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Optimizing Last-Mile Delivery with Crowdshipping and Considering Carriers' Acceptance Probability

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Abstract

The rapid growth of digital businesses in recent years, along with the inherent complexity of Last-Mile Delivery (LMD), has posed significant challenges to urban logistics in terms of cost, traffic congestion, and environmental pollution. This study develops a mathematical model that assigns parcel delivery tasks (via delivery lockers) to Public Transport (PT) passengers and Ride-Hailing Vehicles (RHVs) using a crowdshipping approach. The objective is to optimize both logistics and environmental costs. Because crowdshipping carriers may accept delivery requests with uncertainty, a logit model predicts the probability of accepting a given delivery offer based on parcel characteristics. This probability is incorporated into the objective function of a Mixed-Integer Programming (MIP) formulation as an expected cost of non-acceptance. To estimate the behavioral parameters, a fractional factorial design was used to construct a twelve-scenario stated-preference survey. We collected 200 responses from PT passengers and RVH drivers and used them to calibrate the logit model coefficients. We then solved a numerical example in Python using the PuLP optimization library. The results indicate that PT passengers are more sensitive to financial incentives, while RVH drivers are more sensitive to parcel volume. We explicitly integrated these differences into the objective function, and the findings show that neglecting carrier behavior can significantly affect decision-making and potentially lead to misleading "optimal" solutions. Overall, the proposed framework enables smarter and more sustainable management of LMD systems.

Keywords: Last-mile delivery, Delivery lockers, Crowdshipping, Logit model, Urban logistics.

1 | Introduction

The exponential growth of e-commerce, particularly following global pandemics, has revolutionized purchasing patterns while placing unprecedented pressure on urban logistics systems, especially the costly and complex Last-Mile Delivery (LMD) stage. The increasing volume of parcels, customers' expectations for faster delivery (same-day or within a few hours), and the need for cost-effective solutions have intensified the

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challenges logistics companies face. These challenges increasingly highlight the need to move away from traditional logistics models toward innovative and sustainable solutions. In response, various approaches have gained attention, including alternative delivery points such as parcel lockers, crowdshipping models, and the integration of freight and passenger transportation. However, each of these solutions alone cannot address all dimensions of the problem. This study focuses on a novel hybrid solution that strategically integrates the unused capacities of Ride-Hailing Vehicles (RHVs), the voluntary participation of Public Transport (PT) passengers, and a parcel locker network, while considering the probability of parcel acceptance by carriers, to establish a flexible, efficient, and sustainable last-mile logistics system. This study's results are expected to provide valuable managerial insights for logistics companies and urban policymakers to improve efficiency, reduce costs, and move toward more sustainable urban transportation systems.

2 | Problem Statement

The growing demand for fast and cost-effective delivery, alongside the expansion of e-commerce, has created significant challenges for urban logistics systems. The increasing volume of deliveries has led to higher freight vehicle traffic, urban congestion, increased operating costs, and adverse environmental impacts. In this context, utilizing the unused capacities of RHVs and the voluntary participation of PT passengers have emerged as innovative approaches for addressing these challenges. These approaches, developed within the framework of integrated parcel and passenger transportation systems, have considerable potential to reduce delivery costs, improve resource utilization, and mitigate environmental impacts. In such systems, parcels are transported from their origins, such as warehouses or distribution centers, to their final destinations, such as customers' homes. Intermediate parcel lockers can also be used as storage and transfer points, allowing parcels to be transported from an origin to a locker and subsequently from the locker to their final destinations. A key challenge in designing such an integrated system is the effective management of vehicle and passenger routes under capacity constraints. Each RHV or PT passenger has a predetermined origin and destination and can deviate from their original route only within a limited range. Moreover, the weight and volume capacities available for carrying parcels are limited. Therefore, these constraints must be incorporated into the parcel assignment process to ensure the feasibility of transportation decisions and prevent impractical assignments. In addition to these operational constraints, user behavior and the probability of parcel acceptance represent another critical aspect of the system. The willingness of PT passengers to accept parcels may depend on factors such as parcel weight and volume, the extent of route deviation, and the financial incentive offered. Similarly, for RHVs, parcel acceptance may be influenced by operational factors, including vehicle capacity, fuel costs, and the extent of route deviation. Ignoring these acceptance probabilities may result in assignments that are theoretically feasible but impractical from the perspective of carriers. Accordingly, an effective decision-making framework should simultaneously consider transportation routes, capacity limitations, route deviations, and the probability of parcel acceptance by different types of carriers. In this context, the proposed model aims to efficiently utilize existing transportation capacities while minimizing total system costs, improving service quality, and optimizing resource utilization. Furthermore, the model seeks to enhance carrier satisfaction by limiting unnecessary route deviations and providing appropriate financial incentives. By integrating these considerations within a unified framework, the proposed approach aims to provide a practical basis for developing a flexible and efficient LMD system that can better exploit existing urban transportation resources.

3 | Literature Review

The rapid growth of e-commerce and customers' increasing expectations for fast and reliable delivery have created significant challenges in the field of LMD, particularly in urban environments [1], [2]. As the most costly and complex component of the supply chain, LMD requires innovative solutions to improve efficiency, reduce costs, and mitigate environmental impacts [3], [4]. In recent years, three main approaches have emerged in the literature as promising solutions: the use of parcel lockers, the adoption of crowdshipping, and the integration of passenger and freight transportation. This section reviews the existing research in these

three areas and highlights the research gaps that motivate the present study. Parcel lockers, as automated pickup and delivery points, are recognized as an effective solution for increasing customer flexibility and improving last-mile logistics efficiency [5], [6]. By reducing the need for recipients to be present and consolidating deliveries, parcel lockers have the potential to reduce operating costs, failed deliveries, and adverse environmental impacts such as traffic congestion and pollution [4], [7], [8]. Research in this area has addressed several dimensions of parcel locker systems. Early studies examined the financial and operational performance of different locker configurations, including Schneider et al.'s comparison of fixed and modular lockers [9] and studies addressing service pricing [10]. A substantial body of research has subsequently focused on network design and the optimal location of parcel lockers, including the development of two-level mathematical models [7], consideration of customer choices and preferences [3], [5], and the application of multi-criteria decision-making methods for location selection based on accessibility, sustainability, and security criteria [11], [12]. More recently, researchers have investigated the integration of parcel lockers with other delivery solutions. These studies have considered lockers as intermediate nodes in two-level delivery systems involving temporary couriers or crowdshipping [13], [14], integration with Autonomous Mobile Lockers (AMLs) [15], and incorporation into PT networks [16]. The impacts of parcel locker systems on customer satisfaction [5], courier operating time [6], and carbon emissions [4], [8] have also been examined.
Another promising approach to improving LMD is crowdshipping, which relies on ordinary individuals as temporary carriers to transport parcels. Research in this area has primarily focused on operational optimization, including the development of minimum-cost flow models [17] and the joint optimization of parcel assignment to intermediate points and crowd-courier routing using advanced algorithms [18]. The integration of crowdshipping with existing transportation infrastructure, particularly public transportation and parcel lockers, has emerged as an important research direction. Studies have investigated the potential and challenges of such integrated systems using stated-preference surveys [19] and various optimization approaches, including Stochastic Programming (SP) [20], genetic algorithms [21], and multi-objective optimization [22], as well as field experiments [16]. Beyond operational planning, understanding carriers' behavior and willingness to participate is critical to the practical implementation of crowdshipping systems. Accordingly, discrete choice and latent class models have been employed to analyze factors influencing task acceptance among PT passengers, including financial incentives, task characteristics, and demographic and attitudinal factors [23], [24]. In parallel with crowdshipping, the utilization of unused capacity in passenger vehicles for simultaneous freight transportation has been investigated as another means of improving the efficiency of urban transportation resources. A substantial portion of the early literature focused on modeling and solving the Shared Autonomous Ride Problem (SARP) in taxi systems. Li et al. [25], [26], for example, developed approaches based on Mixed-Integer Linear Programming (MILP), Adaptive Large Neighborhood Search (ALNS), and SP. Subsequent studies extended and improved these models and solution methods, including extensions to the simultaneous transportation of multiple passengers and parcels, such as the Generalized SARP (G-SARP) [27], and the application of advanced metaheuristic approaches, including the integration of SAMS and SP [28] and the combination of ALNS with Ant Colony Optimization (ACO) [29]. The integration of emerging technologies and alternative vehicle fleets has also received attention, including autonomous vehicles [30], mixed electric and gasoline-powered fleets [27], and electric taxis with intelligent management based on reinforcement learning [31]. Furthermore, the potential for incorporating public transportation modes, such as buses [32], [33], and integrating ride-hailing services with other transportation modes, such as electric motorcycles [34], has been explored. Overall, the literature demonstrates that parcel lockers, crowdshipping, and the integration of freight and passenger transportation each offer considerable potential for improving the efficiency and sustainability of LMD. Nevertheless, a notable research gap remains in the simultaneous integration of these three approaches within a comprehensive and unified logistics system. In particular, while previous studies have examined combinations of two or more of these approaches, limited attention has been given to a framework that jointly incorporates a parcel locker network, RHVs, and PT passengers. Moreover, most existing models do not explicitly account for the inherent uncertainty associated with carriers' willingness to accept delivery tasks. This issue is particularly important in crowdshipping systems, where transportation capacity depends not only on physical constraints but also on the behavioral

decisions of potential carriers. In addition, there is a need for integrated models capable of addressing the trade-offs among conflicting economic, environmental, and service-related objectives, including timely delivery. To address these gaps, this study develops a mathematical optimization model that integrates a parcel locker network with RHV and PT carriers within a unified LMD framework. The proposed approach explicitly incorporates carriers' acceptance probabilities by using a logit model, thereby accounting for behavioral uncertainty in parcel assignment decisions. Furthermore, the model considers operational constraints, such as vehicle and passenger capacity and route deviations, while optimizing a multi-component objective function that incorporates economic and environmental costs. Through this integrated framework, the study seeks to provide a more comprehensive approach to the design and operation of flexible, efficient, and sustainable LMD systems.

4 | Model Description

The proposed model aims to determine an optimal operational strategy for the allocation and transportation of parcels by simultaneously exploiting the available capacities of RHVs, PT passengers, and a network of parcel lockers. The model is designed to provide an efficient response to the challenges of urban last-mile logistics by minimizing the expected total system cost while improving service efficiency. To this end, the proposed logistics system is formulated as a Mixed-Integer Programming (MIP) model that integrates the physical, operational, and behavioral characteristics of the different components involved in the delivery process.

The main components of the modeled logistics system include parcels, parcel lockers, RHVs, and PT passengers. Parcels (P) represent the basic units of freight flow. Each parcel has a predefined origin, which is the central warehouse, a final destination, and physical characteristics, including weight (w) and volume (v). Parcel lockers (L) serve as intermediate facilities for the temporary storage and transfer of parcels. Each locker facility (l) includes a set of individual lockers (B_l), each with a specified weight and volume capacity ($Q_{l,b}^{wLocker}$, $Q_{l,b}^{vLocker}$). RHV drivers (K) and PT passengers (M) act as carriers in the second stage of the delivery process. Each carrier has a predetermined route from an origin (O) to a destination (D), a limited weight and volume carrying capacity (Q^v , Q^w), and a maximum allowable deviation from their original route, denoted by ($\Delta_m^{passenger}$ ،Δ_k^{RVH}), respectively, for the corresponding carrier types.

In addition to these physical and operational characteristics, the model explicitly considers the uncertainty associated with carriers' willingness to accept parcel delivery tasks. This behavioral aspect is particularly important for PT passengers, whose participation is voluntary and who may reject a proposed parcel. To represent this selective behavior, a logit model is employed to estimate the probability of parcel acceptance (P_{lp}) by a given carrier. The acceptance probability is determined as a function of key factors influencing carriers' decisions, including the physical characteristics of the parcel, such as its weight and volume, the extent of route deviation required to transport the parcel, and the attractiveness of the financial incentive offered. Incorporating this probability into the optimization model allows carrier behavior and the uncertainty associated with parcel acceptance to be considered when making allocation decisions.

The delivery process is modeled as a two-stage transportation system. In the first stage, parcels are transported from the central warehouse to one of the selected parcel lockers in the network, incurring an initial transportation cost (C_1). In the second stage, parcels stored at the lockers are transported to their final destinations by available RHV or PT carriers. A parcel can be assigned to a carrier only if the carrier passes sufficiently close to the corresponding locker along their original route, satisfies the relevant capacity and route-deviation constraints, and is willing to accept the delivery task. Thus, the proposed structure enables the system to exploit existing transportation capacities while using parcel lockers as intermediate transfer points between the warehouse and final destinations.

Based on this structure, the primary objective of the model is to minimize the expected total system cost. The objective function incorporates four main cost components. The first is the initial transportation cost, which represents the cost of transporting each parcel from the central warehouse to a parcel locker. The second is

the environmental cost, which is calculated based on the additional distance traveled by carriers to pick up and deliver parcels. The third component is the carrier operating cost or incentive cost, which represents the financial incentives paid to RHV drivers and PT passengers to encourage their participation in parcel transportation. The fourth component is the parcel non-acceptance cost, which accounts for parcels that are not assigned to any locker in the first stage, as well as parcels that are assigned to a locker but are not subsequently accepted by any available carrier.

To determine the optimal allocation decisions, the model employs a set of binary decision variables. The variable ($z_{p,l,b}$) determines whether parcel (p) is assigned to locker (b) within locker facility (l). The binary variable ($y_{p,l,b,m}$) takes a value of 1 if parcel (p) is picked up from locker (b) within locker facility (l) by PT passenger (m). Similarly, the binary variable ($x_{p,l,b,k}$) determines whether parcel (p) is picked up from locker (b) within locker facility (l) by RHV (k). These decision variables establish the assignment relationships among parcels, lockers, RHV carriers, and PT passengers and form the basis for determining the optimal transportation plan. The feasibility and operational performance of the proposed system are governed by a set of constraints addressing flow, assignment, capacity, and route-deviation requirements. Flow and assignment *Constraints (10)*, *(11)*, and *(19)* ensure that each parcel is assigned to at most one locker and, if assigned to a locker, is subsequently picked up by at most one carrier. Capacity *Constraints (12)-(17)* ensure that the total weight and volume of parcels assigned to each locker and carrier do not exceed their respective capacities. Route-deviation *Constraints (18)* and *(19)* ensure that the deviation required for a carrier to pick up and deliver a parcel does not exceed the maximum allowable deviation for that carrier. Together, these constraints ensure that the resulting allocation decisions remain physically feasible and operationally consistent.

Finally, the model is developed based on several simplifying assumptions. First, all information required for decision-making, including the locations, parcel characteristics, and carrier characteristics, is assumed to be fully available. Second, the operating and environmental costs associated with carriers are assumed to be fixed and independent of traffic conditions. Third, Manhattan distance is used to calculate transportation and route-deviation distances. These assumptions provide a tractable modeling framework while retaining the main operational and behavioral characteristics of the proposed integrated LMD system.

5 | Mathematical Model

Sets

P: Set of parcels ($p \in P$).

K: Set of RHVs ($k \in K$).

M: Set of PT passengers ($m \in M$).

L: Set of lockers ($l \in L$).

B_l: Set of lockers available at locker facility l ($\subseteq bB_l$).

D: Set of warehouses ($d \in D$).

Parameters

Parcel characteristics

$O_p \in D \quad \forall p \in P$: Warehouse d is the origin of parcel p.

$D_p = \left(x_p^{dest}, y_p^{dest}\right)$: Coordinates of the destination of package p.

w_p: Weight of package p.

v_p: Volume of package p.

Warehouse characteristics

O_d^{stock}: (x_d, y_d).

Characteristics of lockers and compartments

$O_l^{locker} = (x_l, y_l)$: Coordinates of locker l.

$Q_{l,b}^{wLocker}$: Weight capacity of compartment b in locker l.

$Q_{l,b}^{vLocker}$: Volume capacity of compartment b in locker l.

Costs

C_1: Parcel transportation cost from the warehouse to the locker per unit distance.

C_2: Return cost.

C_3 : Cost of reshipping parcels.

C_4: Penalty for unassigned parcels.

C_5: Penalty for packages not being accepted by carriers.

$f_m^{Passenger}$: Operating cost of passenger m per unit distance.

f_k^{RHV}: Transportation cost of vehicle n per unit distance.

$e_m^{Passenger}$: Greenhouse gas emissions cost of passenger m per unit distance.

e_k^{RHV}: Greenhouse gas emissions cost of vehicle k per unit distance.

Passenger characteristics

$O_m^{Passenger} = (x_{O_m}, y_{O_m})$: Coordinates of the origin of passenger m.

$D_m^{Passenger} = (x_{D_m}, y_{D_m})$: Coordinates of the destination of passenger m.

$Q_m^{wPassenger}$: Maximum weight that can be carried by passenger m.

$Q_m^{vPassenger}$: Maximum volume that can be carried by passenger m.

$\Delta_m^{passenger}$: Maximum allowable route deviation for passenger m.

Vehicle characteristics

$O_k^{RHV} = (x_{O_k}, y_{O_k})$: Coordinates of the origin of vehicle k.

$D_k^{RHV} = (x_{D_k}, y_{D_k})$: Coordinates of the destination of vehicle k.

Q_k^{wRHV}: Maximum weight capacity of vehicle k.

Q_k^{vRHV}: Maximum volume capacity of vehicle k.

Δ_k^{RHV} : Maximum allowable route deviation for vehicle k.

Logit model

$\pi_{lmp}^{passenger}$: Probability of passenger m accepting package p from locker l.

π_{lkp}^{RHV}: Probability of vehicle k accepting package p from locker l.

P_{lp}: Overall probability of accepting package p from locker l.

Behavioral parameters

Utility coefficients for public transportation passengers:

β_1 : Incentives.

β_2: Cargo volume.

β_3: Cargo weight.

β_4: Route deviation.

Utility coefficients for ride-hailing services:

γ_1: Incentives.

γ_2: Cargo volume.

γ_3: Cargo weight.

γ_4: Route deviation.

Decision variables

$z_{p,l,b}$: A binary variable that equals 1 if parcel p is assigned to compartment b in locker l.

$y_{p,l,b,m}$: A binary variable that equals 1 if parcel p is picked up from compartment b in locker l by passenger m.

$x_{p,l,b,k}$: A binary variable that equals 1 if parcel p is picked up from compartment b in locker l by vehicle k.

Distance calculations

Distance between the locker and the passenger's origin:

$$d_{O_l^{locker},O_m^{Passenger}} = |x_l - x_{O_m}| + |y_l - y_{O_m}|. \quad (1)$$

Distance between the locker and the package destination:

$$d_{O_l^{locker},D_p} = |x_l - x_{D_p}| + |y_l - y_{D_p}|. \quad (2)$$

Distance between the passenger's destination and the parcel destination:

$$d_{D_m^{Passenger},D_p} = |x_{D_m} - x_{D_p}| + |y_{D_m} - y_{D_p}|. \quad (3)$$

Distance between the locker and the vehicle's origin:

$$d_{O_l^{locker},O_k^{RHV}} = |x_l - x_{O_k}| + |y_l - y_{O_k}|. \quad (4)$$

Distance between the parcel destination and the vehicle's destination:

$$d_{D_k^{RHV},D_p} = |x_{D_k} - x_{D_p}| + |y_{D_k} - y_{D_p}|. \quad (5)$$

Distance between the passenger's origin and destination:

$$d_{D_m^{Passenger},O_m^{Passenger}} = |x_{D_m} - x_{O_m}| + |y_{D_m} - y_{O_m}|. \quad (6)$$

Distance between the vehicle's origin and destination:

$$d_{D_k^{RHV},O_k^{RHV}} = |x_{D_k} - x_{O_k}| + |y_{D_k} - y_{O_k}|. \quad (7)$$

Distance between the locker and the warehouse:

$$D_{O_l^{locker},O_{O_p}^{stock}} = |x_l - x_d| + |y_l - y_d|. \quad (8)$$

Objective function

Represents the objective function for minimizing the total system costs:

$$\begin{aligned}\text{Minimize } Z = & \sum_{p\in P}\sum_{l\in L}\sum_{b\in B_l} C_1 \cdot z_{p,l,b} \cdot d_{O_l^{locker},O_{O_p}^{stock}} \\ & + \sum_{p\in P}\sum_{l\in L}\sum_{b\in B_l}\sum_{m\in M}\left(f_m^{Passenger} + e_m^{Passenger}\right)\cdot y_{p,l,b,m}\cdot\left(d_{O_l,O_m} + d_{O_l,D_p}\right) \\ & + \sum_{p\in P}\sum_{l\in L}\sum_{b\in B_l}\sum_{k\in K}\left(f_k^{RHV} + e_k^{RHV}\right)\cdot x_{p,l,b,k}\cdot\left(d_{O_l,O_k} + d_{O_l,D_p}\right) \\ & + \Big(\sum_{p\in P}\sum_{l\in L}\sum_{b\in B_l}\sum_{m\in M} y_{p,l,b,m}\cdot\left(1-\pi_{lmp}^{passenger}\right) \\ & \qquad + \sum_{p\in P}\sum_{l\in L}\sum_{b\in B_l}\sum_{k\in K} x_{p,l,b,k}\cdot\left(1-\pi_{lkp}^{RHV}\right)\Big)\cdot(C_2 + C_3) \\ & + \sum_{p\in P}\sum_{l\in L}\sum_{b\in B_l} C_4\cdot(1 - z_{p,l,b}) \\ & + \sum_{p\in P}\sum_{l\in L}\sum_{b\in B_l} C_5\cdot\left(z_{p,l,b} - \sum_{m\in M} y_{p,l,b,m} - \sum_{k\in K} x_{p,l,b,k}\right).\end{aligned} \quad (9)$$

Constraints

According to *Eq. (10)*, each parcel must be assigned to at most one compartment in one locker:

$$\sum_{l\in L}\sum_{b\in B_l} z_{p,l,b} \le 1, \quad \forall p \in P. \quad (10)$$

According to *Eq. (11)*, each compartment can hold at most one parcel.

$$\sum_{p\in P} z_{p,l,b} \le 1, \quad \forall l \in L, b \in B_l. \quad (11)$$

Eqs. (12)-(16) and *(17)* impose weight and volume capacity constraints for compartments, passengers, and vehicles.

For compartments:

$$\sum_{p\in P} w_p \cdot z_{p,l,b} \le Q_{l,b}^{wLocker}. \quad (12)$$

$$\sum_{p\in P} v_p \cdot z_{p,l,b} \le Q_{l,b}^{vLocker}. \quad (13)$$

For passengers:

$$\sum_{p\in P} w_p \cdot y_{p,l,b,m} \le Q_m^{wPassenger}. \quad (14)$$

$$\sum_{p\in P} v_p \cdot y_{p,l,b,m} \le Q_m^{vPassenger}. \quad (15)$$

For vehicles:

$$\sum_{p\in P} w_p \cdot x_{p,l,b,k} \le Q_k^{wRHV}. \quad (16)$$

$$\sum_{p\in P} v_p \cdot x_{p,l,b,k} \le Q_k^{vRHV}. \quad (17)$$

Eqs. (18) and *(19)* account for the route deviation constraints.

For passengers:

$$y_{plbm} \cdot \left(d_{O_l^{locker},O_m^{Passenger}} + d_{O_l^{locker},D_p} + d_{D_m^{Passenger},D_p} - d_{D_m^{Passenger},O_m^{Passenger}}\right), \le \Delta_m^{passenger} \quad (18)$$

$$\forall p \in P, l \in L, b \in B_l, m \in M.$$

For vehicles:

$$x_{p,l,b,k} \cdot \left(d_{O_l^{locker},O_k^{RHV}} + d_{O_l^{locker},D_p} + d_{D_k^{RHV},D_p} - d_{D_k^{RHV},O_k^{RHV}}\right) \le \Delta_k^{RHV} \quad \forall p \in P, l \in L, b \in B_l, k \in K. \quad (19)$$

Package transportation: According to *Eq. (20)*, each package must be transported either by a passenger or by a vehicle.

$$\sum_{m\in M} y_{p,l,b,m} + \sum_{k\in K} x_{p,l,b,k} \le z_{p,l,b}, \quad \forall p \in P, l \in L, b \in B_l. \quad (20)$$

Logit model: The probability of package acceptance by passenger (m) from locker (l) is calculated based on *Eqs. (21)* and *(22)*:

$$\pi_{lmp}^{passenger} = \frac{\exp(V_{lmp}^{Passenger})}{1+\exp(V_{lmp}^{Passenger})}. \quad (21)$$

$$V_{lmp}^{Passenger} = \beta_1 \cdot (f_m^{Passenger} \cdot (d_{O_l,O_m} + d_{O_l,D_p})) + \beta_2 \cdot w_p + \beta_3 \cdot v_p + \beta_4 (d_{O_l^{locker},O_m^{Passenger}} + d_{O_l^{locker},D_p} + d_{D_m^{Passenger},D_p} - d_{D_m^{Passenger},O_m^{Passenger}}). \quad (22)$$

The probability of package acceptance by vehicle (k) from locker (l) is calculated based on *Eqs. (23)* and *(24)*:

$$\pi_{lkp}^{RHV} = \frac{\exp(V_{lkp}^{RHV})}{1+\exp(V_{lkp}^{RHV})}. \quad (23)$$

$$V_{lk}^{RHV} = \gamma_1 \cdot (f_k^{RHV} \cdot (d_{O_l,O_k} + d_{O_l,D_p})) + \gamma_2 \cdot w_p + \gamma_3 \cdot v_p + \gamma_4 \cdot (d_{O_l^{locker},O_k^{RHV}} + d_{O_l^{locker},D_p} + d_{D_k^{RHV},D_p} - d_{D_k^{RHV},O_k^{RHV}}). \quad (24)$$

6 | Numerical Example

To evaluate the performance of the proposed model in an operational environment, a numerical example was designed comprising 200 packages, 5 locker centers (each containing 20 lockers), 20 PT passengers, and 20 RHV drivers. The coordinates of all packages, centers, and carriers were randomly generated over a (50\times 50) network, and distances were calculated using the Manhattan metric. To estimate the coefficients of the Logit model, a survey was designed using the fractional factorial design method. The survey covered various package attributes, including financial incentive, weight, volume, and route deviation, through 12 scenarios. A total of 200 responses were collected from PT passengers and RHV drivers, based on which the Logit model coefficients were calculated, as presented in *Table 1*.

Table 1. Logit model coefficients for PT and RHV carriers.

Carrier Type	Financial Incentive	Package Weight	Package Volume	Route Deviation
PT	0.099	-0.383	-0.135	-0.046
RHV	0.055	-0.248	-0.326	-0.029

The estimated coefficients of the Logit model for the two carrier groups, namely PT passengers and ride-hailing service drivers, indicate significant differences in the behavioral sensitivity of these groups to package attributes and transportation conditions. For PT passengers, the positive coefficient of the financial incentive (0.099) indicates that an increase in the reward amount considerably increases the probability of package acceptance by passengers, whereas the negative and relatively large coefficients of weight (−0.383) and volume (−0.135) indicate that PT passengers are highly sensitive to the weight and size of packages and are therefore less willing to accept such packages. Moreover, the negative coefficient of route deviation (−0.046) indicates that an increase in the distance or deviation from the original route reduces the probability of acceptance. In contrast, for ride-hailing service drivers, the financial incentive also has a positive effect (0.055), but its magnitude is lower than that for PT passengers. Instead, their sensitivity to package volume (−0.326) is greater than their sensitivity to package weight (−0.248). This finding indicates that cargo-space constraints are more important to ride-hailing service drivers than weight constraints. The coefficient of route deviation is also negative but smaller in magnitude than that for PT passengers, indicating that ride-hailing service drivers have greater tolerance for route deviations. Overall, these coefficients indicate that neglecting these behavioral differences may result in unrealistic allocations and increase the overall costs of the system.

Subsequently, the MIP model was implemented in the Python PuLP environment using the CBC solver. A summary of the model solution results is presented in *Table 2* and *Figs. 1* and *2*.

Table 2. Model solution results.

Key Indicator	Value
Number of packages	200
Number of packages assigned to PT	118
Number of packages assigned to RHV	82
Optimal objective function value (total cost units)	2837.45
Initial transportation cost	1210
Expected non-acceptance cost	840.75
Operational/environmental costs	786.70

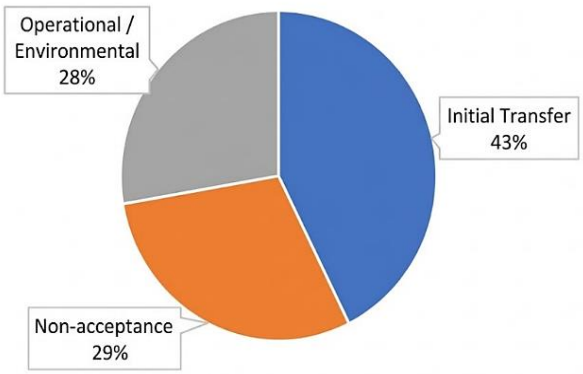


Fig. 1. Distribution of packages by carrier type.

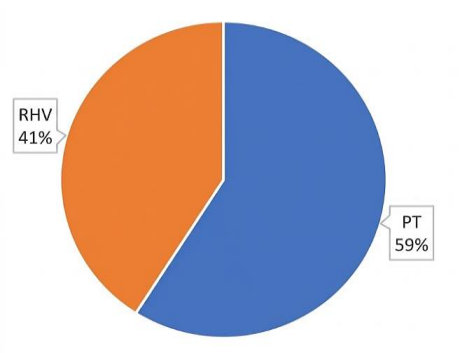


Fig. 2. Share of each cost component in the total system cost.

The solution results showed that the output allocation consisted of 118 packages (59%) assigned to PT and 82 packages (41%) assigned to RHV. Lightweight and low-volume packages were predominantly assigned to PT, whereas bulky or heavy packages were assigned to RHV. The optimal objective function value was 2,837.45 total cost units, comprising the initial transportation cost (1,210), expected non-acceptance cost (840.75), and operational/environmental costs (786.70). Lightweight and low-volume packages were predominantly assigned to PT, whereas bulky or heavy packages were assigned to RHV. This finding is fully consistent with the behavioral coefficients of the Logit model *Table 1*. Furthermore, the expected cost share associated with package non-acceptance accounted for approximately 30% of the total system cost, highlighting the importance of the behavioral aspect. An example of package allocation to carriers is presented in *Table 3*.

Table 3. An example of package allocation to carriers.

Parcel No.	Carrier Type	Carrier No.	Weight	Volume	Route Deviation	Acceptance Probability
1	PT	8	1.2	0.3	12	0.581
2	RHV	21	3.1	0.7	18	0.286
3	PT	13	0.8	0.2	10	0.642
4	RHV	7	5.8	0.6	15	0.187

The results demonstrated that incorporating the actual behavior of carriers through the Logit coefficients plays a vital role in carrier selection and reducing total costs. The model, even at a large scale, was able to satisfy all constraints and provide a balanced and operationally feasible allocation, indicating the applicability of the proposed approach to real-world urban logistics scenarios.

7 | Conclusion

This study addressed the optimization of LMD in urban environments by combining the use of smart lockers with crowdsourcing capacities, including PT passengers and RHV drivers. The proposed framework is a MIP model that estimates the probability of acceptance of each transportation offer based on the Logit model, considering financial incentives, route deviation, and the physical characteristics of packages, and incorporates this probability into the objective function as the expected non-acceptance cost. In addition to behavioral aspects, the model fully incorporates operational constraints, such as locker capacity, carrier transportation capacity, and maximum allowable route deviation. The implementation of the model in a realistic scenario involving 200 packages, 5 locker centers, and 40 active carriers demonstrated that all packages were allocated and transported while satisfying the constraints, with a balanced utilization of carriers. The allocation pattern resulting from the actual behavioral coefficients, particularly the differentiation of packages between PT and RHV, led to a reduction in expected costs. The coefficient analysis showed that applying a uniform policy to PT and RHV is not effective; it is preferable to provide greater financial incentives for PT, while greater attention should be paid to volume constraints and optimal loading design for RHV. The analysis of cost components showed that the largest share of the total cost was associated with the initial transportation of

packages, followed by the predicted non-acceptance cost and operational environmental costs. These findings indicate that optimally combining locker capacity and crowdsourcing while accounting for the actual responses of carriers can enhance the efficiency and sustainability of urban logistics operations and provide a practical tool for decision-makers. Despite the positive results, the current model is a static, single-period framework and does not directly account for dynamic changes in demand, traffic conditions, or carrier availability. Future research could include the development of dynamic or multi-period models, the use of advanced behavioral models or machine-learning-based approaches, extensions to multi-destination routes and delivery time windows, the application of robust or stochastic optimization to better manage uncertainties, and field validation of the model using real-world data. Pursuing these directions could substantially improve the accuracy and practical applicability of LMD optimization models.

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Data Availability

The data used in this study are available from the corresponding author upon reasonable request.

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