duration, travel time per kilometer, and average speed. Table 2 summarizes the results.

**Table 2. Traffic Congestion Indicators**

| Congestion Indicator          | Daily Average |
|-------------------------------|---------------|
| Congestion duration (minutes) | 95 minutes    |
| Travel time (minutes/km)      | 7.2 minutes   |
| Average speed (km/hour)       | 13.5 km/hour  |

Source primary data 2024

On average, logistics fleets in Bogor experienced 95 minutes of traffic congestion per day. Travel time reached 7.2 minutes per kilometer, while average speeds dropped to 13.5 km/h. These figures

highlight the severity of congestion in Bogor, consistent with findings from INRIX's Global Traffic Scorecard and comparable studies (Louf & Barthélemy, 2014; Zheng & Huang, 2020).

This congestion profile directly impacts logistics efficiency by increasing delivery times and reducing route reliability. Congested road networks, especially around central business districts and intersections, were key contributors. These results support previous observations that small increases in vehicle density can cause disproportionate drops in travel speed ((Li et al., 2024), confirming the non-linear congestion cost dynamic in urban logistics (Vichiensan et al., 2021).

Moreover, the prevalence of outdated traffic management systems and lack of synchronized infrastructure exacerbate the bottlenecks. Real time monitoring tools like GPS and AI based traffic modeling systems could enhance operational agility if deployed effectively (Dikshit et al., 2023; Fu et al., 2022).

## Logistics Operational Costs

The study measured the average daily operational costs incurred by logistics fleets, focusing on fuel, driver wages, overtime due to congestion, and maintenance. Table 3 presents the cost breakdown.

**Table 3. Daily Logistics Operational Costs**

| Cost Component                          | Daily Average (Rp) |
|-----------------------------------------|--------------------|
| Fuel cost                               | 185,000            |
| Driver wage per hour                    | 80,000             |
| Overtime cost due to traffic congestion | 55,000             |
| Vehicle maintenance cost                | 70,000             |

Daily operational costs (Table 3) averaged IDR 185,000 for fuel, IDR 80,000 for wages, IDR 55,000 for overtime, and IDR 70,000 for maintenance. Fuel dominated overall costs, followed by wages and congestion-related overtime. These findings confirm that congestion directly elevates operational expenses through higher fuel use, longer delivery times, and increased maintenance frequency (Bokor, 2010).

Cost differentials between urban zones are considerable. Studies in Jakarta report per kilometer logistics costs at USD 1.25–1.50, while cities with lower congestion like Semarang average closer to USD 1.00. These disparities necessitate dynamic pricing strategies by logistics firms to offset operational inefficiencies.

## Regression Analysis

To statistically examine the relationship between traffic congestion and logistics costs, a simple linear regression was conducted. Table 4 shows the regression model results.

**Table 4. Regression Model Results: Effect of Congestion on Logistics Operational Costs**

| Regression Model                              | Coefficient | Sig. (p-value) |
|-----------------------------------------------|-------------|----------------|
| Congestion → Logistics Operational Cost       | 0.674       | 0.000          |
| R <sup>2</sup> (Coefficient of Determination) | 0.455       | —              |

Regression analysis (Table 4) shows a significant positive relationship between congestion and logistics costs ( $\beta = 0.674$ ,  $p < 0.001$ ). The  $R^2$  value (0.455) indicates that congestion explains 45.5% of cost variation. While robust, the model suggests that other variables such as vehicle condition, driver experience, and routing practices also contribute to cost dynamics.

It should be noted that the analysis focuses only on congestion indicators and core cost components. External factors such as fuel price volatility, driver behavior, and company-level logistics policies were not incorporated. These limitations should be considered in interpreting the results (Murata & Naitoh, 2015).

### **Traffic Congestion as a Constraint to Logistics Efficiency**

The findings confirm that traffic congestion is a major constraint to logistics efficiency in Bogor. With fleets facing an average of 95 minutes of congestion daily and speeds reduced to 13.5 km/h, delivery reliability and supply chain continuity are severely disrupted. These results are consistent with the theory of transport bottlenecks Rodrigue et al. (2020) but also reflect Bogor's unique context high vehicle growth, limited road expansion, and the large presence of angkot minibuses intensifying congestion.

The root causes of Bogor's congestion problem stem from the mismatch between vehicle growth and the expansion of road infrastructure. In addition, the city's 3,100 angkot units (minibuses) compound congestion, particularly during peak hours and in high traffic distribution zones. These localized factors exacerbate congestion beyond standard thresholds, reducing the efficiency of goods movement. As highlighted by Bokor (2012) and Kusnadi & Siregar (2021) similar patterns in the Jabodetabek region have led to a 35% increase in logistics travel times, which is mirrored in the present study.

In essence, traffic congestion functions not merely as a logistical inconvenience but as a disruptive environmental factor that hinders supply chain reliability and cost effectiveness. Rodrigue et al. (2020) categorize such disruptions as external shocks that deteriorate logistics performance through delivery delays, wasted fuel, and diminished payload capacity. These adverse effects necessitate a reframing of traffic congestion from a municipal planning issue to a core strategic concern in logistics management.



## Impact of Congestion on Operational Costs

A critical consequence of traffic congestion, as reflected in Table 3, is the increase in logistics operational costs. The study found that daily fuel expenses average IDR 185,000, with an additional IDR 55,000 incurred due to overtime caused by congestion. These expenditures reflect inefficiencies triggered by extended idle times and reduced average speeds, echoing Bokor (2012) assertion that stop and go driving significantly inflates fuel consumption.

Maintenance costs also rise due to the mechanical strain imposed by frequent braking, acceleration, and idling. Yuliana, (2020) emphasizes that maintenance expenditures for logistics fleets increase by up to 20% in high congestion corridors compared to routes with smoother traffic flow. This strain is especially burdensome for small and medium sized logistics enterprises, which often operate on thin profit margins. Prabowo & Kartika (2022) report that over 60% of mid-sized logistics operators in Indonesian urban centers experienced a marked surge in operational costs post pandemic, largely attributed to rising fuel prices and worsening congestion.

The upward pressure on logistics costs not only burdens service providers but also undermines end consumer affordability and supply chain competitiveness. Rising cost to serve metrics compel logistics companies to increase tariffs, disrupting downstream price structures and diminishing national logistics efficiency. These trends corroborate the conceptual link between traffic induced inefficiencies and macroeconomic productivity losses in urban supply chains.

## Empirical Link Between Congestion and Logistics Costs

Regression results ( $\beta = 0.674$ ,  $R^2 = 0.455$ ) confirm congestion as a strong predictor of logistics costs. While comparable with studies in Bandung (Mahardika & Susanto, 2022), the model captures only 45.5% of variance, suggesting other drivers such as fleet age, scheduling, and digital optimization remain unaccounted for. This highlights a methodological limitation of relying on a simple regression model. Future research should test multivariate or AI-based models (Murata & Naitoh, 2015) to better capture complex dynamics influencing logistics efficiency in urban Indonesia.

This finding is consistent with Mahardika & Susanto (2022), who observed that each hour of congestion correlates with a 14% increase in logistics operational costs in Bandung. The cost elasticity of congestion is a well-documented principle in transport economics, where minor changes in traffic density yield disproportionately large impacts on logistics expenditures (Rodrigue et al., 2020). While the regression model confirms this relationship, it also highlights the need for multivariate analyses incorporating additional predictors, such as fleet age, scheduling flexibility, and digital route optimization.

Regression analysis remains a critical tool in logistics research for quantifying the impact of exogenous factors on cost structures. However, emerging techniques such as machine learning models Murata & Naitoh (2015) could enhance predictive accuracy by capturing nonlinear



interactions and contextual nuances. Future research may thus benefit from hybrid analytical approaches that combine statistical modeling with AI driven insights.

## Policy Implications and Adaptive Logistics Strategies

The empirical evidence from this study underscores the necessity of comprehensive policy interventions targeting congestion's adverse impact on urban logistics. Traditional traffic engineering solutions are insufficient on their own. Cities such as Singapore and Stockholm have adopted congestion pricing mechanisms, charging users for peak time road access, which has led to measurable reductions in traffic volume and logistics delays (Hammam et al., 2024; Helmi & Wahab, 2023).

Bogor could benefit from similar mechanisms tailored to its urban context, especially along critical freight corridors. In addition, dedicated freight lanes have proven effective in cities like New York and London by improving cargo transit times and lowering delivery variability (Taylor et al., 2013). These lanes reduce conflict between commercial and private traffic, creating a more predictable logistics environment.

Public transportation investments also indirectly benefit logistics by reducing the number of private vehicles on the road. Studies by Bigazzi & Figliozzi (2011) suggest that robust transit systems, including Bus Rapid Transit (BRT), can alleviate traffic congestion and improve freight flow. Further, dry port infrastructure linking seaports to inland logistics hubs can decentralize urban freight movements and reduce inner city truck volumes.

In tandem with infrastructural strategies, logistics providers must implement adaptive operational practices. The adoption of dynamic routing technologies, informed by real time traffic data, enables responsive delivery scheduling that minimizes exposure to congestion hotspots (Dong et al., 2019). AI based load optimization algorithms have also been shown to improve delivery efficiency and fuel economy (Zhang, 2023).

Collaborative logistics platforms present additional opportunities for cost reduction. Shared transport systems and cargo consolidation initiatives allow multiple operators to coordinate delivery schedules and pool resources, thereby reducing the number of vehicles on the road (Bosona, 2020). Urban Consolidation Centers (UCCs), where goods are aggregated before entering the city core, have similarly demonstrated success in lowering fuel use and delivery times (Sweet, 2013).

## Global Best Practices and the Role of Smart Mobility

International examples provide valuable benchmarks for Bogor. Barcelona's implementation of adaptive traffic signals, which adjust in real time based on road conditions, has led to improved freight mobility (Li et al., 2015). Germany's investment in multimodal logistics terminals enables efficient transitions between road, rail, and maritime transport, significantly easing the burden on urban roads (Liu et al., 2014).

Smart mobility solutions integrating IoT devices, AI, and cloud based platforms enhance transparency and coordination among stakeholders. Real time data sharing fosters synchronized deliveries and supports agile supply chain management (Hopkins & Hawking, 2018; Šemanjski & Gautama, 2019). When embedded in urban freight planning, these technologies can optimize travel patterns, reduce emissions, and improve stakeholder responsiveness.

Additionally, green logistics policies such as low emission zones (LEZs) and incentives for electric vehicle (EV) fleets can reduce the environmental footprint of urban freight operations. Cities adopting these measures report not only cleaner air but also more predictable delivery patterns due to preferential treatment for EVs (Dong et al., 2019).

Urban freight planning must thus embrace smart mobility and sustainability principles to remain resilient amidst rising congestion. Aligning logistics strategies with intelligent urban transport frameworks offers the dual benefit of operational efficiency and environmental stewardship, paving the way for sustainable city logistics in rapidly urbanizing contexts like Bogor.

Finally, this study acknowledges several limitations. The analysis did not account for external factors such as fluctuating fuel prices, seasonal demand variation, or company-specific logistics policies, which may bias results. Moreover, the use of purposive sampling restricts generalizability. Despite these constraints, the study provides valuable localized evidence for Bogor and highlights the need for future studies employing multivariate and comparative approaches across Indonesian cities.

## CONCLUSION

This study demonstrates that urban traffic congestion significantly increases logistics operational costs in Bogor City. With fleets experiencing up to 95 minutes of daily congestion and average speeds reduced to 13.5 km/h, congestion directly contributes to higher fuel consumption, overtime wages, and vehicle maintenance expenses. Regression analysis confirmed a strong positive relationship ( $\beta = 0.674$ ,  $p < 0.001$ ), with congestion explaining 45.5% of cost variation. These findings provide new empirical evidence on the cost elasticity of congestion in a mid-sized Indonesian city, filling a research gap that has been largely dominated by studies in Jakarta or passenger transport contexts.

The novelty of this study lies in its quantitative focus on Bogor as a secondary urban center, highlighting how localized congestion patterns affect logistics differently compared to larger metropolitan areas. For policymakers and practitioners, the key takeaway is that traffic congestion should not be viewed solely as a mobility problem but as a strategic logistics challenge. Adaptive measures such as freight-priority lanes, integrated urban freight planning, and smart mobility solutions must be tailored to Bogor's institutional and infrastructural realities. By embedding logistics considerations into urban transport policy, secondary cities can improve efficiency, enhance competitiveness, and move toward more sustainable urban freight systems.

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