MORFAI JOURNAL Multidisciplinary Output Research For Actual and International Issue
INDEX COPERNICUS INTERNATIONAL
Multidisciplinary Output Research For Actual and International Issue (MORFAI Journal) ISSN (e): 2808-6635
Volumes 6 No. 5 (2026)

ANALYSIS OF THE INFLUENCE OF COMMERCIAL TIME WINDOW, DELIVERY TIME CONSTRAINTS, AND TRAFFIC CONGESTION ON FIRST-ATTEMPT DELIVERY SUCCESS RATE WITH FLEET ALLOCATION MANAGEMENT AS A MEDIATING VARIABL E (CASE STUDY: LION PARCEL BANDUNG)

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Received:04/07/2026 | **Revised** : 10/07/2026 | **Accepted:** 27/07/2026 | **Published** :11/08/2026

Abstract
This study aims to identify the factors contributing to the high rate of first-attempt delivery failures in Lion Parcel's last-mile delivery operations in the city of Bandung, which are caused by various operational obstacles faced by couriers in the field. The objective is to examine how Commercial Time Window, Delivery Time Constraints, and Traffic Congestion affect the first-attempt delivery success rate, while also testing whether Fleet Allocation Management acts as a mediating factor among these variables. This study employs a quantitative approach with an explanatory research design. Given the relatively small population size, the entire population was used as the sample (census/saturated sampling), consisting of 90 respondents made up of active motorcycle couriers and van drivers. Primary data were collected directly through a closed-ended Likert-scale questionnaire and subsequently processed using the Structural Equation Modeling–Partial Least Squares (SEM-PLS) method with the aid of SmartPLS 4 software. The structural model testing results show that Delivery Time Constraints and Traffic Congestion both have a positive and significant effect on Fleet Allocation Management, whereas Commercial Time Window shows no significant effect. Meanwhile, in testing the direct effects, all three obstacle variables, together with Fleet Allocation Management, were proven to have a significant effect on the first-attempt delivery success rate. In terms of mediation testing, Fleet Allocation Management was proven to successfully bridge the effects of Delivery Time Constraints and Traffic Congestion on delivery success, but was unable to mediate the effect of the Commercial Time Window constraint. This indicates that the issue of the commercial acceptance time limit (commercial time window) cannot be resolved solely through fleet management in the field; rather, improvements are needed in the dispatch work system at the warehouse that are more preventive in nature.

Keywords: Last-Mile Delivery, Commercial Time Window, Traffic Congestion, Fleet Allocation Management, First-Attempt Delivery Success Rate, SEM-PLS

INTRODUCTION

Commercial time windows, such as store or office operating hours, serve as acceptance thresholds that can determine whether a delivery is successful on the first attempt. Packages arriving after a commercial location closes are at risk of being undelivered, especially when the location lacks security or storage. Furthermore, limited delivery times limit couriers' capacity to complete all delivery points in a single day. Uncertainty about arrival times also makes routing and task allocation more challenging in dynamic last-mile operations (Chu et al., 2023; Sumekar et al., 2022). Traffic congestion extends travel times and reduces the number of destinations couriers can complete during delivery hours. In urban logistics, dynamically changing traffic patterns impact the accuracy of estimated arrival times, the sequence of visits, the need for rerouting, and fleet utilization. The literature on route optimization indicates that the ability to respond to traffic conditions in real time is a critical factor in maintaining last-mile delivery productivity (Cvetek et al., 2021; Oloko, 2025; Ünal, 2025).

From the perspective of the logistics company that is the object of the research, namely the door-to-door package and document delivery expedition under the name Lion Parcel, experiencing problems with first-attempt delivery that often fails, which can incur higher costs when a package fails to be delivered on the first delivery attempt. Based on data obtained from the company, the number of packages entering the city of Bandung and having to be delivered to consumers on average per month is 56,721 packages per month. The following table details the number of goods or packages inbound to the city of Bandung.

Table 1. Volume of inbound Lion Parcel packages in the Bandung area

Month	Receipt Amount
January	59,618
February	60,052
March	59,965
April	60,289
May	62,477
June	63,170
July	31,482
Total	397,053

Lion Parcel's last-mile delivery operations utilize a mixed fleet of couriers, including motorcycles, vans, single-axle trucks (CDE or light trucks), and double-axle trucks (CDD). However, the package dispatch process is still manual and is based solely on the destination address district, without considering the operating hours of commercial buildings, road access to the delivery address, and the courier's travel distance, which can impact delivery time limits if the package arrives too late at night at the recipient's address. Because the operational process, especially the dispatch process, does not yet have specific standards that take into account delivery time limits, the operating hours of commercial buildings that serve as addresses, and road access to the delivery address, delivery on the first attempt (first-attempt delivery) often fails. Based on other data obtained from the company, there were 26,290 packages that experienced first-attempt delivery failures, which affected the service level agreement promised to consumers. Of the total 26,290 failed packages, the most common obstacles encountered in the field were "Delivery outside courier delivery hours" and "shop closed" which were used as independent variables in this study. For details on field obstacles that frequently occur in the field, please see the following table.

Based on the data above, the most common first-attempt delivery failures are field obstacles such as "delivery outside courier delivery hours" and "store closed," contributing 26% and 16%, respectively, to the total number of failed deliveries on the first attempt. These obstacles have a minimal risk of failed delivery if delivery can be delivered on time. Furthermore, traffic congestion is another obstacle that companies must address to maintain the service level agreement promised to consumers. Research consistently shows that on-time delivery significantly impacts customer satisfaction in logistics and e-commerce services (Pradini, 2023). Last-mile delivery performance is significantly influenced by a company's ability to manage delivery times effectively, particularly in the context of modern e-commerce and the challenges of urban logistics. Research shows that meeting order completion deadlines is a key factor in the success of last-mile delivery operations, especially during disruptions such as the COVID-19 pandemic (Suguna et al., 2022). Furthermore, other research indicates that performance expectations in terms of delivery reliability, delivery mode, and shipping costs significantly influence intentions to use courier services. Performance expectations in terms of delivery time emerged as the most dominant factor Dynamic traffic patterns are one of the main challenges in last mile delivery logistics operations, where traffic congestion contributes to shipping costs that can reach up to 53% of total shipping costs in the United States e-commerce sector (Oloko, 2025).

For deliveries in urban areas like Bandung, store operating hours (Commercial Time Window) are a mandatory deadline, as packages can only be received while the store is open. If the courier arrives after the store closes, delivery will not be possible that day. Furthermore, delivery time constraints are also a significant factor, as each courier and driver has limited working hours and/or a maximum time to complete all deliveries in a single day. The more packages that must be delivered within a limited timeframe, the greater the likelihood that some packages will not be delivered on time. This situation becomes even more challenging when traffic congestion occurs, as congestion can increase travel times and reduce the number of destinations couriers and drivers can complete during delivery periods. These three factors require a decision-making system capable of determining the most appropriate fleet for each delivery. Therefore, Fleet Allocation Management is used, a work procedure that can determine the type of fleet based on operational conditions. Unlike biased assignments by dispatchers, which simply divide or assign deliveries to couriers and drivers based solely on the destination district, this work procedure considers various factors, such as remaining store operating hours, delivery time constraints, and the level of congestion on the delivery route. If the risk of delays increases, dispatchers are expected to shift deliveries from vans to motorcycles, which are more maneuverable amidst heavy traffic, thus increasing the chance of packages arriving on time. The implementation of Fleet Allocation Management (Y) is expected to increase the First-Attempt Delivery Success Rate (Z), which is the success rate of deliveries on the first attempt. By selecting the most appropriate fleet based on time and route conditions, companies can reduce the number of packages that fail to deliver and must be returned to the hub. As a result, the need for redelivery can be reduced, operational costs become more efficient, and the quality of service to customers can be improved.

Table 2. Field constraints that cause first-attempt delivery failure

Field Obstacles	Number of Packages	%
Delivery outside courier delivery hours	6,941	26%
Location closed	4,202	16%
Recipient not at location	3,448	13%
Agent entered the wrong address	3,341	13%
Address not found	3,312	13%
Weather constraints or environmental conditions do not support	1,727	7%
Customer Rejects Package	1,166	4%
Sorting error	1,071	4%
Recipient cannot be contacted	230	1%
Motorbike or cell phone problems	213	1%
Location change	185	1%
The recipient did not order a COD package	171	1%
The recipient wants to change the delivery schedule	123	0%
COD fee is not ready yet	74	0%
Damaged package	52	0%
Package lost	19	0%
COD fee is not correct	15	0%
Grand Total	26,290	100%

The operational data shows that the two biggest causes of delivery failures on the first attempt were deliveries outside courier delivery hours (6,941 packages; 26%) and closed locations (4,202 packages; 16%). These two categories directly represent the dimensions of delivery time constraints and commercial time windows. They also demonstrate that delivery success is determined not only by fleet availability, but also by the system's ability to place packages on vehicles and in the order of visits that align with actual time constraints.

The research problem was then expanded to include traffic congestion as an operational factor not specifically recorded as a failure code in company data but directly perceived by couriers and drivers as it lengthens trips. Therefore, the study collected delivery personnel's perceptions to examine the relationship between commercial time windows, delivery time constraints, traffic congestion, fleet allocation management, and first-attempt delivery success rate within a single structural model.

Practically, this study aims to explain whether fleet allocation management can be an intervention mechanism linking operational constraints to delivery success. Academically, the study integrates three operational constraints typically studied separately into a SEM-PLS-based mediation model. The context of Lion Parcel Bandung provides scope to test whether static constraints, such as commercial location closing hours, and dynamic constraints, such as remaining working hours and congestion, require different managerial responses.

LITERATURE REVIEW

Last-Mile Delivery and First-Attempt Delivery Success Rate

Last-mile delivery is the distribution stage that directly interacts with end customers and is highly complex due to the number of destinations, heterogeneity of recipient characteristics, varying road conditions, and time pressure. The literature on vehicle routing in urban areas shows that route quality, mode choice, demand density, recipient availability, and trip uncertainty interact to determine distribution performance (Jazemi et al., 2023; Escudero-Santana et al., 2022). In the e-commerce context, customer demands for fast and accurate delivery magnify the operational consequences of any failure on the first attempt.

The first-attempt delivery success rate (FSR) reflects a service provider's ability to complete a delivery on the first attempt without redelivery. Failure on the first attempt increases rework, the need for re-handling at the hub, vehicle costs, and courier time. Balaska et al. (2022) identified first-attempt failure as a significant challenge in last-mile systems. Lorenzo-Espejo et al. (2025) also found that courier workload and service density correlated with the service completion rate. Therefore, the first-attempt delivery success indicator in this study is positioned as an operational output reflecting the success rate, low redelivery, and on-time arrival.

Commercial Time Window

A commercial time window is the range of available reception times for commercial customers, such as stores, offices, or business facilities. This boundary differs from a simple internal time target because reception may become impossible when the facility is closed. The time-window routing literature indicates that the tightness or looseness of the time window can alter route feasibility, vehicle utilization, and system efficiency. Aydın et al. (2022) demonstrated that the choice of time window influences vehicle allocation decisions, while Hosseini et al. (2025) discussed service time window design as a critical component of last-mile planning.

In this study, the commercial time window is operationalized through tolerance for store closing delays, loading/unloading or administrative gaps, and recipient availability. These three indicators capture two facets of the problem: absolute on-site time limits and service times that reduce the remaining route time. Seghezzi and Mangiaracina (2023) demonstrated that improved scheduling based on customer availability information can reduce missed deliveries. Thus, the commercial time window can theoretically directly impact delivery success and can also inform fleet allocation decisions.

Delivery Time Limitation

Delivery time constraints refer to the effective amount of time available for couriers to complete all assignments. Sosedová et al. (2021) emphasize that delays occur when delivery exceeds a predetermined timeframe. In e-commerce, time pressures are even greater because couriers must manage the number of delivery points, customer waiting times, service congestion, and working hour constraints. Escudero-Santana et al. (2022) demonstrate that delivery time and location choices can be leveraged to improve distribution, while Oloko (2025) highlights the potential of predictive analytics to reduce travel time through dynamic route optimization.

This study measures time constraints through the maximum effective delivery time, the ratio of the number of points to the remaining time, and the average dwell time. These concepts are important because time constraints that accumulate in the afternoon or evening can render some packages unviable. In such situations, dispatchers need the ability to shift workloads or redistribute routes so that resources with remaining time capacity can take over points at risk of failure.

Traffic congestion

Traffic congestion occurs when travel demand exceeds network capacity, resulting in reduced speeds, increased travel times, and arrival uncertainty. Cvetek et al. (2021) show that congestion estimation requires the use of multiple data sources because traffic conditions change spatially and temporally. For last-mile delivery, this uncertainty causes initial route plans to quickly lose relevance and drives the need for more adaptive decision-making.

Ahani et al. (2023) showed that congestion intensity can influence optimal fleet composition. Ünal (2025) specifically discussed routing that takes into account traffic awareness and vehicle failures, thus emphasizing that route reliability cannot be separated from network conditions. In this study, congestion is proxied by arterial route density, vehicle delay duration, and vehicle type maneuverability. These three indicators are related to the decision whether packages should remain in vans, be diverted to motorcycles, or be rerouted through a different route.

Fleet Allocation Management

Fleet allocation management is the process of determining which vehicles to use, distributing the load, and reassigning them when operational conditions change. Shehadeh et al. (2021) demonstrated that fleet sizing and allocation are critical decisions in a demand-driven last-mile transportation system. Banjarnahor et al. (2021) also demonstrated that fleet availability impacts delivery accuracy. In this study, fleet allocation management is treated as an operational capability, not simply the number of vehicles owned.

These capabilities are represented by inter-fleet packet switching mechanisms, vehicle load calculation accuracy, and route reassignment response speed. When remaining delivery time is running low or congestion increases, the value of fleet allocation management lies in the ability to change initial decisions before failure occurs. Conversely, under absolute commercial time window constraints, fleet changes may no longer be effective once the destination location has closed. This difference in constraint characteristics underlies the mediation test in this study.

Hypothesis Development and Research Model

The literature shows that time constraints, fleet availability, and traffic are related to distribution efficiency. Aydın et al. (2022) and Moreno et al. (2025) demonstrate the implications of time windows on vehicle decisions; Chairunnisa et al. and Banjarnahor et al. (2021) demonstrate the relationship between fleet availability and delivery accuracy; while Ahani et al. (2023) and Ünal (2025) emphasize the importance of fleet responsiveness to traffic conditions. Studies on missed deliveries also show that customer time information can improve delivery success (Seghezzi & Mangiaracina, 2023).

Based on these arguments, the study tested ten direct and indirect relationships. Three constraint variables were assumed to influence fleet allocation management, all three were tested against first-attempt delivery success rate, fleet allocation management was tested against delivery success, and three mediating pathways were evaluated to determine whether fleet allocation could translate operational constraints into responses that increase the likelihood of success.

Table 3. Research hypothesis

Hypothesis	The relationship is tested	Expected direction
H1	Commercial Time Window → Fleet Allocation Management	Significant
H2	Commercial Time Window → First-Attempt Delivery Success Rate	Significant
H3	Delivery Time Constraints → Fleet Allocation Management	Significant
H4	Delivery Time Limitation → First-Attempt Delivery Success Rate	Significant
H5	Traffic Congestion → Fleet Allocation Management	Significant
H6	Traffic Congestion → First-Attempt Delivery Success Rate	Significant
H7	Fleet Allocation Management → First-Attempt Delivery Success Rate	Significant
H8	Commercial Time Window → Fleet Allocation → FADSR	Significant mediation
H9	Delivery Time Limitation → Fleet Allocation → FADSR	Significant mediation
H10	Traffic Congestion → Fleet Allocation → FADSR	Significant mediation

A research gap lies in the integration of three operational constraints with fleet allocation management as a mediator in the context of first-time delivery success. This model allows for comparison between relatively static constraints (commercial time window) and dynamic constraints (remaining time and congestion), so that operational implications extend beyond whether a factor is influential, but also to how the organization can respond to that influence.

Synthesis of Previous Research and Research Position

The first group of studies places the time window as a planning constraint. Aydın et al. (2022) show that loosening or tightening the time window affects the economic and environmental consequences of vehicle allocation decisions. Moreno et al. (2025) use a simulation and optimization approach in urban logistics to demonstrate that more adaptive distribution decisions can improve operational sustainability. Both studies reinforce the idea that recipient time information should be available before vehicle dispatch. However, these studies do not specifically compare the commercial time window with courier time constraints as two distinct sources of time pressure.

The second group focuses on missed deliveries and recipient availability. Seghezzi and Mangiaracina (2023) showed that using customer presence information can reduce failed deliveries, although route adjustments can increase travel distance. The implication is that delivery success depends not only on the shortest distance, but also on the ability to align routes with recipient opportunities. In the context of this research, this logic applies to commercial customers, who have stricter delivery hours than residential customers.

The third group addresses fleet availability, size, and allocation. Shehadeh et al. (2021) developed a fleet sizing and allocation model for a last-mile transportation system facing demand uncertainty. Banjarnahor et al. (2021) demonstrated that fleet availability impacts delivery accuracy. These findings emphasize that fleets are resources that must be actively allocated. This study expands this perspective by positioning fleet allocation management as a mediator, thus testing whether vehicle allocation decisions truly serve as a mechanism explaining how time and traffic constraints translate into delivery success or failure.

The fourth group emphasizes the relationship between delivery time, workload, and courier performance. Lorenzo-Espejo et al. (2025) demonstrated the relationship between courier workload, service density, and service success rate. Sosedová et al. (2021) emphasized the importance of delivery periods and delays in transportation obligations. Together, these studies support the use of indicators such as maximum effective time, point-to-remaining time ratio, and dwell time. Lion Parcel's research then examined whether these time pressures only directly impact success or also trigger changes in fleet allocation.

The fifth group identifies congestion as a source of travel uncertainty. Cvetek et al. (2021) discuss a multi-source fusion-based congestion estimation method, Ahani et al. (2023) show that congestion intensity influences optimal fleet structure, and Ünal (2025) develops traffic-aware routing. These findings suggest that congestion has broader implications than increasing travel time because it can alter the most suitable vehicle, feasible routes, and order of visits. Therefore, this study examines the congestion pathway to Fleet Allocation Management as well as the direct pathway to First-Attempt Delivery Success Rate.

The dynamic optimization literature also shows a trend toward using data and analytics for last-mile decisions. Chu et al. (2023) discuss data-driven optimization, while Oloko (2025) emphasizes dynamic route optimization with predictive analytics. Grzelak and Borucka (2026) also demonstrate the use of distribution time modeling to support operational excellence. Although this research does not yet develop an optimization algorithm, fleet allocation management variables represent a conceptually necessary decision capability before data-driven automation can be implemented.

This research sits at the intersection of these five streams. Its contribution is not to propose a new routing algorithm, but rather to provide empirical evidence on which constraints drive fleet adaptation and which constraints are not addressed by such adaptation. This distinction is important for implementation because organizations can determine the appropriate location for intervention: commercial time windows are addressed early through dispatch priorities, while time constraints and congestion can be managed through dynamic responses in the field. Using a mediation model, the research provides a basis for separating preventive functions in the warehouse from adaptive functions at the delivery stage.

METHOD

Research Design, Population, and Sample

This study uses a quantitative method with an explanatory design. The explanatory approach was chosen because it aims to reveal the cause-and-effect relationship between variables. The independent variables studied include Commercial Time Window, Delivery Time Limitations, and Traffic Congestion, which are suspected to affect the First-Attempt Delivery Success Rate, with Fleet Allocation Management acting as a mediating variable in the context of distribution at Lion Parcel Bandung. The study population consisted of 90 personnel actively involved in Lion Parcel Bandung's last-mile delivery service. Because all members of the population could be reached, the study employed saturated or census sampling. The sample composition used in the analysis was 70 motorcycle couriers and 20 van drivers. All respondents were active delivery personnel and used the company's operational system to carry out their daily tasks.

Primary data collection was conducted through a closed-ended questionnaire using a five-point Likert scale, ranging from strongly disagree to strongly agree. The questionnaire was designed to capture respondents' perceptions of the conditions they experienced during delivery, not to replace company transaction data. Company data was used as initial context regarding package volumes and failure causes, while questionnaire data was used to test the relationship model between variables.

Operationalization of Variables

Table 4. Operationalization of research variables

Variables	Brief operational definition	Measurement indicators
Commercial Time Window (X1)	Acceptance deadlines at commercial locations limit the eligibility of package deliveries.	Tolerance for closing time delays; commercial dwell time; recipient availability.
Delivery Time Limitation (X2)	The limited effective time available for couriers to complete daily assignments.	Maximum effective time; ratio of points to remaining time; customer waiting time.
Traffic Jam (X3)	Travel obstacles that increase the duration and uncertainty of travel times.	Arterial route density; delay time; flexibility of vehicle maneuvers.
Fleet Allocation Management (Y)	The system's ability to allocate, divert, and reassign fleets according to operating conditions.	Fleet switch; vehicle load accuracy; rerouting response.
First-Attempt Delivery Success Rate (Z)	Successful delivery on the first attempt without the need for redelivery.	First success rate; zero redelivery; on-time arrival.

Data Analysis Techniques

The analysis used Structural Equation Modeling–Partial Least Squares (SEM-PLS) with the SmartPLS application. The analysis stages consisted of evaluating the measurement model (outer model), evaluating the structural model (inner model), and testing the mediation effect. The outer model was evaluated through outer loading, construct reliability, and Average Variance Extracted (AVE). The inner model was evaluated through R-square and path coefficients. The significance of direct and indirect paths was tested through a bootstrapping procedure of 5,000 resamples with a $p < 0.05$ criterion.

The use of SEM-PLS suited the research objectives because the model contained five latent constructs, several simultaneous relationships, and three mediating pathways. The measurement model was constructed reflectively with three indicators for each construct. After the indicators were deemed adequate, testing continued on the structural relationships to evaluate H1 through H10. The decision to accept the hypothesis was based on the direction of the coefficients, the t-value, and the p-value from bootstrapping.

RESULTS AND DISCUSSION

Respondent Characteristics and Operational Context

The analysis used 90 respondents, all of whom were active last-mile delivery personnel. Seventy respondents worked as motorcycle couriers and 20 as van drivers. This composition reflects a mixed fleet operation, providing a logical basis for testing fleet allocation management, as the different vehicle characteristics allow for fleet switching and rerouting mechanisms when times or traffic conditions change.

The operational context in Tables 1 and 2 demonstrates a significant delivery burden and failures concentrated on time factors. The total number of inbound packages from January to July reached 397,053 receipts, while the total number of first-attempt failures recorded in the constraints data reached 26,290 packages. The predominance of deliveries outside courier delivery hours and closed locations reinforces the relevance of the delivery time constraints and commercial time window variables in the research model.

Evaluation of Measurement Model

Convergent validity was evaluated from the outer loading of each indicator. All indicators across the five constructs showed high loadings, with the lowest value being 0.817 and the highest being 0.942. These results indicate that the indicators have a strong relationship with the constructs they measure. No indicators needed to be eliminated from the measurement model, so all indicators were retained for structural testing.

Table 5. Results of outer loading indicators

Indicator	Construct	Outer Loading
X1.1	X1	0.903
X1.2	X1	0.942
X1.3	X1	0.817
X2.1	X2	0.910
X2.2	X2	0.883
X2.3	X2	0.912
X3.1	X3	0.911
X3.2	X3	0.877
X3.3	X3	0.874
Y.1	Y	0.895
Y.2	Y	0.868
Y.3	Y	0.887
Z.1	Z	0.884
Z.2	Z	0.823
Z.3	Z	0.839

Construct reliability also showed strong results. Cronbach's alpha ranged from 0.808 to 0.885, composite reliability (rho_c) ranged from 0.886 to 0.929, and AVE ranged from 0.721 to 0.813. These values support internal consistency and construct convergence. Thus, the measurement model is considered adequate for interpreting structural relationships.

Table 6. Construct Reliability and Average Variance Extracted

Construct	Cronbach's α	rho_a	rho_c	AVE
X1	0.879	1,000	0.919	0.790
X2	0.885	0.893	0.929	0.813
X3	0.865	0.874	0.918	0.788
Y	0.859	0.861	0.914	0.780
Z	0.808	0.823	0.886	0.721

The discriminant validity evaluation of the thesis manuscript was conducted using the Fornell-Larcker criteria and showed that the constructs were empirically differentiated. The reported inter-construct correlations showed the highest relationship between Fleet Allocation Management and First-Attempt Delivery Success Rate at 0.617, followed by the relationship between Delivery Time Constraints and First-Attempt Delivery Success Rate at 0.566. This pattern is consistent with the assumption that time factors and allocation decisions are important components in delivery success, but the constructs are still treated as separate concepts in the model.

Structural Model Evaluation

The R-square value is used to determine the proportion of variation in endogenous constructs that the model can explain. Fleet Allocation Management obtained an R^2 of 0.255 and an adjusted R^2 of 0.229. First-Attempt Delivery Success Rate obtained an R^2 of 0.445 and an adjusted R^2 of 0.419. Thus, the three operational constraints explain approximately a quarter of the variation in fleet allocation, while the combination of constraints and fleet allocation explains almost half of the variation in first-attempt delivery success.

Table 7. Coefficient of determination of the structural model

Endogenous Construct	R-square	Adjusted R-square
Fleet Allocation Management (Y)	0.255	0.229
First-Attempt Delivery Success Rate (Z)	0.445	0.419

Direct Effect and Hypothesis Testing

Bootstrapping results show different patterns between the influence of obstacles on fleet allocation and the influence of obstacles on delivery success. Commercial Time Window does not significantly influence Fleet Allocation Management (β = 0.120; t = 1.275; p = 0.202), so H1 is rejected. On the other hand, Delivery Time Limitations have a positive and significant influence on Fleet Allocation Management (β = 0.271; t = 3.190; p = 0.001) and Traffic Congestion also has a positive and significant influence (β = 0.349; t = 4.125; $p < 0.001$), so H3 and H5 are accepted.

For First-Attempt Delivery Success Rate, all three constraint variables showed a significant direct effect. Commercial Time Window had β = 0.238 (p = 0.004), Delivery Time Constraints had β = 0.293 ($p < 0.001$), and Traffic Congestion had β = 0.203 (p = 0.016). Fleet Allocation Management also had a positive and significant effect on first-attempt delivery success with β = 0.303 ($p < 0.001$). These results support H2, H4, H6, and H7.

Table 8. Results of direct influence testing

Hip.	Track	β	t	p	Decision
H1	X1 → Y	0.120	1,275	0.202	Rejected
H2	X1 → Z	0,238	2,867	0,004	Diterima
H3	X2 → Y	0,271	3,190	0,001	Diterima
H4	X2 → Z	0,293	3,731	<0,001	Diterima
H5	X3 → Y	0,349	4,125	<0,001	Diterima
H6	X3 → Z	0,203	2,419	0,016	Diterima
H7	Y → Z	0,303	3,555	<0.001	Accepted

The bootstrapping model representation shows all outer loadings, path coefficients, t-values, and R-square of the endogenous constructs. This figure confirms that the largest path to Fleet Allocation Management comes from Traffic Congestion (β = 0.349), while the largest direct path to First- Attempt Delivery Success Rate comes from Fleet Allocation Management (β = 0.303), followed by Delivery Time Constraints (β = 0.293).

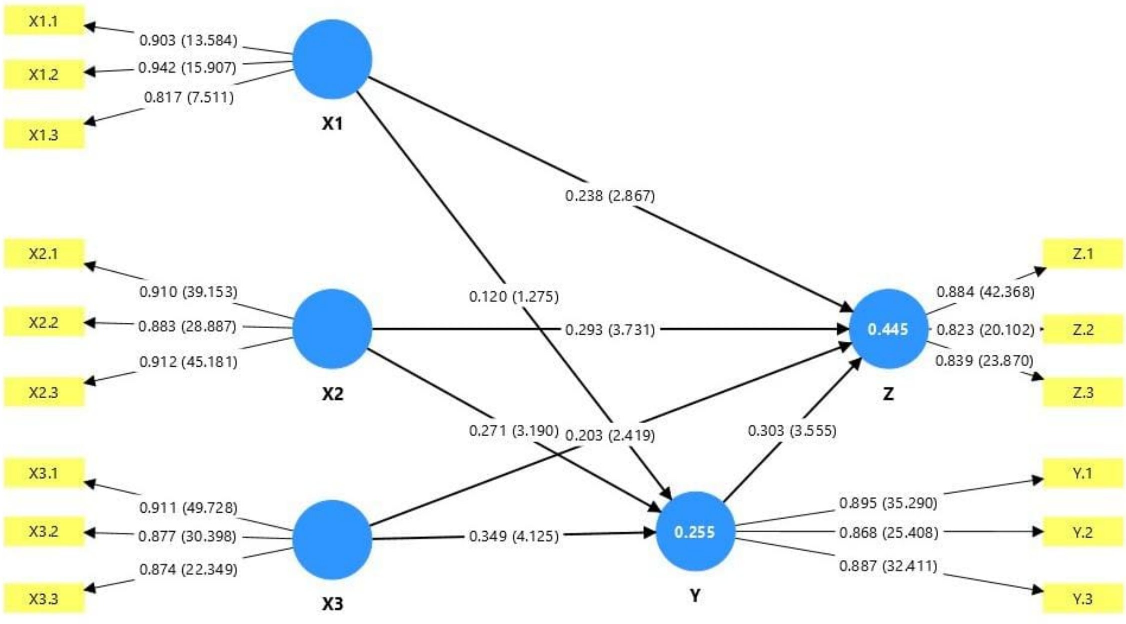

Image 1. SEM-PLS model bootstrapping results

Testing the Mediation Effect

The indirect effect shows that Fleet Allocation Management does not mediate the influence of Commercial Time Window on First-Attempt Delivery Success Rate. The indirect effect coefficient of the path X1 → Y → Z is only 0.036 with t = 1.130 and p = 0.258. H8 is thus rejected. This means that changes in fleet allocation in the field are not enough to translate commercial receiving hour constraints into increased success when the receiving location has entered the closing time limit.

In contrast, Fleet Allocation Management mediates the effect of Delivery Time Constraints on First-Attempt Delivery Success Rate (β = 0.082; t = 2.316; p = 0.021) and mediates the effect of Traffic Congestion on First-Attempt Delivery Success Rate (β = 0.106; t = 2.561; p = 0.010). H9 and H10 are accepted. These findings indicate that fleet allocation has value when constraints can still be responded to dynamically, for example by moving packages, redistributing loads, or changing routes before the remaining time runs out.

Table 9. Results of testing the mediation effect

Hip.	Mediation Path	β Indirect	t	p	Decision
H8	X1 → Y → Z	0.036	1,130	0.258	Rejected
H9	X2 → Y → Z	0.082	2,316	0.021	Accepted
H10	X3 → Y → Z	0.106	2,561	0.010	Accepted

Discussion: Operational Barriers and Fleet Allocation Adaptation

The insignificant effect of the Commercial Time Window on Fleet Allocation Management indicates that not all time pressures automatically result in vehicle reallocation. The commercial time window is relatively fixed and exists on the receiving end: once operating hours are determined, dispatchers must take them into account from the beginning of the dispatch process. This finding is consistent with the time-window routing literature, which considers the time window as a planning constraint, not simply a signal for rerouting once vehicles are on the road (Aydın et al., 2022; Hosseini et al., 2025).

Delivery time constraints significantly impact fleet allocation because remaining time varies throughout the day. When the number of unfinished points is disproportionate to the remaining time , the initial decision becomes less feasible and requires redistribution. This finding reinforces the importance of fleet availability and load sharing in maintaining delivery accuracy, as demonstrated by Banjarnahor et al. (2021) and studies related to fleet availability and delivery accuracy.

Traffic congestion is the most powerful factor influencing Fleet Allocation Management. This result is logical because congestion directly changes travel time, route reliability, and the relative advantages of vehicle types. On congested routes, motorcycles have different maneuvering flexibility than vans; conversely, vans have a capacity advantage for large cargo volumes. Ahani et al. (2023) showed that congestion levels can influence optimal fleet composition, while Ünal (2025) pointed to the need for traffic-aware routing. The findings of this study translate this logic into the operational context of Lion Parcel couriers and drivers.

Discussion: Determining Factors for the Success of the First Delivery

The significance of the Commercial Time Window on the First-Attempt Delivery Success Rate indicates that the correct sequence of visits to commercial customers is a direct factor. Although fleet allocation does not significantly react to X1, packages can still be missed if they arrive outside of receiving hours. This finding aligns with Seghezzi and Mangiaracina (2023), who showed that utilizing customer availability information can reduce missed deliveries. The main implication is that operational hours information should be included in the dispatch prioritization process, rather than waiting for handling after the route is running.

Delivery time constraints also directly impact success. The higher the pressure on the number of points compared to the effective time, the greater the risk of some packages being returned to the hub. This direct effect is amplified by the indirect effect through fleet allocation. This means companies face two levels of action: controlling the initial load to ensure it is proportional to the time and providing a reallocation mechanism when deviations occur. A combination of preventive and adaptive measures is more relevant than relying on either alone.

Traffic congestion directly impacts First-Attempt Delivery Success Rate and also through Fleet Allocation Management. This dual path indicates that congestion is a physical friction that cannot be completely eliminated by managerial decisions, but its impact can be mitigated by allocation responses. The predictive modeling and dynamic route optimization discussed by Chu et al. (2023) and Oloko (2025) align with this need: traffic information needs to be transformed into operational decisions regarding destination sequencing, routes, and vehicle types.

The positive influence of Fleet Allocation Management on First-Attempt Delivery Success Rate reinforces the view that fleet management does not stop at vehicle ownership. Management value arises from the ability to allocate resources appropriately and correct assignments when the initial plan is no longer optimal. This supports the findings of Banjarnahor et al. (2021) on the effect of fleet availability on delivery accuracy and Shehadeh et al.'s (2021) framework on fleet allocation in demand-based last-mile systems.

Managerial Implications

Mediation findings clearly distinguish between challenges that can be addressed on the ground and those that must be addressed upstream. To address delivery time constraints and congestion, companies can strengthen fleet switching, rerouting, load sharing, and time-remaining monitoring mechanisms. Dispatch systems should be able to identify at-risk packages, calculate each courier's remaining effective time, and prioritize rerouting before packages become unsuitable for same-day delivery.

For commercial time windows, interventions must be more preventative. Packages destined for stores, offices, and commercial customers need to be assigned a time of receipt from the inbound or sorting process. Dispatchers can then prioritize packages with the tightest time windows in the initial dispatch wave, assign them to the appropriate fleet, and avoid commercial package deliveries that begin near closing time. The research shows that attempting to solve this problem solely by reallocating fleets in the field is insufficient.

Overall, companies need decision rules that integrate commercial time windows, remaining delivery times, traffic conditions, vehicle capacity, and address characteristics. In the short term, these rules can be implemented as standard operating procedures for dispatchers. In the longer term, the rules can be developed into a decision-support system that combines time window and traffic data to provide more objective fleet recommendations and order of visits.

Table 10. Summary of findings and operational implications

Key Findings	Operational Meaning	Suggested Responses
X1 → Y is not significant	Commercial operating hours do not automatically trigger fleet reallocation.	Prioritize commercial packages from the initial dispatch and sorting process.
X2 → Y is significant	The remaining time of the courier is a signal of the need for load redistribution.	Monitor the remaining delivery time and activate the fleet switch before the time limit expires.
X3 → Y is significant	Congestion is the most powerful driver of fleet adaptation.	Use traffic awareness for more flexible rerouting and mode selection.
X1, X2, X3 → Z is significant	Any obstacle can reduce the chances of success on the first try.	Manage constraints through a combination of upstream prevention and on-the-ground adaptation.
Y → Z is significant	The quality of fleet allocation increases the chances of on-time arrival and zero redelivery.	Standardize load allocation rules, vehicle switches, and dispatcher responses.
Mediation of X2 and X3 is significant	Fleet allocation can mitigate dynamic constraints.	Establish escalation procedures when remaining time or delay exceeds operational thresholds.
X1 mediation is not significant	Reallocation cannot address closed commercial recipients.	Add commercial time window attributes to master address and dispatch priority.

Operational Implementation Recommendations

Implementation can begin with address classification. Packages destined for stores, offices, shopping centers, or other commercial locations are assigned a commercial time window and separated from residential addresses during the dispatch phase. Departure priority is determined by the earliest closing time, not solely by the destination district. This approach directly addresses the finding that commercial time window constraints cannot be adequately addressed by reallocation once couriers are in the field. The next step is time capacity control. Dispatchers can compare the remaining delivery points with the remaining effective working time at specific intervals. When the load-to-time ratio exceeds the operational limit, the system triggers a redistribution of packages to other couriers or vehicles with remaining capacity. This mechanism aligns with the X2 mediation results, which show that fleet allocation management can mitigate the impact of time constraints on delivery success.

For congestion, operational decisions need to consider vehicle characteristics. Motorcycles can be prioritized for points scattered in dense areas that require maneuverability, while vans remain for loads requiring larger capacity. Traffic condition data can be used to assess when initial routes need to be changed and when transferring a portion of a package offers greater benefits than maintaining the original assignment. Implementation evaluation should use the same indicators as the research constructs: first-time delivery success rate, redelivery rate, on-time arrival rate, rerouting frequency, fleet switching rate, and failures due to closed locations and deliveries outside courier hours. With these indicators, companies can assess whether changes to dispatch procedures have significantly reduced the failure categories that are the primary problem in operational data.

Research Limitations

The study was limited to Lion Parcel delivery personnel in the Bandung operational area, with 90 respondents. Because organizational context, fleet structure, address characteristics, and traffic patterns can vary across regions, the model results should be read as empirical evidence within the context of the case study, not as estimates that automatically apply to all logistics companies or cities. Traffic congestion variables were measured through courier and driver perceptions. The thesis also notes that the company does not yet have a failure code that specifically identifies congestion as a cause of first-attempt delivery failure. Therefore, the study has not incorporated granular data such as actual speed, GPS trace, stop time, or comparison of ETA to actual arrival time. Integrating such data could strengthen congestion measurements in future studies. The model focuses on the last-mile downstream process.

Findings regarding the commercial time window suggest that some of the problems stem from processes occurring before the vehicle departs, particularly sorting and dispatch priorities. Therefore, further research could incorporate warehousing operational effectiveness, cross-docking performance, inbound cut-off times, or dispatch accuracy as additional variables to more fully explain first-time delivery failures.

CONCLUSION

This study shows that last-mile delivery operational constraints have different patterns of influence on fleet adaptation and first-time delivery success. Delivery Time Constraints and Traffic Congestion have a positive and significant effect on Fleet Allocation Management, while Commercial Time Window has no significant effect on fleet allocation. Among the factors influencing allocation, Traffic Congestion has the largest coefficient, making traffic conditions the strongest driver of fleet adaptation in the model.

All three operational constraints—Commercial Time Window, Delivery Time Constraints, and Traffic Congestion—significantly impact First-Attempt Delivery Success Rate. Fleet Allocation Management also has a positive and significant impact on first-attempt delivery success. Thus, delivery success is determined by a combination of external conditions and an organization's capacity to manage vehicle resources and courier assignments.

The mediating role of Fleet Allocation Management only occurs in Delivery Time Constraints and Traffic Congestion. Fleet allocation does not mediate the Commercial Time Window. These results demonstrate the limits of on-the-ground intervention capabilities: vehicle reallocation is effective for dynamically changing and compensable constraints, but cannot address closed commercial locations. These constraints need to be addressed through a more preventative dispatch process starting at the warehouse.

For Lion Parcel, improvement priorities include incorporating commercial customer operating hours into the dispatch process, strengthening the interfleet package transfer mechanism when remaining time is running low, and using traffic conditions as a basis for rerouting. Future research could expand the model upstream by incorporating warehouse operational effectiveness or cross-docking performance to explain whether dispatch delays contribute to the increased risk of commercial time window violations.

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