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Operational and Technological Determinants of On-Time Delivery Performance in Urban Freight Distribution: Evidence from Indonesian Cities

Bhima Shakti Arrafat[1], Fardan Zeda Achmadi Yuda[2], Quirina Ariantji Patrisia Mintje[3]
[1]Politeknik Penerbangan Indonesia Curug, Indonesia
[2]Politeknik Penerbangan Palembang, Indonesia
[3]Akademi Penerbang Indonesia Banyuwang, Indonesia
Correspondent: bhima.shakti@ppicurug.ac.id[1]

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ABSTRACT: Urban freight distribution has grown increasingly complex due to e-commerce growth, rising customer expectations, and traffic congestion. This study investigates operational and technological determinants of on-time delivery performance in Indonesian urban freight distribution, evaluating the relative contribution of operational, environmental, technological, and customer-related factors. A quantitative cross-sectional design used 480 delivery observations from Jakarta, Surabaya, Bandung, and Medan. On-time delivery was coded as a binary outcome, with explanatory variables including congestion index, departure delay, loading time, number of stops, distance, peak-hour operation, rainfall, route optimization, real-time tracking, and customer availability, analyzed through binary logistic regression. Results show an overall on-time delivery rate of 90.63%. Traffic congestion was the strongest constraint, significantly reducing punctuality odds with each unit increase. Route optimization and real-time tracking significantly improved on-time delivery probability, demonstrating that digital logistics technologies enhance reliability through better planning and visibility. Delivery distance showed a marginal negative effect, while departure delay, loading time, peak-hour operation, rainfall, and customer availability were not significant. Number of stops showed a positive association, interpreted as reflecting efficient route configuration rather than a direct causal benefit. The study concludes that delivery reliability depends on the interaction between traffic conditions and digital logistics capabilities, with route optimization and real-time tracking mitigating congestion's adverse effects—offering practical guidance for improving urban freight performance in developing-country contexts.

Keywords: Urban Freight Distribution, On-Time Delivery, Traffic Congestion, Route Optimization, Real-Time Tracking, Binary Logistic Regression, Last-Mile Logistics

INTRODUCTION

Urban freight distribution has become an indispensable component of modern supply chains as rapid urbanization, the expansion of electronic commerce, and increasing consumer expectations continue to intensify demand for reliable and timely delivery services. In metropolitan areas, logistics providers are expected to deliver goods within increasingly narrow delivery windows while simultaneously coping with complex transportation networks, fluctuating traffic conditions, and operational constraints. Consequently, on-time delivery (OTD) has emerged as one of the most important indicators of logistics performance because it reflects not only operational efficiency but also customer satisfaction, service quality, and overall supply chain competitiveness. Maintaining high delivery punctuality has therefore become a strategic priority for logistics operators, particularly in densely populated urban environments where traffic uncertainty is unavoidable.

Urban freight systems operate within highly dynamic environments in which congestion, infrastructure limitations, delivery density, and unpredictable travel conditions continuously challenge logistics performance. Among these challenges, traffic congestion has consistently been identified as one of the principal causes of delivery delays because it increases travel time variability, reduces schedule reliability, and elevates the risk of violating customer time windows. Previous studies have demonstrated that congestion substantially degrades delivery reliability while simultaneously motivating logistics providers to adopt more sophisticated routing strategies and multimodal freight solutions. Reviews of urban freight transportation further indicate that congestion encourages the development of intermodal and synchromodal logistics systems capable of reducing dependence on conventional road transport (Assis et al., 2021; Zhao et al., 2019; Amrani et al., 2024). Similarly, investigations into urban delivery operations report that off-peak delivery strategies are frequently adopted to reduce congestion-related delays and improve schedule adherence (Dias et al., 2019). These findings collectively suggest that congestion represents both an operational constraint and a catalyst for innovation in urban logistics planning.

To maintain delivery reliability despite increasing operational complexity, logistics companies have increasingly relied on advanced planning technologies and digital decision-support systems. Route optimization, intelligent vehicle routing, real-time fleet monitoring, and predictive traffic information have become integral components of contemporary urban logistics operations. Vehicle Routing Problem (VRP) models and their extensions, particularly the Vehicle Routing Problem with Time Windows (VRPTW), provide mathematical frameworks for minimizing travel time while ensuring compliance with delivery schedules(Ekayanti & Efendi, 2024; Qin et al., 2019). Recent studies have further extended these models by incorporating metro-integrated freight transportation, synchromodal planning, and adaptive routing strategies that exploit multiple transportation modes and real-time information to improve delivery reliability (Zheng et al., 2021). These technological developments demonstrate that delivery performance depends not only on external traffic conditions but also on an organization's capability to dynamically optimize routing decisions under uncertain operating environments.

Besides congestion and routing technology, numerous operational characteristics influence delivery punctuality. Loading time, departure delay, travel distance, and the number of delivery stops directly affect vehicle scheduling and the ability to satisfy promised delivery windows. Optimization models for urban e-grocery distribution explicitly incorporate loading duration, service time, and delivery time windows because these variables substantially influence routing feasibility and schedule adherence (Leyerer et al., 2020). Likewise, studies of urban logistics networks emphasize that route complexity, represented by travel distance, multiple delivery stops, and transfer activities, affects delivery efficiency and operational reliability (Chocholáč et al., 2023; Santinha et al., 2022). Research on hub-based and intermodal distribution further indicates that appropriate route consolidation and efficient network design can reduce travel time while improving delivery punctuality (Cui et al., 2021; Hu et al., 2020). Consequently, operational planning decisions remain fundamental determinants of delivery performance even when digital technologies are employed.

Environmental and customer-related conditions also contribute to delivery outcomes. Peak-hour traffic, adverse weather, parking availability, and recipient availability influence the probability that deliveries are successfully completed within the promised time frame. However, empirical evidence regarding these variables remains mixed. Some studies argue that peak-hour traffic and weather conditions significantly increase delivery delays, whereas others report that their effects become statistically insignificant once direct operational indicators, such as congestion intensity and routing decisions, are incorporated into multivariable models (Amrani et al., 2024; Dias et al., 2019). Similarly, customer availability affects first-attempt delivery success and operational efficiency because unsuccessful delivery attempts generate additional travel time and increase overall distribution costs. These findings indicate that delivery punctuality is determined by a combination of operational, technological, environmental, and customer-related factors rather than by a single operational characteristic.

From a theoretical perspective, research on urban freight performance has evolved from traditional VRP formulations toward more comprehensive decision-making frameworks that integrate uncertainty, real-time information, and multimodal transportation. The Vehicle Routing Problem with Time Windows (VRPTW) remains the dominant theoretical framework for evaluating delivery punctuality because it explicitly models delivery schedules and customer time constraints(Zhao et al., 2019;Ghannadpour et al., 2014; Shen et al., 2018). More recent developments, including Time-Dependent VRP with Soft Time Windows, account for fluctuating travel times and schedule deviations under uncertain traffic conditions (Liao & Shao, 2025). Synchromodal transportation extends this perspective by enabling dynamic mode switching in response to real-time disruptions, thereby improving both operational efficiency and punctuality (Yee et al., 2021). In parallel, adaptive multi-agent coordination models and intelligent transportation systems have been proposed to enhance decision-making under dynamic urban conditions (Pingen et al., 2022). Together, these theoretical developments provide a robust foundation for analysing delivery reliability in increasingly complex urban logistics environments.

Despite these advances, several research gaps remain. First, much of the existing literature focuses on either operational variables or digital logistics technologies independently, with relatively few studies examining their combined effects within a unified empirical framework. Second, evidence from emerging economies, particularly Indonesia, remains limited despite rapid growth in e-commerce and increasing urban logistics activity. Third, many previous investigations rely on optimization experiments or simulation models, whereas comparatively fewer studies analyse delivery-level operational observations to quantify the relative importance of multiple determinants of on-time delivery. Addressing these gaps is important because the operational realities of Indonesian cities including heterogeneous traffic conditions, diverse delivery zones, and varying technology adoption may produce different empirical relationships from those reported in developed economies.

Accordingly, this study investigates the operational and technological determinants of on-time delivery performance in Indonesian urban freight distribution using a calibrated dataset comprising 480 delivery observations collected across Jakarta, Surabaya, Bandung, and Medan. The study examines the effects of traffic congestion, departure delay, loading time, number of delivery stops, travel distance, peak-hour operation, rainfall, route optimization, real-time tracking, and customer availability on the probability of achieving on-time delivery through binary logistic regression. By integrating operational, environmental, technological, and customer-related variables within a single analytical framework, this research contributes empirical evidence from a developing-country context, extends the application of contemporary urban freight theories to Indonesian logistics systems, and provides practical insights for logistics providers seeking to improve delivery reliability through operational planning and digital technology adoption.

METHOD

Research Design

This study employed a quantitative, explanatory, and cross-sectional research design to investigate the operational and technological determinants of on-time delivery (OTD) performance in Indonesian urban freight distribution systems. The explanatory design was selected because the objective was to quantify the effects of multiple operational, environmental, technological, and customer-related variables on the probability of achieving on-time delivery. The unit of analysis was an individual delivery operation, allowing the investigation of delivery-level determinants rather than aggregate organizational performance.

The methodological approach was informed by the urban freight literature, which commonly applies regression-based analyses, optimization models, and multivariate statistical techniques to explain logistics performance. Although the reviewed literature extensively applies regression methods, Partial Least Squares (PLS), simulation, and optimization models, explicit applications of binary logistic regression to model on-time versus late deliveries remain relatively limited (Cagliano et al., 2017; Karakikes & Nathanail, 2022; Wong et al., 2018). Because the dependent variable in this study is binary, binary logistic regression provides an appropriate analytical approach for estimating the probability of successful on-time delivery while simultaneously controlling for multiple explanatory variables.

Study Dataset

The empirical analysis utilized a calibrated operational dataset consisting of 480 individual delivery observations representing urban freight distribution activities in four major Indonesian cities:

Jakarta, Surabaya, Bandung, and Medan. The dataset was designed to reflect typical operational characteristics of Indonesian urban logistics while avoiding attribution to any specific logistics provider.

Each observation represents a completed delivery and contains information describing operational conditions, environmental characteristics, technological support, and customer-related factors influencing delivery performance.

The dataset includes three vehicle categories (motorcycle, van, and light truck), three delivery service types (same-day, next-day, and scheduled), and three delivery zones (central business district, inner urban, and peripheral). In addition, the dataset records operational performance indicators, technology adoption variables, and customer availability information.

The dependent variable is On-Time Delivery (OTD), while ten explanatory variables represent operational, environmental, technological, and customer-related determinants.

Variable Measurement

Dependent Variable

The dependent variable was On-Time Delivery (OTD), representing whether a shipment was completed within the promised delivery time. It was measured as a binary outcome, distinguishing deliveries completed on schedule from those that were delayed. This binary classification is commonly adopted in logistics performance research because it directly reflects service reliability from both operational and customer perspectives.

Independent Variables

Ten explanatory variables were included in the analysis to capture the multidimensional nature of urban freight operations.

Traffic Congestion was measured using a continuous congestion index ranging from 0 to 100, representing the severity of traffic conditions encountered along the delivery route. Previous studies frequently operationalize congestion through time-dependent travel times and travel-time variability because these measures directly influence routing decisions and delivery reliability (Yee et al., 2021; Zhao et al., 2019; Zheng et al., 2021).

Departure Delay refers to the difference between the scheduled departure time and the actual departure time of the delivery vehicle. In the urban freight literature, departure delays are commonly associated with schedule deviations, time-window violations, and disruption propagation throughout delivery operations (Cagliano et al., 2017; Wong et al., 2018; Liao & Shao, 2025).

Loading Time measures the duration required for operational activities before departure, including sorting, inspection, loading, documentation, and vehicle preparation. These activities are widely recognized as service times that influence routing feasibility and schedule adherence b(Behiri et al., 2018).

Number of Stops represents the total number of customer locations served during a single delivery route. This variable reflects route complexity and operational workload and has been identified as an important determinant of scheduling efficiency and delivery reliability (Santinha et al., 2022; Chocholáč et al., 2023).

Travel Distance measures the distance travelled from the depot or distribution center to the assigned delivery destinations. Distance is frequently incorporated into urban logistics models because it directly affects travel time, vehicle utilization, operating costs, and exposure to traffic congestion (Wong et al., 2018; Bhuyan et al., 2021).

Peak Hour identifies whether deliveries were conducted during periods of heavy traffic demand, whereas Rain indicates whether deliveries occurred under rainy weather conditions. These variables were included to capture environmental conditions that may influence operational performance.

Route Optimization identifies whether delivery routes were generated using route optimization systems rather than manual planning. Previous studies consistently demonstrate that optimized routing improves scheduling efficiency and delivery punctuality by identifying more efficient travel sequences while satisfying customer time constraints (Liao & Shao, 2025).

Real-Time Tracking indicates whether delivery vehicles were continuously monitored throughout the delivery process. Continuous monitoring improves operational visibility, enables rapid responses to unexpected disruptions, and supports adaptive routing decisions under changing traffic conditions (Yee et al., 2021).

Finally, Customer Availability represents whether the intended recipient was available during the first delivery attempt. Previous urban logistics studies frequently operationalize this concept through customer time-window availability because recipient presence directly affects successful first-attempt delivery and overall service efficiency (Liao & Shao, 2025).

Statistical Analysis

The empirical analysis was conducted in three stages.

First, descriptive statistics were used to summarize the characteristics of delivery operations. Frequencies, percentages, means, and standard deviations were calculated to describe delivery performance, congestion levels, departure delays, loading times, technology adoption, and customer characteristics.

Second, bivariate analyses were performed to examine preliminary relationships between each explanatory variable and on-time delivery. Pearson's Chi-square test or Fisher's Exact Test was applied to categorical variables where appropriate, while continuous variables were evaluated using the independent-samples *t*-test or the Mann–Whitney *U* test when the assumptions of parametric testing were not satisfied.

Finally, binary logistic regression was employed as the primary analytical technique to estimate the independent effects of operational, environmental, technological, and customer-related variables on the likelihood of achieving on-time delivery. This approach is appropriate because the dependent variable consists of two possible outcomes: on-time delivery or delayed delivery. Regression coefficients, odds ratios, confidence intervals, and significance levels were estimated to evaluate the direction, magnitude, and statistical significance of each determinant while controlling for the effects of the remaining variables.

Research Framework

The analytical framework assumes that on-time delivery performance is jointly influenced by operational conditions, environmental factors, technological capabilities, and customer characteristics. Operational variables include traffic congestion, departure delay, loading time, number of stops, and travel distance. Environmental conditions are represented by peak-hour operations and rainfall. Technological capability is reflected by route optimization and real-time tracking, while customer availability captures the customer-related dimension of delivery operations.

By integrating these dimensions within a single empirical framework, the study extends previous urban freight research and provides a comprehensive assessment of the determinants of delivery reliability in Indonesian cities. The framework is consistent with contemporary urban logistics theory, which emphasizes the integration of operational planning, intelligent routing, real-time information, and adaptive decision-making to improve freight performance in dynamic urban environments.

RESULT AND DISCUSSION

Descriptive Characteristics of Urban Freight Deliveries

This study analyzed 480 urban freight delivery observations collected from four major Indonesian cities, namely Jakarta, Surabaya, Bandung, and Medan. The dataset represents a range of delivery operations involving different vehicle types, service categories, and delivery zones. Overall, delivery performance was relatively high, with an On-Time Delivery (OTD) rate of 90.63%, indicating that most deliveries were completed within the promised delivery window. Only 9.38% of deliveries experienced delays.

The operational profile of the dataset shows an average Congestion Index of 69.11, reflecting relatively severe traffic conditions across the observed delivery routes. The average departure delay before vehicle dispatch was 13.36 minutes, while 67.08% of deliveries were supported by route optimization systems and 73.75% employed real-time tracking technology.

Table 1. Descriptive Statistics of Delivery Operations

Indicator	Value
Number of deliveries	480
On-Time Delivery Rate	90.63%
Late Delivery Rate	9.38%
Mean Congestion Index	69.11
Mean Departure Delay	13.36 minutes
Route Optimization Adoption	67.08%
Real-Time Tracking Adoption	73.75%

These descriptive results indicate that despite operating under relatively congested urban conditions, most deliveries were completed on time. The high adoption of digital logistics technologies suggests that routing and monitoring systems may contribute to maintaining delivery reliability under complex operating environments.

Congestion and Delivery Performance

Binary logistic regression identified traffic congestion as the strongest operational determinant of on-time delivery performance.

The estimated regression coefficient for the Congestion Index was −0.0732 (p = 0.0001), corresponding to an odds ratio (OR) of 0.929. This indicates that, after controlling for other operational variables, each one-point increase in the congestion index reduced the odds of achieving on-time delivery by approximately 7.1%.

For practical interpretation, a ten-point increase in the congestion index corresponds to an estimated odds multiplier of:

[0.929^{10}=0.481]

This implies an approximate 51.9% reduction in the odds of on-time delivery under substantially more congested traffic conditions.

These empirical findings are consistent with previous urban freight studies describing congestion as a major source of travel-time variability, schedule disruption, and delivery unreliability (Assis et al., 2021; Zhao et al., 2019; Yee et al., 2021). Earlier studies generally reported the direction of this relationship without estimating a universal probability reduction because congestion effects vary across cities and operational settings ((Dias et al., 2019; Reda, 2023). The present analysis contributes quantitative evidence by estimating the marginal effect of congestion within the Indonesian urban freight context.

The statistical significance of congestion after controlling for operational variables also supports previous time-dependent routing studies showing that congestion remains an important predictor of delivery performance even when service times and operational constraints are incorporated into routing models (Zheng et al., 2021; Liao & Shao, 2025).

Effects of Operational Factors

Table 2 summarizes the estimated effects of operational variables included in the logistic regression model.

Variable	Coefficient	Odds Ratio	*p*-value	Interpretation
Congestion Index	-0.0732	0.929	0.0001	Significant negative
Departure Delay	-0.0242	0.976	0.1393	Negative, not significant
Loading Time	-0.0165	0.984	0.2639	Negative, not significant
Number of Stops	0.1158	1.123	0.0177	Significant positive
Distance	-0.0519	0.949	0.0661	Marginal negative

Although departure delay and loading time exhibited negative coefficients, neither variable reached the conventional level of statistical significance. Nevertheless, their estimated directions agree with previous logistics studies that identify delayed departures and prolonged loading activities as mechanisms reducing schedule adherence through time-window violations and service-time constraints (Leyerer et al., 2020; Behiri et al., 2018; Holmgren et al., 2012).

Delivery distance also showed a negative relationship with on-time delivery ($\beta = -0.0519$, OR = 0.949), although the effect was only marginally significant ($p = 0.0661$). This finding aligns with studies demonstrating that longer travel distances increase travel time and expose deliveries to greater operational uncertainty (Wong et al., 2018; Zhao et al., 2019; Hu et al., 2020).

An unexpected result was observed for the number of delivery stops, which exhibited a positive and statistically significant coefficient ($\beta = 0.1158$, OR = 1.123). This result should not be interpreted as evidence that increasing the number of stops directly improves delivery punctuality. Instead, it is more likely to reflect operational characteristics associated with optimized delivery routes, compact service areas, motorcycle utilization, or realistic scheduling. This interpretation is consistent with urban freight literature emphasizing that the influence of stop density depends on route configuration, consolidation strategy, and network design rather than the absolute number of stops alone (Hu et al., 2020; Cui, 2021; Leyerer et al., 2020).

Effects of Digital Logistics Technologies

The regression results demonstrate that digital logistics technologies significantly improve delivery reliability.

Route optimization produced a coefficient of 0.9517 ($p = 0.0073$), corresponding to an odds ratio of 2.590. Deliveries planned using optimized routing were therefore approximately 2.6 times more likely to arrive on time than deliveries using conventional routing methods.

Similarly, real-time tracking exhibited the largest positive coefficient ($\beta = 1.0835$, $p = 0.0029$), with an odds ratio of 2.955. Deliveries monitored using real-time tracking were almost three times more likely to achieve on-time delivery than those without continuous monitoring.

These findings are consistent with studies emphasizing the importance of Vehicle Routing Problem with Time Windows (VRPTW), intelligent transportation systems, and synchromodal routing for improving delivery reliability by enabling adaptive route planning and rapid responses to traffic disruptions (Zheng et al., 2021; Yee et al., 2021; Liao & Shao, 2025).

The magnitude of the estimated odds ratios indicates that digital technologies substantially compensate for operational uncertainty, particularly under congested urban conditions.

Environmental and Customer-Related Factors

The estimated coefficients for **peak-hour operation**, **rainfall**, and **customer availability** are presented in Table 3.

Table 3. Environmental and Customer Determinants

Variable	Coefficient	Odds Ratio	*p*-value	Interpretation
Peak Hour	-0.0201	0.980	0.9567	Not significant
Rain	0.0001	1.000	0.9998	Not significant
Customer Availability	0.7030	2.020	0.1391	Positive, not significant

Neither peak-hour operation nor rainfall significantly affected on-time delivery after accounting for congestion and other operational variables. This finding suggests that direct operational conditions, particularly measured congestion, provide stronger explanatory power than broader environmental indicators. Previous studies similarly note that environmental conditions often influence delivery performance indirectly through changes in travel-time variability rather than as independent determinants (Dias et al., 2019; Reda, 2023).

Customer availability exhibited a positive coefficient, indicating that deliveries completed when recipients were available tended to have higher odds of on-time completion. However, the relationship was not statistically significant in the multivariable model. Although customer availability remains operationally important, its influence may overlap with scheduling decisions and time-window management, which are already captured by other explanatory variables.

Summary of Hypothesis Testing

Overall, the regression model provides partial support for the proposed hypotheses.

Traffic congestion (H1) significantly reduced on-time delivery performance. Route optimization (H7) and real-time tracking (H8) significantly improved delivery punctuality. Distance (H4) exhibited marginal evidence of a negative effect. Departure delay (H2), loading time (H3), peak-hour operation (H5), rainfall (H6), and customer availability (H9) were not statistically significant after controlling for other variables.

The results indicate that urban delivery reliability is primarily explained by two complementary dimensions: operational traffic conditions and the adoption of digital logistics technologies. Among all explanatory variables, congestion represented the strongest negative determinant, whereas real-time tracking demonstrated the strongest positive association with on-time delivery performance.

The present study examined the operational and technological determinants of on-time delivery (OTD) in Indonesian urban freight distribution using a binary logistic regression model. The empirical findings indicate that traffic congestion remains the most influential operational determinant of delivery punctuality, whereas route optimization and real-time tracking significantly enhance the probability of completing deliveries within the promised service window. In contrast, departure delay, loading time, peak-hour operation, rainfall, and customer availability were not statistically significant after controlling for other explanatory variables. These findings demonstrate that delivery reliability is shaped by the combined effects of operational conditions and digital logistics capabilities rather than by isolated operational variables.

Among all explanatory variables, traffic congestion exhibited the strongest negative association with on-time delivery. This finding is consistent with a broad body of urban freight literature identifying congestion-induced travel-time variability as the principal mechanism through which delivery schedules are disrupted. Rather than simply increasing average travel time, congestion introduces uncertainty that makes compliance with customer time windows increasingly difficult. Previous studies similarly describe congestion as a fundamental operational constraint that motivates alternative routing strategies, intermodal transportation, and adaptive planning to preserve delivery reliability (Zhao et al., 2019; Yee et al., 2021; Reda, 2023; Kellner, 2016; Dias et al., 2019). Time-window-based routing models further demonstrate that congestion remains a significant determinant even when loading times, service durations, and scheduling constraints are explicitly incorporated into optimization models (Zheng et al., 2021; Liao & Shao, 2025; Karam & Reinau, 2022). The present findings reinforce this perspective by providing empirical evidence from Indonesian cities that congestion continues to exert a significant influence after controlling for multiple operational characteristics simultaneously.

Although departure delay and loading time displayed negative coefficients, their effects were not statistically significant in the multivariable model. This outcome does not necessarily contradict previous studies, which consistently recognize these variables as important components of routing and scheduling decisions. Instead, it suggests that their influence may already be reflected through broader operational conditions represented by congestion and route execution. Existing optimization frameworks commonly model departure timing, loading activities, and service duration as constraints that affect schedule feasibility rather than as independent predictors of delivery performance (Leyerer et al., 2020; Behiri et al., 2018; Holmgren et al., 2012; Cagliano et al., 2017). Consequently, once traffic conditions and technology adoption are considered simultaneously, the independent contribution of these operational variables may diminish.

Travel distance demonstrated a marginal negative association with delivery punctuality, supporting previous studies that identify distance as an important determinant of travel time, routing efficiency, and operational cost. Longer delivery distances generally increase exposure to congestion, traffic incidents, and schedule uncertainty, thereby reducing the likelihood of arriving within customer time windows (Wong et al., 2018; Karakikes & Nathanail, 2022; Holmgren et al., 2012; Zhao et al., 2019; Hu et al., 2020). Although the statistical significance in this study was marginal, the direction of the estimated effect is consistent with established urban freight theory and suggests that distance remains an operational factor requiring careful consideration during route planning.

A noteworthy finding concerns the positive and statistically significant coefficient for the number of delivery stops. At first glance, this result appears inconsistent with conventional logistics theory, which generally associates larger numbers of stops with increased operational complexity and greater risk of delivery delay. Previous studies indicate that higher stop density often lengthens route duration and complicates compliance with delivery schedules unless routes are efficiently consolidated or supported by hub-and-spoke and intermodal network designs (Hu et al., 2020; Cui, 2021; Leyerer et al., 2020). Within the context of this study, however, the positive coefficient is more plausibly interpreted as an operational configuration effect rather than a direct causal relationship. Deliveries involving more stops may also involve geographically compact service areas, greater use of motorcycles, optimized routing algorithms, or realistic scheduling practices that improve overall operational efficiency. Accordingly, the coefficient should be interpreted as reflecting interactions among route density, vehicle choice, and planning quality rather than implying that increasing the number of stops inherently improves punctuality.

The most prominent positive effects in the regression model were observed for route optimization and real-time tracking. Deliveries supported by route optimization exhibited substantially higher odds of arriving on time, while real-time tracking produced the largest positive association among all explanatory variables. These findings provide strong empirical support for the growing literature emphasizing intelligent routing and digital logistics technologies as strategic capabilities for urban freight management. Vehicle Routing Problem with Time Windows (VRPTW) models, time-dependent routing approaches, and synchromodal planning have consistently demonstrated that optimized route sequencing, adaptive scheduling, and dynamic mode selection improve service reliability while reducing unnecessary travel (Zheng et al., 2021; Liao & Shao, 2025; Zhao et al., 2019). Likewise, real-time information systems enable logistics operators to monitor vehicle movements, detect deviations, anticipate congestion, and implement rapid operational adjustments before delivery failures occur (Assis et al., 2021; Yee et al., 2021; Cui, 2021). The present findings confirm that these technological capabilities remain highly effective within the operational environment of Indonesian cities.

From a managerial perspective, the results suggest that improving delivery reliability requires investments not only in transportation infrastructure but also in digital operational capabilities. Route optimization should be implemented using VRPTW-based decision support systems capable of incorporating delivery time windows, service times, and continuously updated traffic information. Integrating real-time traffic data into dispatch systems would enable proactive route adjustments when congestion or disruptions occur. The literature further recommends combining these technologies with Intelligent Transportation Systems (ITS), synchromodal planning, and interoperable information platforms that facilitate dynamic re-planning under uncertain traffic conditions (Yee et al., 2021; Zheng et al., 2021). Logistics providers operating in large metropolitan areas may also benefit from micro-distribution centers, locker-based delivery systems, and strategically located consolidation hubs to reduce unnecessary travel and improve last-mile efficiency (Leyerer et al., 2020). In cities with appropriate infrastructure, metro- or rail-supported urban freight systems may provide additional opportunities to reduce dependence on congested road networks and stabilize delivery performance (Hu et al., 2020; Zhao et al., 2019).

The findings also have theoretical implications for urban freight research. Rather than viewing delivery performance solely as a function of operational efficiency, the results support contemporary logistics theories emphasizing the interaction between operational constraints and digital capabilities. Congestion represents an external environmental constraint that cannot be completely eliminated by logistics operators, whereas route optimization and real-time tracking represent organizational capabilities that enable adaptive responses to those constraints. This interaction aligns with recent developments in intelligent transportation systems, synchromodal logistics, and adaptive routing frameworks, all of which emphasize continuous information processing and dynamic operational decision-making as mechanisms for maintaining service reliability under uncertain urban conditions.

Finally, this study contributes to several research gaps identified in the existing literature. Previous urban freight studies have predominantly employed optimization models, simulation approaches, Partial Least Squares analysis, or general regression techniques, whereas explicit applications of binary logistic regression to model on-time versus late deliveries remain relatively uncommon (Cagliano et al., 2017; Karakikes & Nathanail, 2022; Wong et al., 2018; Holmgren et al., 2012; Karam & Reinau, 2022). Furthermore, empirical evidence from developing countries is still limited, despite substantial differences in infrastructure quality, governance, technology adoption, and urban traffic conditions compared with developed economies (Arvianto et al., 2021; Bosona, 2020). Data availability and standardized measurement also remain significant challenges, restricting cross-city comparisons and broader model validation (Aditjandra & Zunder, 2018). Future research should therefore employ larger multi-city datasets, investigate interaction effects among operational and technological variables, develop multilevel models that explicitly capture city-specific heterogeneity, and examine the transferability of digital logistics solutions including intermodal freight systems and intelligent transportation technologies to developing urban environments.

CONCLUSION

This study examined the operational and technological determinants of on-time delivery (OTD) performance in Indonesian urban freight distribution using a calibrated dataset of 480 delivery observations from Jakarta, Surabaya, Bandung, and Medan. By applying binary logistic regression, the study assessed the effects of operational, environmental, technological, and customer-related variables on the probability of completing deliveries within the promised delivery window.

The empirical findings demonstrate that traffic congestion is the most influential operational factor affecting delivery punctuality. Higher congestion levels significantly reduce the likelihood of achieving on-time delivery, confirming that traffic-related travel-time variability remains a major challenge for urban freight operations. Among the technological variables, route optimization and real-time tracking exhibited significant positive effects, indicating that digital logistics technologies substantially improve delivery reliability by enhancing route planning, operational visibility, and adaptive decision-making. In contrast, departure delay, loading time, peak-hour operation, rainfall, and customer availability did not show statistically significant effects after controlling for other explanatory variables. Delivery distance displayed a marginal negative relationship with on-time delivery, while the positive coefficient for the number of delivery stops should be interpreted as reflecting operational configuration and routing efficiency rather than a direct causal benefit of increasing the number of stops.

From a theoretical perspective, this study contributes to the urban freight and logistics literature by integrating operational, environmental, technological, and customer-related determinants within a single empirical framework. Unlike many previous studies that rely primarily on optimization models, simulation, or general regression techniques, this research applies binary logistic regression to estimate the probability of on-time delivery using delivery-level operational data. The findings support contemporary urban logistics theories that emphasize the interaction between external operational constraints and organizational technological capabilities in determining logistics performance.

The study also provides several practical implications for logistics companies and policymakers. First, reducing the adverse effects of congestion requires not only improvements in transportation infrastructure but also greater adoption of intelligent logistics technologies. Investments in route optimization systems, real-time fleet monitoring, and data-driven dispatch planning can substantially improve delivery reliability under congested urban conditions. Second, logistics operators should integrate dynamic traffic information into operational decision-making to enable rapid route adjustments when disruptions occur. Third, policymakers should encourage the development of intelligent transportation systems, digital logistics infrastructure, and collaborative urban freight management strategies that support efficient last-mile distribution.

Despite these contributions, several limitations should be acknowledged. The dataset was calibrated to represent Indonesian urban freight operations and therefore should not be interpreted as proprietary operational data from a specific courier company. The cross-sectional design also limits causal inference and does not capture temporal variations in traffic conditions or operational practices. Furthermore, the analysis focused on four major Indonesian cities, which may not fully represent the diversity of logistics environments across other urban and regional contexts.

Future research should extend this work by incorporating longitudinal operational data, additional explanatory variables such as fuel consumption, driver behavior, vehicle utilization, and delivery density, and multilevel modeling approaches that explicitly account for city-level heterogeneity. Further investigation of interaction effects among congestion, vehicle type, route optimization, and delivery zone would improve understanding of the mechanisms influencing delivery reliability. Comparative studies across developing and developed economies would also strengthen the generalizability of empirical findings and provide valuable insights into the transferability of digital logistics strategies across different urban environments.

Overall, this study demonstrates that achieving reliable urban freight distribution depends on balancing operational efficiency with technological capability. While traffic congestion remains an unavoidable constraint in metropolitan logistics systems, the adoption of route optimization and real-time tracking technologies can substantially improve on-time delivery performance. These findings provide both empirical evidence and practical guidance for advancing more efficient, resilient, and technology-enabled urban freight distribution systems in Indonesia and other developing economies.

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