

When Do Parcel Lockers Pay? A Cost-To-Serve MILP For Two-Wheeler Last-Mile Delivery in Mumbai

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Purpose – Research on last-mile delivery has often focused on new technologies, while the financial impact of failed first delivery attempts and the cost of each successfully delivered parcel receives much less attention. This study reviews the research landscape and examines when redirecting customers to parcel lockers can reduce the cost of serving deliveries made by two-wheeler fleets.

Design/methodology/approach – We reviewed 75 journal articles published from 2015 to 2025 using OpenAlex and the required “operations AND research” terms, then checked 1,086 records for research gaps using keyword-based searches. We also developed a mixed-integer linear programming model (MILP) that extends the capacitated vehicle routing problem by including locker assignments, expected failed-delivery costs and penalties for deferring deliveries. The model was solved with CBC using Mumbai delivery instances and road distances from OpenStreetMap.

Findings – Drones feature in 31% of the screened articles, but failed deliveries appear in just 1.1% and cost per parcel in only 0.5% of the broader set of records. Compared with nearest-neighbour routing, exact routing lowered daily costs by 4.9–8.2%. Locker diversion contributed a further saving of up to 1.9% and was chosen only when a failed attempt cost at least INR 90 or the customer incentive was no more than INR 5. Driver wages had the greatest effect on cost per parcel.

Originality – The study connects a bibliometric review of research gaps with a reproducible MILP, translating routing choices into unit economics for a two-wheeler delivery fleet in an emerging-market city. **Practical implications –** In a congested city where wages are relatively low, lockers make financial sense mainly when the full cost of a failed delivery is high, not simply because they improve route efficiency.

Keywords: last-mile delivery; vehicle routing; mixed-integer linear programming; parcel lockers; failed deliveries; bibliometric analysis

1. Introduction

Online retail has made the final stage of delivery a major challenge for city logistics. Parcels are often small, streets are crowded, and customers expect convenient service (Savelsbergh & Van Woensel, 2016; Olsson et al., 2019). At the same time, delivery companies face labour shortages, higher fuel costs and tight margins, encouraging them to rethink how last-mile operations are organised (Janinhoff et al., 2024). Operational research has explored many approaches, including crowdsourced delivery, drones and parcel lockers (Boysen et al., 2021). The underlying routing problem, however, has a long history: Dantzig and Ramser’s (1959) truck dispatching problem laid the foundation for the vehicle routing problems used today (Toth & Vigo, 2014). One important source of wasted effort is a failed first

weights and a ranking of cost drivers. Section 2 reports the bibliometric review, delivery attempt. As many as 20% of business-to-consumer deliveries may fail on the first try, creating extra costs and potentially damaging customer relationships (Lim et al., 2023). Some routing models try to improve the chance of finding customers at home (Florio et al., 2018). A survey of retailers in the United States, the United Kingdom and Germany estimated that 8% of first-time domestic deliveries fail, at an average cost of USD 17.20 per failed order (Loqate, 2021). A failed attempt can turn one planned stop into two, directly increasing the cost of each parcel that is ultimately delivered. Parcel lockers and pickup points can reduce this risk and group deliveries together, but customers must be willing to walk to them and may need an incentive to do so (Galiullina et al., 2024; Janinhoff et al., 2024).

Mumbai shows why the value of lockers depends on local conditions. In 2025, the city's average road speed was 20.8 km/h and fell to 17.6 km/h during peak periods (TomTom, 2026). The statutory minimum wage for unskilled workers in Mumbai's wage zone was INR 524.42 per day under the Maharashtra notification effective from July 2025 (Ascent HR, 2025). For the petrol scooters considered in this study, relatively low labour costs limit the savings from skipping a home stop, while congestion increases the time cost of travelling. Whether lockers are worthwhile in these conditions needs to be tested rather than assumed from findings in Europe or North America.

The review in Section 2 shows that this practical question receives little attention. In last-mile optimisation research, drones and electric vehicles are discussed much more often than failed deliveries, cost per parcel or two-wheeler fleets in emerging economies (Figure 4). We therefore focus on three research questions:

- **RQ1.** How is OR research on last-mile delivery optimisation structured in terms of output, venues, themes and methods, and which economic dimensions remain under-studied?
- **RQ2.** How much does exact MILP routing reduce the cost per delivered parcel of a two-wheeler fleet in Mumbai relative to nearest-neighbour routing?
- **RQ3.** For which values of the failed-delivery cost and the locker incentive does diversion to metro-station lockers reduce the cost-to-serve, and which cost drivers matter most?

This study makes three contributions. First, it combines bibliometric performance analysis and science mapping with a keyword-based audit that measures how rarely studies discuss failed-delivery costs and cost per parcel. Second, it develops a compact MILP combining capacitated vehicle routing, locker assignment, expected failure costs and the option to defer a delivery, using open data and freely available software. Third, it translates the model's solutions into practical unit economics, including break-even penalties and a ranking of the main cost drivers.

Section 3 the model, Section 4 the data, Sections 5 and 6 the results and sensitivity analysis, Section 7 the discussion and Section 8 the conclusions and re-search agenda.

2. Literature review and bibliometric analysis

2.1 Search protocol

We followed the bibliometric performance-analysis and science-mapping approach described by Donthu et al. (2021), building on Donthu et al. (2020), and used a similar approach to identifying research trends to that of Verma and Gustafsson (2020). The course protocol specified EBSCO, but library access was unavailable during the project period. We therefore used OpenAlex, an open bibliographic database that provides citation counts and publication metadata through an API (Priem et al., 2022). We retained the required search terms. The main title-and-abstract search string was:

("last mile" OR "last-mile" OR "home delivery" OR "parcel delivery" OR "urban delivery" OR "city logistics" OR "e-commerce delivery") AND ("vehicle routing" OR "mixed integer" OR "integer

programming" OR "MILP" OR "transportation problem" OR "transportation model" OR "linear programming" OR "mathematical model" OR "optimization model" OR "optimisation model") AND (operations AND research)

We limited the search to English-language journal articles published from 2015 through 2025. We excluded 2026 because an incomplete year would distort growth comparisons. For a robustness check, we also used a search string without the compulsory terms. Titles and abstracts were screened, and editorial introductions, retracted papers, duplicate publications, student work and studies outside commercial goods delivery were excluded. Examples of out-of-scope topics included humanitarian relief, passenger transport and terminal operations. Each exclusion was recorded with its document type and reason in Appendix A. Figure 1 summarises the process: 95 records were identified, 20 were excluded and 75 were retained. Bibliometric indicators were calculated in Python using definitions implemented in bibliometrix (Aria & Cuccurullo, 2017), with citation counts taken from OpenAlex.

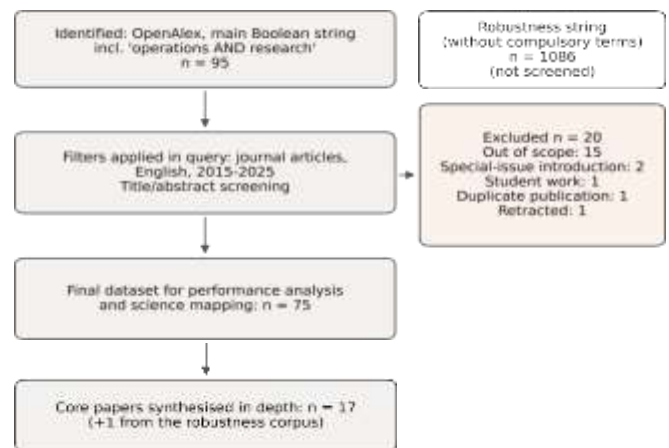


Figure 1. PRISMA-style flow of records (after Page et al., 2021). Source: authors' analysis of OpenAlex data retrieved 2026-10-08.

2.2 Performance analysis

The number of articles rose from 3 in 2015 to 18 in 2025, with 81% of the screened articles published between 2021 and 2025 (Figure 2). The broader robustness corpus also grew quickly, recording a compound annual growth rate of 29.5% over the same period. This suggests that the increase after 2020 is not simply a result of the required search terms.

The 75 screened articles are spread across 55 journals. The European Journal of Operational Research, Sustainability and Transportation Research Part E have the largest article counts (Table 1). Citations are concentrated in a small number of papers: Murray and Chu's (2015) study of the flying sidekick travelling salesman problem accounts for 38% of the 4,577 citations, while the median article has 13 citations.

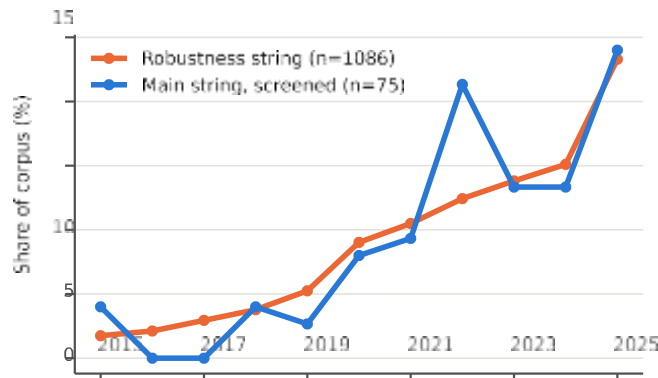


Figure 2. Annual scientific production, 2015–2025, as a share of each corpus. Source: authors' analysis of OpenAlex data.

Table 1. Leading journals and most-cited articles in the screened corpus (n = 75).

	Articles	Citations
European Journal of Operational Research	5	337
Sustainability	4	326
Transportation Research Part E Logistics and Transportation Review	4	297

Annals of Operations Research	3	114
Transportation Science	3	69
Computers & Operations Research	3	67

Most-cited article	Year	Citations
The flying sidekick traveling salesman problem: Optimization of drone-...	2015	1,732
Two echelon vehicle routing problem with drones in last mile delivery	2019	333
Drone routing with energy function: Formulation and exact algorithm	2020	233
Collaborative truck multi-drone routing and scheduling problem: Packag...	2022	197
Optimization and Machine Learning Applied to Last-Mile Logistics: A Re...	2022	164

Collaboration across the field is limited. The 75 articles include 247 different authors across 64 separate co-authorship groups; the largest group has only nine authors, and just six authors have contributed to more than one article. China leads with 18 first-author articles, followed by the United States with seven. Authors from more than one country are involved in 37% of the articles. No Indian institution appears among the leading countries, pointing to a gap in research on the setting examined here.

2.3 Science mapping

We analysed keyword co-occurrence using the keywords attached to each article in OpenAlex. Similar terms, such as “UAV” and “drones”, were combined, and only terms appearing at least twice were retained. We identified clusters using the Louvain algorithm (Blondel et al., 2008) and positioned them by centrality and density following Callon et al. (1991) and Cobo et al. (2011).

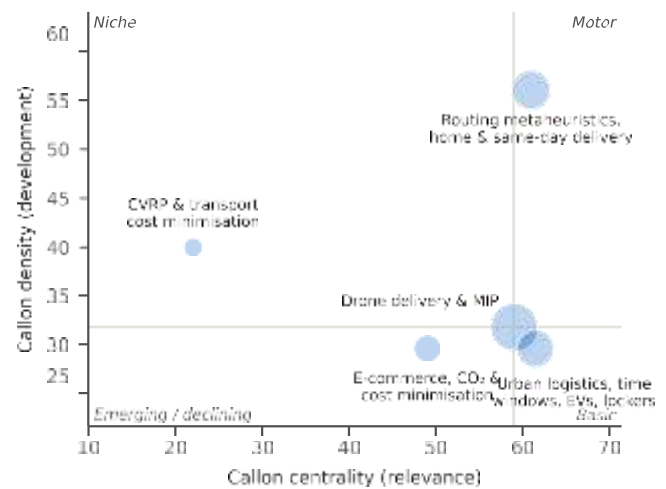


Figure 3. Thematic map of keyword clusters (bubble size = keyword occurrences; axes split at the median). Source: authors' analysis of OpenAlex data.

Table 2 groups methods based on what is mentioned in article titles and abstracts. Exact integer programming, metaheuristics, and constructive or local-search heuristics each appear in about one-quarter of the screened articles. Their shares are very similar in the robustness corpus. Machine learning appears in 13.3% of the screened set but 8.2% of the broader set, suggesting that the required terms may pull in a higher share of methodological reviews and data-driven studies.

Table 2. Method families mentioned in titles or abstracts (an article may use several).

Method family	Screened n	%	Broad n	%
Metaheuristic	19	25.3	266	24.5
Exact MILP / integer programming	18	24.0	285	26.2
Constructive / local-search heuristic	18	24.0	228	21.0
Literature review	11	14.7	51	4.7
Machine learning / data-driven	10	13.3	89	8.2
Stochastic / dynamic programming	7	9.3	105	9.7
Simulation	7	9.3	82	7.6
Multi-criteria / fuzzy	4	5.3	28	2.6

Figure 3 highlights two well-developed, central themes. The largest focuses on drone-assisted last-mile delivery using mixed-integer programming. The other centres on vehicle routing solved with metaheuristics for home delivery, same-day delivery and e-grocery, including crowdshipping and bi-level models. Urban logistics with time windows is a cross-cutting theme that also includes electric vehicles, parcel lockers and exact methods such as branch-and-price. Cost-focused terms sit closer to the edge of the map. “Cost minimisation” appears alongside e-commerce logistics, emissions and customer satisfaction in an emerging or declining area, while “transportation cost minimisation” forms a small niche linked to capacitated routing, collaborative logistics and uncertain demand. Because the corpus and number of clusters are small, individual papers can shift the map's boundaries; the positions should therefore be read as broad patterns rather than precise measurements. Recent trend topics include e-

commerce logistics, delivery-route optimisation, customer satisfaction and valid inequalities, pointing to increased interest in customer-facing service design and stronger exact models.

Thematic synthesis of core papers

We selected 17 core papers based on their citation impact and relevance to this topic, then added one closely related study from the robustness corpus, Tilk et al. (2021) (Table 3). The selected studies fall into four broad research streams.

Drone-assisted routing. Murray and Chu (2015) introduced coordinated truck-and-drone delivery. Later studies extended this idea to two-echelon networks (Kitjacharoenchai et al., 2020), drone ranges that depend on energy use (Cheng et al., 2020), and multiple drones with flexible launch locations (Salama & Srinivas, 2022). This is a mature methodological area, but most studies focus on time or distance rather than cost per parcel. They also assume that drones can operate in urban airspace, which is not yet a straightforward option in megacities such as Mumbai.

Demand management and data-driven routing. Koch and Klein (2020), together with the review by Fleckenstein et al. (2023), show how pricing and delivery-slot decisions can be combined with routing. Giuffrida et al. (2022) review the use of optimisation and machine learning in last-mile logistics. Chu et al. (2023) use delivery-time predictions when assigning orders and building capacitated routes, while Cook et al. (2024) adapt local search to practical constraints found in Amazon delivery routes. These studies consider how customer demand can be managed, but they do not attach a price to a failed delivery attempt.

Failed deliveries and out-of-home options. Lim et al. (2023) show that failed attempts can be predicted using routing, demand and market information. Tilk et al. (2021) allow requests to be served at alternative locations, including lockers. Galiullina et al. (2024) model uncertainty in whether customers accept pickup-point incentives; X. Wang et al. (2024) study neighbours who hold parcels; and Q. Wang et al. (2026) evaluate a shared locker network in Singapore. Janinhoff et al. (2024) confirm that interest in out-of-home delivery has grown quickly. However, much of this work focuses on Europe, North America or Singapore and on van fleets operating in higher-wage settings.

Fleet and constraint economics. Lebeau et al. (2015) compare conventional, hybrid and electric fleets using a fleet-size-and-mix routing model. Schaumann et al. (2023) examine how time windows and vehicle capacity can reduce route efficiency, Lu et al. (2024) study alternative ways to use driver helpers, and Gayialis et

al. (2022) integrate operational research models into a city-logistics information system. Although these studies consider costs, they do not combine cost analysis with out-of-home delivery and failed attempts.

the language of cost, yet none combines it with out-of-home delivery or failed attempts.

Table 3. Synthesis of core papers (bibliographic details verified against OpenAlex/Crossref; content from the published abstracts).

Author(Year)	Problem variant	Method	Data	Key finding	Limitation for this study
Murray & Chu (2015)	Flying sidekick TSP (truck + drone)	MILP + heuristic	Test instances	Introduces truck–drone tandem delivery	Time objective; no cost per parcel
Kitjacharoensri et al. (2020)	Two-echelon VRP with drones	Mathematical model	Not stated in abstract	Extends drone routing to two echelons	Airspace access assumed
Cheng et al. (2020)	Drone routing with energy function	Formulation + exact algorithm	Not stated in abstract	Energy use makes drone range load-dependent	Drone-only fleet
Salama & Srinivas (2022)	Truck–multi-drone, flexible launch sites	Routing and scheduling model	Not stated in abstract	Flexible launch and recovery sites	No failure or locker option
Koch & Klein (2020)	Attended home delivery, dynamic pricing	Route-based approximate dynamic programming	Not stated in abstract	Couples delivery pricing with route cost	Time slots, not lockers
Fleckenstein et al. (2023)	Demand management + routing	Methodological review	Literature	Classifies integrated online-to-offline problems	No empirical cost evidence
Chu et al. (2023)	Order assignment + CVRP, food delivery	Smart predict-then-optimize + heuristics	Platform multi-source data	About 5% better than benchmark methods	Failures not modelled
Cook et al. (2024)	Constrained last-mile routing	Penalty-based local search (LKH)	Amazon challenge routes	Practical constraints can be handled efficiently	Van routes, United States
Lim et al. (2023)	Routing with attempt predictors	Prediction + two-stage greedy routing	Retailer data (South America); field experiment (Singapore)	Up to 20% of deliveries fail; algorithm cut failed attempts by 10%	No locker alternative
Tilk et al. (2021)*	VRP with delivery options (incl. lockers)	Branch-price-and-cut	Benchmark instances, up to 100 options	Exact solutions with shared-locker capacities	Van fleet; no unit economics
Ganapathina et al. (2024)	Home vs pickup-point steering	Two-stage stochastic programme; branch-and-bound	Instances up to 50 customers	Targeted incentives cut cost by 4–8% versus industry practice	European context
X. Wang et al. (2024)	Crowdkeeping	Bilevel model → MILP, row generation	Amazon data set	Keepers raise profit by consolidating and avoiding failures	Behavioural parameters assumed
U. Wang et al. (2026)	Shared locker network design	Continuous approximation + non-linear optimisation	Singapore pilot data	Poor locker network design can reduce productivity	Policy, not routing, focus
Janinchoff et al. (2024)	Out-of-home delivery	Review	Literature	OOH reduces failures and consolidates drops	No new evidence
Lebeau et al. (2015)	Fleet technology choice	Fleet size and mix VRP with time windows	Generated instances	Mixed-technology fleets can cut last-mile cost	Vans and trucks
Schaumann et al. (2023)	First/last-mile integration	Continuum approximation + symbolic regression	Numerical experiments	Time windows and capacity can eliminate integration gains	No failures
Lu et al. (2024)	Parcel delivery with driver helpers	Routing model with repeat visits	Numerical and field experiments	Hybrid helpers outperform other methods	Helper labour, not lockers
Gayialis et al. (2022)	City-logistics freight system	OR routing within an IT system	Not stated in abstract	Integrates information technology and OR	No lockers or failures

* From the robustness corpus. Years follow the journal issue. “Not stated in abstract” marks fields that could not be verified from the abstract.

2.4 Research gap

Figure 4 compares how often eight themes appear in the two sets of records. Drones (31% of the screened set and 21% of the broader set) and electric vehicles receive the most attention, while time windows are common. In the

broader corpus, parcel lockers or pickup points appear in 6.4% of records, failed deliveries in 1.1%, cost per parcel or cost-to-serve in 0.5%, two- or three-wheeler fleets in 1.0%, and Indian or other emerging-economy settings in 0.8%. Only eight of the 1,086 broader records mention

both lockers and failed deliveries, and just one also reports cost per parcel. The literature review helps explain this gap: studies of out-of-home delivery tend to optimise routes for high-wage van fleets, while cost-focused studies often leave failed attempts out of the model. This study addresses the economics of diverting deliveries to lockers when failure risk is present in a two-wheeler fleet operating in an emerging-market megacity. Each customer can be served in one of three ways: at home, where the first attempt fails with probability p_i and each failure costs π ; at a nearby parcel locker, with an incentive λ paid to the customer; or on the following day, with a deferral penalty ρ per parcel. The operator chooses each customer's service option, which lockers to visit and routes for up to K riders, each with capacity Q , to minimise daily cost-to-serve. The formulation builds on the two-index capacitated vehicle routing

problem (Toth & Vigo, 2014) and adds the elements needed to answer RQ3.

3.2 Formulation

Sets and indices. C : customers i ; L : candidate lockers l ; 0 : depot; $V = \{0\} \cup C \cup L$; $A \subseteq \{(i, j) \in V^2 : i \neq j\}$: arcs; $E_i \subseteq L$: lockers within straight-line distance r of customer i .

Parameters. q_i : parcels for customer i [parcels]; p_i : first-attempt failure probability [-]; d_{ij} : road distance [km]; v : average speed [km/h]; w : wage [INR/h]; $c^{km} = P^{\text{fuel}}/\eta$: fuel cost [INR/km] from fuel price P^{fuel} [INR/l] and efficiency η [km/l]; $c_{ij} = c^{km}d_{ij} + w d_{ij}/v$: arc cost [INR]; $F = c^{\text{veh}} + w h^{\text{dep}}$: fixed cost per route [INR], from vehicle cost per day c^{veh} and paid depot time h^{dep} [h]; s^H, s^L : service time per home and locker stop [h]; Q : rider capacity [parcels]; K : fleet size [riders]; U_l : locker capacity [parcels]; π : cost per failed attempt [INR]; λ : incentive per diverted customer [INR]; ρ : deferral penalty [INR/parcel].

Decision variables. $x_{ij} \in \{0, 1\}$: 1 if a rider traverses arc (i, j) ; $f_{ij} \geq 0$: parcels on board along (i, j) ; $y_i \in \{0, 1\}$: 1 if i is served at home; $z_{il} \in \{0, 1\}$: 1 if i is diverted to locker $l \in E_i$; $u_i \in \{0, 1\}$: 1 if i is deferred; $o_l \in \{0, 1\}$: 1 if locker l is visited.

Objective.

$$\min F \sum_{j: (0, j) \in A} x_{0j} + \sum_{\substack{(i, j) \in A \\ i \in C \\ j \in L}} c_{ij} x_{ij} + w s^H \sum_{i \in C} y_i + w s^L \sum_{l \in L} o_l + \pi \sum_{i \in C} p_i y_i + \lambda \sum_{i \in C} \sum_{l \in E_i} z_{il} + \rho \sum_{i \in C} q_i u_i \quad (1)$$

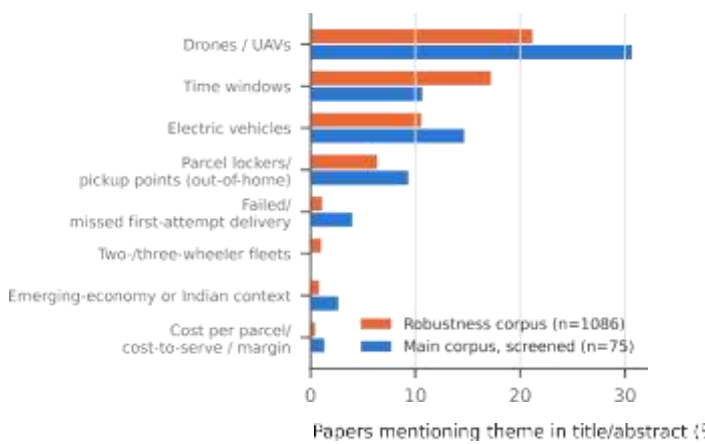


Figure 4. Share of articles mentioning each theme in title or abstract (regular-expression audit,

patterns in the replication code). Source: authors' analysis of OpenAlex data.

3. Problem description and model formulation

3.1 Problem description

A delivery station in Andheri East sends riders on petrol scooters to serve customers during a single delivery wave. Each customer may receive the delivery at home, collect it from an eligible nearby locker, or have the delivery deferred until the next day.

The objective includes seven cost components: fixed route costs, distance and driving-time costs, service time at homes and lockers, expected failed-delivery costs, locker incentives and deferral penalties.

Constraints.

$y_i + \sum_{l \in E_i} z_{il} + u_i = 1 \quad \forall i \in C$ (2) – each customer is served at home, at one eligible locker or deferred.

$$\sum_j x_{ij} = \sum_j y_i \quad \forall i \in C \quad (3) - \text{a rider enters and leaves a customer only}$$

if that customer is served at home.

$$\sum_j x_{lj} = \sum_j y_l \quad \forall l \in L \quad (4) - \text{a locker is entered and left once if it is visited.}$$

Compared with exponential subtour-elimination constraints (Öncan et al., 2009), these compact formulations have weaker linear-programming relaxations. The valid inequalities in constraints (12)–(14) help improve them.

$$z_{il} \leq o_l \quad \forall i, l \in E_i \quad (5) - \text{customers can be assigned only to visited lockers.}$$

$$\sum_{i:l \in E_i} z_{il} \leq o_l \quad \forall l \quad (6) - \text{a locker is visited only if it receives parcels.}$$

$$\sum_{i:l \in E_i} q_i z_{il} \leq U_l o_l \quad \forall l \quad (7) - \text{locker capacity (the supply side of the transportation layer).}$$

$$\sum_i x_{0i} = \sum_i x_{i0} \leq K \quad (8) - \text{routes start and end at the depot and do not exceed}$$

$$\sum_j f_{ji} - \sum_j f_{ij} = q_i y_i \quad \forall i \in C \quad (9) - \text{a home-served customer receives exactly its parcels.}$$

$$\sum_j f_{jl} - \sum_j f_{lj} = \sum_{i:l \in E_i} q_i z_{il} \quad \forall l \quad (10) - \text{a locker receives the parcels of all customers assigned to it.}$$

$$f_{ij} \leq (Q - q_i) x_{ij}, f_{i0} = 0 \quad \forall (i, j) \in A \quad (11) - \text{load never exceeds capacity and riders return empty } (q_0 = q_l = 0).$$

$$f_{ij} \geq q_j x_{ij} \quad \forall (i, j), j \in C \quad (12) - \text{a rider arriving at a customer still carries that customer's parcels (valid inequality).}$$

$$x_{ij} + x_{ji} \leq 1 \quad \forall i, j \in C, i < j \quad (13) - \text{no two-customer cycles (valid inequality).}$$

$$Q \sum_j x_{0j} \geq \sum_i q_i (1 - u_i) \quad (14) - \text{enough routes to carry all non-deferred parcels (valid inequality).}$$

Domains are as defined above (15).

3.3 Why integer variables are necessary

Constraints (2), (5) and (7) describe a capacitated transportation problem in which customers' parcels can be assigned to lockers. If the routes are fixed, the constraint matrix is totally unimodular, so the linear-programming relaxation would still produce integer locker assignments. Once routing is linked to the assignment decisions, that property no longer holds. A fractional value for x_{ij} would effectively send part of a rider along an arc or split a customer between home delivery and a locker, neither of which is operationally meaningful. In the toy instance, the LP relaxation bound is 17.9% below the integer optimum (Section 5.1), showing why simply rounding a relaxed solution would not be reliable. Binary variables are therefore needed for

et al., 1960), the flow formulation handles capacity and optional locker nodes within one family of constraints. Both compact formulations have weaker LP

3.5 Assumptions

- **A1** Demand and failure probabilities are deterministic, and failures enter as expected costs. This understates cost variance.
- **A2** There is a single delivery wave without time windows. This understates routing cost for quick-commerce settings (restrictive).
- **A3** Eligible customers accept diversion when offered λ . This overstates locker uptake relative to stochastic acceptance (Galiullina et al., 2024) (restrictive).
- **A4** π is a constant per failed stop, and re-delivery is not routed explicitly. This is a linear approximation.
- **A5** Road distances use the OSRM car profile and the city average speed. Two-wheelers can filter through traffic, so travel time is likely overstated.
- **A6** The fleet is homogeneous and served from one depot. Lockers never fail, carry no rental fee beyond λ , and have a fixed capacity. This overstates the locker benefit.
- **A7** Scaled instances use a granular arc set (Section 4.3). The reported optimum is therefore an upper bound on the full-graph optimum.

route arcs, service choices and locker visits.

3.4 Subtour elimination

Constraints (9)–(11) use a single-commodity flow formulation. A cycle disconnected from the depot would require a net inflow of parcels at each node, but a cycle on its own cannot supply that flow. This prevents subtours. Compared with the Miller–Tucker–Zemlin (MTZ) constraints (Miller et al., 1960), the flow formulation handles capacity and optional locker nodes within one group of constraints.

Table 4. Parameter values, sources and sensitivity ranges.

4. Data and implementation

4.1 Instance construction

The depot is in Andheri East (19.1136°N, 72.8697°E), a densely developed area with both residential and commercial activity. Four potential locker sites are metro-station access points: Airport Road, Marol Naka, Western Express Highway (WEH) and SEEPZ. Their coordinates were taken from OpenStreetMap, and the corresponding object identifiers are included in the data file. We generated 60 customer locations uniformly within a 2.5 km radius using a fixed random seed of 2026, then matched each location to the nearest drivable road. Each customer was assigned 1 + Poisson(0.4) parcels, giving 76 parcels in total, and a failure

probability drawn from {0.04, 0.08, 0.12}. The average probability of 0.08 matches the industry estimate reported by Loqate (2021) and falls within the range discussed by Lim et al. (2023). Road distances between all 65 nodes were calculated with OSRM using OpenStreetMap data (Luxen & Vetter, 2011). The nested instances S30, S45 and S60 use the first 30, 45 and 60 customers, respectively, with all four lockers. The toy instance contains four locker-eligible and four non-eligible customers and uses two lockers.

4.2 Parameters

Table 4 lists the model parameters, their sources or justifications, and the ranges used for sensitivity testing. All costs are expressed in Indian rupees (INR).

Parameter	Base value	Source/justification	Sensitivity
Fuel price P^{fuel}	111.21 INR/l	Mumbai retail petrol price, Sept 2026 (The Hans India, 2026)	±30%
Fuel efficiency η	45 km/l	ARAI-claimed 59.5 km/l for a Honda Activa 110 (BikeDekho, 2026), derated by ~25% for stop-start delivery (assumption)	—
Fuel cost c^{km}	2.47 INR/km	Derived: P^{fuel}/η	via fuel price
Wage w	65.55 INR/h	Maharashtra Zone I unskilled minimum wage INR 524.42/day (Ascent HR, 2025) ÷ 8 h; statutory floor	±30%
Vehicle cost c^{veh}	52 INR/day	Ex-showroom INR 78,025 (BikeDekho, 2026) over 5 years × 300 days; insurance and maintenance excluded	±30%
Depot time h^{dep}	1 h/route	Loading and briefing per route (assumption)	—
Fixed route cost F	117.55 INR	Derived: $c^{\text{veh}} + w h^{\text{dep}}$	via inputs
Speed v	20.8 km/h	Mumbai average speed 2025 (TomTom, 2026)	±30%
Service time s^H, s^L	5/8 min	Parking, building access and hand-over; locker loading (assumption)	—
Capacity Q	25 parcels	Scooter top box and rear rack (assumption)	15–40
Fleet K	$\lceil \text{demand}/Q \rceil + 1$	Available riders (assumption)	1–4
Locker capacity U_l	30 parcels	One locker bank (assumption)	—
Walking radius r	0.8 km	About a 10-minute walk at 4.8 km/h (assumption)	0.4–1.2 km
Failure probability p_i	0.04/0.08/0.12	Mean 0.08 = industry estimate (Loqate, 2021); within the up-to-20% range of Lim et al. (2023)	—
Failed-attempt cost π	60 INR	Re-delivery stop plus handling, about three times the optimal S30 cost per delivered parcel (assumption)	0–240
Locker incentive λ	10 INR	Discount coupon per diverted order (assumption)	0–80
Deferral penalty ρ	150 INR/parcel	Next-day re-handling and lost goodwill (assumption)	50–300
Demand q_i	1+Poisson(0.4)	Seeded generator; 1.4 parcels per stop on average (assumption)	±30%

4.3 Software, solver settings and hardware

We implemented the model in Python 3.9.6 using PuLP 3.3.1 and solved it with CBC 2.10.3 (Forrest & Lougee-Heimer, 2005). Runs used one thread on an Apple Mac with eight CPU cores and 8 GB of RAM. The relative optimality tolerance was 10^{-6} . The time limit was 600 seconds for the toy and scaled instances and 180 seconds for sensitivity runs. For the scaled instances, we limited the arc set to a granular graph: each node connected to its eight nearest customers in each direction, along with all depot and locker arcs. This follows the granular-neighbourhood approach of Toth and Vigo (2003). Since the neighbours are selected only from customers, the home-only model is an exact restriction of the locker model.

For S30, we also solved the full-graph model to proven optimality. It returned the same objective value, INR 777.58, in 166 seconds, so the arc restriction did not change the result for that instance. The paper's replication package includes the OpenAlex retrieval pipeline, instance generator, model, experiments and figures (Appendix B).

5. Results

5.1 Toy instance

The toy instance has eight customers, 11 parcels, two lockers and rider capacity $Q = 8$. CBC found the proven optimum in 0.2 seconds. Table 5 presents the full solution so readers can check the model's results.

Table 5. Toy instance: optimal solution and comparators.

Solution	Routes	km	Diverted	Cost
(INR)	INR/parcel			
MILP with lock-ers (optimal)	Depot → C1 → C4 → C2 → Marol Naka(L) → C16 → Depot	16.5	3	418.09
MILP home-only (optimal)	Depot → C1 → C2 → C3 → Depot	19.2	0	425.34
Nearest-neighbour	Depot → C16 → C23 → C21 → C26 → C4 → C2 → C1 → Depot	20.1	0	430.42
LP relaxation (bound)	Depot → C3 → Depot	—	—	343.11

In the optimal solution, three customers (C21, C23 and C26) are redirected to the Marol Naka locker. This removes their home-delivery stops and expected failure costs, in exchange for one locker visit and three customer incentives. Daily cost falls from INR 425.34 for the home-only optimum to INR 418.09, a 1.7% reduction. Nearest-neighbour routing costs INR 430.42, so the full model is 2.9% cheaper than current practice. The optimal solution costs INR 235.10 in fixed route costs, INR 40.85 in fuel, INR 52.09 in driving time, INR 36.05 in service time, INR 24.00 in expected failures and INR 30.00 in incentives. These components can be recalculated using

rent practice. The cost breakdown of the optimum is fixed route cost INR 235.10, fuel INR 40.85, driving time INR 52.09, service time INR 36.05, expected failures INR 24.00 and incentives INR 30.00. Each component can be recomputed by hand from Table 4 and the route distances in the data file. The LP relaxation bound of INR 343.11 lies 17.9% below the optimum, which confirms that the relaxation alone would misstate the cost.

5.2 Scaled instances and baseline comparison

Table 6 reports the scaled instances. S30 and S45 were solved to proven optimality

S30 and S45 were solved to proven optimality in 14 and 80 seconds, respectively. S60 reached the time limit with a relative gap of 1.00%, so its reported cost is an upper bound on the true optimum. Compared with nearest-neighbour routing, the MILP lowers daily cost by 4.9–8.2%. routing, the MILP reduces daily cost by 4.9–8.2%. The cost per delivered parcel

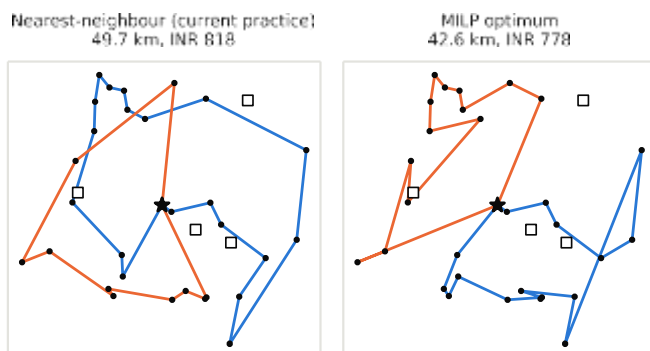
Table 4 and the route distances in the data file. The LP relaxation gives a bound of INR 343.11, which is 17.9% below the integer optimum and illustrates why the relaxed result alone would be misleading.

Cost per delivered parcel ranges from INR 19.00 to INR 20.46 and decreases as delivery density rises. The extra savings from locker diversion are smaller: 0.0% for S30, where no customers are diverted; 0.6% for S45, with two customers diverted; and 1.9% for S60, with eight customers diverted. Because both S60 solutions have an optimality gap of about 1%, its locker saving should be treated as indicative rather than definitive.

Table 6. Scaled instances: model size, solver performance and cost comparison (cost in INR per day).

Inst.	Parcels	Vars/cons	NN Home-only	MILP	Gap	Time(s)	Routes	MILP/NN	Diverted	INR/parcel
MILP	INR/parcel	NN Saving	vs NN (%)	Locker saving (%)	LP gap (%)					
S30	38 949/1,145	777.58	777.58	14	2/2	0	20.46	21.51	4.9	0.0
	817.56	0.00%								9.8
S45	56 1,391/1,704	1,122.92	1,116.15	80	3/3	2	19.93	21.24	6.1	0.6
	1,189.26	0.00%								10.8
S60	76 1,843/2,275	1,472.72	1,444.23	600	4/4	8	19.00	20.69	8.2	1.9
	1,572.64	1.00%								10.1

NN = nearest-neighbour routing with all customers at home and an unlimited fleet (“current practice”). Home-only = MILP with lockers disabled. Gap = CBC relative gap at termination. LP gap = (MILP – LP relaxation)/MILP.

Table 7. Sensitivity of S30 (re-solved to optimality; base values in bold).

Figure 5. S30 routes under nearest-neighbour routing

and the MILP optimum (star = depot; squares = lockers; dots = customers; colours = riders). Source: model output. Figure 5 illustrates how the routing savings arise in S30. Nearest-neighbour routing uses two routes covering 49.7 km, while the optimal plan also uses two routes but covers only 42.6 km. 42.6 km. With the same number of routes, the whole saving comes from dis- Since both solutions use the same number of routes, the entire saving comes from shorter travel: fuel and driving-



time costs fall by INR 39.99. The nearest-neighbour rule repeatedly selects the closest unvisited customer, which can leave the rider crossing the service area later to reach remaining stops. The MILP instead plans the route sequence as a whole. Service-time and expected failure costs are the same in both solutions because every customer is served at home. For RQ2, exact routing reduces S30's cost per parcel from INR 21.51 to INR 20.46.

6. Sensitivity and robustness analysis

Dual values are not defined for the integer optimum of a MILP, and the LP relaxation's dual prices relate to a fractional version of the problem. We therefore tested sensitivity by resolving S30 to proven optimality for each parameter setting. Table 7 covers fleet size, rider capacity, the three penalty weights and the locker catchment radius. Figure 6 ranks the cost drivers under changes of $\pm 30\%$, while Figure 7 shows how fleet size, capacity and break-even conditions affect the results.

Parameter	Value	Cost (INR)	INR/parcel	Routes	Diverted	Deferred	Gap
Fleet size K	1	2,371.97	94.88	1	0	13	0.00%
Fleet size K	2	777.58	20.46	2	0	0	0.00%
Fleet size K	3	777.58	20.46	2	0	0	0.00%
Fleet size K	4	777.58	20.46	2	0	0	0.00%
Capacity Q	15	914.13	24.06	3	3	0	0.00%
Capacity Q	20	777.58	20.46	2	0	0	0.00%
Capacity Q	25	777.58	20.46	2	0	0	0.00%
Capacity Q	30	777.58	20.46	2	0	0	0.00%
Capacity Q	40	648.29	17.06	1	0	0	0.00%
Failed-attempt cost π	0	638.38	16.80	2	0	0	0.00%
Failed-attempt cost π	30	707.98	18.63	2	0	0	0.00%
Failed-attempt cost π	60	777.58	20.46	2	0	0	0.00%
Failed-attempt cost π	90	842.52	22.17	2	3	0	0.00%
Failed-attempt cost π	120	901.67	23.73	2	6	0	0.00%
Failed-attempt cost π	180	1,014.47	26.70	2	6	0	0.00%
Failed-attempt cost π	240	1,122.82	29.55	2	7	0	0.00%
Locker incentive λ	0	728.82	19.18	2	7	0	0.00%
Locker incentive λ	5	758.87	19.97	2	6	0	0.00%
Locker incentive λ	10	777.58	20.46	2	0	0	0.00%
Locker incentive λ	20	777.58	20.46	2	0	0	0.00%
Locker incentive λ	40	777.58	20.46	2	0	0	0.00%
Deferral penalty ρ (K = 1)	50	1,071.97	42.88	1	0	13	0.00%
Deferral penalty ρ (K = 1)	100	1,721.97	68.88	1	0	13	0.00%
Deferral penalty ρ (K = 1)	150	2,371.97	94.88	1	0	13	0.00%
Deferral penalty ρ (K = 1)	300	4,321.97	172.88	1	0	13	0.00%
Walking radius r (km)	0.4	777.58	20.46	2	0	0	0.00%
Walking radius r (km)	0.8	777.58	20.46	2	0	0	0.00%
Walking radius r (km)	1.0	773.32	20.35	2	5	0	0.00%
Walking radius r (km)	1.2	738.29	19.43	2	10	0	0.00%

Fleet size. With only one rider, 13 customers (13 parcels) must be deferred, pushing daily cost up to INR 2,371.97. From two riders onward, cost remains at INR 777.58 because two riders can carry all 38 parcels. At a deferral penalty of $\rho = 150$, the second rider is therefore worth INR 1,594.39 per day, while a third rider adds no further saving. *Capacity.* Reducing capacity to 15 parcels raises cost per parcel to INR 24.06 and requires three routes. Increasing capacity to 40 lowers cost per parcel to INR 17.06 because all deliveries can be completed on one route. Capacity therefore affects cost mainly by changing the number of routes and their fixed costs (Figure 7b). *Penalty weights.* The failed-attempt cost π increases total cost almost linearly because each home-served customer adds an expected cost of $\pi\pi$. With $\lambda = 10$, lockers are selected only when π reaches at least INR 90; with $\pi = 60$, they are selected when λ is INR 5 or lower. A wider walking radius has a similar effect (Table 7, Figure 7c). The deferral penalty ρ matters most when the fleet is too small, because it determines the cost of not having another rider available.

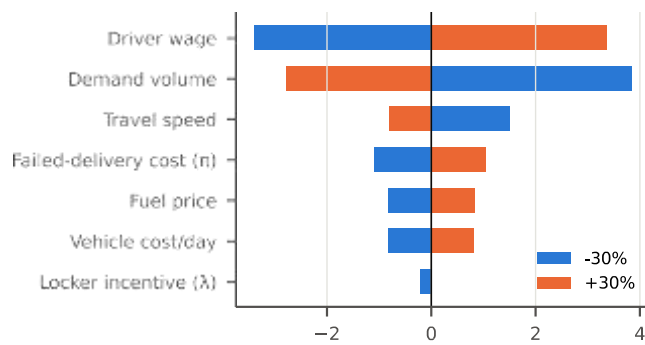


Figure 6 compares the main drivers of cost per parcel. Driver wages have the largest effect, moving the cost from INR 17.07 at a 30% lower wage to INR 23.83 at a 30% higher wage. Demand volume and travel speed are the next most influential factors. Across the tested range, fuel price changes cost per parcel by only INR 1.66 because fuel represents a relatively small share of two-wheeler delivery costs. Higher travel speeds reduce the wage cost associated with driving time, suggesting that congestion in Mumbai affects labour costs more than fuel costs. Demand volume is scaled per stop and rounded to whole parcels, changing total demand from 38 to 32 or 44 parcels. When more parcels share the fixed route costs, the cost per parcel falls. A 30% increase in wages also shifts three customers to lockers, indicating that locker diversion becomes more attractive as labour costs rise.

Figure 6. Tornado chart: change in optimal cost per delivered parcel for $\pm 30\%$ changes in each parameter (S30, re-optimised). Source: model output.

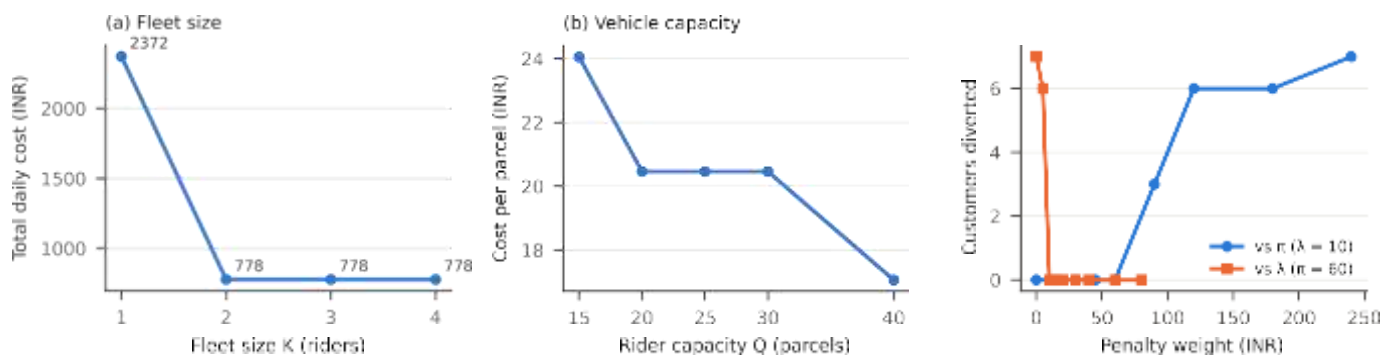


Figure 7. (a) Total cost versus fleet size; (b) cost per parcel versus rider capacity; (c) customers diverted to lockers versus the failed-delivery cost π (with $\lambda = 10$) and the locker incentive λ (with $\pi = 60$). S30, re-optimised. Source: model output.

7. Discussion

7.1 Theoretical implications

The bibliometric results point to a fast-growing field that focuses more on technologies—especially drones—than on the economics of delivery services. The model helps explain why that imbalance matters. Route optimisation produces consistent savings, but the value of an out-of-home option depends on a parameter that is rarely measured: the full cost of a failed delivery attempt. In the S30 base case, expected failure costs account for 17.9% of daily costs. At the base-case prices, lockers attract three customers in the toy instance, two customers in S45 and eight in S60, but none in S30 because the eligible customers are not clustered closely enough around a locker. These results support Lim et al.'s (2023) argument that delivery outcomes should be modelled directly, while qualifying the generally positive view of

out-of-home delivery in Janinhoff et al. (2024): its benefits depend on local cost conditions rather than applying everywhere.

7.2 Managerial and financial implications

The results suggest three practical lessons for delivery-station managers and quick-commerce finance teams. First, better route planning is the most reliable way to reduce costs. In S30, the optimal plan saves INR 39.99 per day (4.9%), or INR 1.05 per parcel; the savings reach 8.2% in S45 and S60. Each rupee saved per parcel directly improves the contribution margin, and these savings come from better software and planning rather than major capital spending. Second, lockers should be assessed using the actual cost of failed deliveries, not route efficiency alone. With relatively low wages in Mumbai, skipping a home stop saves only a small amount of rider time. Incentives above INR 5 per order remove the benefit unless a failed attempt costs at least INR 90. Before negotiating locker

contracts, operators should measure the full cost of failure, including redelivery, customer service and cancelled orders. Third, fleet investment has a step-like effect: a second rider is worth INR 1,594.39 per day when deliveries would otherwise be deferred, but an additional rider has no value once capacity is sufficient. Greater carrying capacity, such as a larger top box or an electric cargo scooter, can reduce costs by eliminating entire routes (Figure 7b). These estimates come from a synthetic instance based on real roads, so they indicate the likely scale of effects rather than serving as company forecasts.

7.3 Limitations

First, requiring the terms “operations AND research” reduced the corpus to 95 records out of 1,086 identified by the robustness search (8.7%). This favours papers that explicitly use operational-research terminology, including review articles, and leaves a relatively small sample for science mapping. The comparisons in Figures 2 and 4 help assess this bias but cannot eliminate it.

The small sample also makes the thematic-map cluster boundaries sensitive to individual papers. Second, we used OpenAlex rather than EBSCO, as specified in the course protocol, because library access was unavailable. OpenAlex assigns some keywords automatically and reports citation counts that differ from Google Scholar, so the review should be repeated using EBSCO. Third, the gap audit uses title and abstract terms and may miss papers that discuss failed deliveries only in their full text. Fourth, the customer locations are synthetic, although they were generated with a fixed seed and mapped to real roads, and several cost inputs are assumptions rather than observed company data (Table 4). Fifth, assumptions A2 and A3 affect results in opposite ways: excluding time windows understates routing costs, while assuming customers always accept locker diversion overstates locker uptake. Finally, the scaled instances use a restricted set of arcs, and the largest instance did not reach a zero optimality gap before the time limit.

8. Conclusion and future research agenda

RQ1. Research on last-mile optimisation has expanded quickly since 2020, spans 55 journals and remains fragmented across collaboration networks. Drone-assisted routing dominates, while failed deliveries are mentioned in only 1.1% of the broad corpus, cost per parcel in 0.5%, and two-wheeler fleets in emerging economies receive little attention.

RQ2. For the Andheri East two-wheeler fleet, exact MILP routing reduced daily costs by 4.9–8.2% compared with nearest-neighbour routing, bringing cost per delivered parcel to INR 19.00–20.46.

RQ3. Locker diversion added savings of up to 1.9% and

was selected only when a failed attempt cost at least INR 90 or the incentive was INR 5 or less. Driver wages had the strongest influence on cost per parcel, followed by demand volume. In practice, operators should optimise routes first, measure the cost of failed deliveries next, and then decide whether lockers are worth introducing. Future research priorities are summarised in Table 8 and follow from the emerging themes and gaps identified in the bibliometric analysis.

**Table 8.** Future research agenda derived from the thematic map and gap audit.

Theme (map position)		Open
question	Suggested method	
Failed deliveries (gap audit: 1.1%)	What is the full cost of a failed attempt in Indian e-commerce, including re-delivery and returns?	Activity-based costing with carrier data; regression on attempt outcomes
Parcel lockers with uncertain acceptance (basic theme)	How does stochastic acceptance of locker incentives change the break-discrete-choice survey even incentive?	Two-stage stochastic MILP;
Crowdshipping and bi-level design (motor theme)	Can neighbourhood shops act as low-cost pickup points in Indian cities?	Bilevel optimisation; field pilot
E-commerce logistics and customer satisfaction (emerging; trend topics)	How do quick-commerce delivery promises change the value of lockers?	VRP with time windows; branch-and-cut with valid inequalities
Drones with MIP (motor theme)	What is the cost per parcel of drone delivery once airspace and battery costs are priced?	Cost-based MILP; life-cycle costing
CO2 emissions and cost minimisation (emerging)	What carbon price would justify electric two-wheelers in Mumbai?	Bi-objective MILP; carbon-price frontier

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**Appendix A. Exclusion log**

Year	Title	Journal	Document type	Reason for exclusion
2023	Last mile delivery Optimisation model for drone-enabled Vehicle Routing Problem	Emerging Minds	Student research journal article	Student work (student research journal)
2024	Urban Air Mobility for Last-Mile Transportation: A Review (review)	Research	Vehicles	Journal article
2025	A combined fleet size and mix vehicle routing model for last-mile distribution in distribution	Out of scope: passenger air mobility	2025 A combined Progress in Disaster Science	Out of scope: disaster-relief
2025	OPTIMIZATION OF LAST-MILE DELIVERY IN KSA	Quantum Journal of Engineering Science	Journal article	Duplicate publication of the same study in a second journal
2025	Optimizing Last-Mile Public Transit Services by Leveraging Modular Autonomous Vehicle	Journal of Transportation Engineering	Journal article	Out of scope: passenger public transit
2025	Enhancing food security at the last-mile: A light-weight and scalable decision support distribution system (welfare	Journal article	Socio-Economic Planning	Out of scope: public food-logistics)
2024	DEVELOPMENT OF A MOBILE WHEELED ROBOT FOR PARCEL DELIVERY	Transport engineering (engineering design)	Journal article	Out of scope: robot hardware design, no OR model
2016	Empirically grounded research in humanitarian operations management: The way forward	Journal of Operations Management	Journal article (research)	Out of scope: humanitarian operations management, no delivery model
2025	Introduction: 2024 Daniel H. Wagner Prize for Excellence in the Practice of Advanced INFORMS Journal on Applied Analytics	Editorial introduction	Introduction to a special issue	
2019	Mathematical model of the technology of transit cargo flows' management within the in	Automobile Transport	Journal article	Out of scope: long-haul international corridor freight
2023	Introduction: 2022 Daniel H. Wagner Prize for Excellence in the Practice of Advanced INFORMS Journal on Applied Analytics	Editorial introduction	Introduction to a special issue	
2024	A Data-Driven Optimization Framework for Static Rebalancing Operations in Bike Sharing	INFORMS journal on computing	Journal article	Out of scope: bike-sharing rebalancing
2021	Food aid supply and distribution in insecure regions: world food programme operation (case study)	Production	Journal article	Out of scope: humanitarian food-aid case study
2023	Integration of Three Vehicle Fleet Types for Delivering Relief Supplies During a Natural	Applied Science and Engineering Progress	Journal article	Out of scope: disaster-relief distribution
2023	Quantum Computing for Supply Chain and Logistics Optimization The Evolution of Computing	International Journal of Scientific Research	Journal article (conceptual)	Out of scope: generic computing
2019	RETRACTED ARTICLE: E-commerce information system data analytics by advanced ACO for a	Information Systems and Business Management	Retracted article	Retracted by publisher
2025	Inbound Truck Scheduling for Workload Balancing in Cross-Docking Terminals	Mathematics	Journal article	Out of scope: cross-dock terminal operations



2023 Truck scheduling with fixed outbound departures in a closed-loop conveyor system with	Flexible Services and Manufacturing Jour	Journal article	Out of scope: intralogistics conveyor scheduling
2025 Detecting Road Defects and Hazards in Metropolitan Environments Using Optimized Deep	Transportation research procedia road-defect computer vision	Journal article	Out of scope:
2022 Survival strategies adopted by microbusinesses during COVID-19: an exploration of eth	International Journal of Entrepreneurial strategy, no delivery	Journal article (qualitative)	Out of scope: restaurant business optimisation

Appendix B. Data and code availability

The replication package contains the OpenAlex retrieval script and raw JSON, the screening and bibliometric analysis code, the final dataset and exclusion log (CSV), the Mumbai instance generator and data file with OSM object identifiers and OSRM distances, the MILP and experiment code, all result files and a README. Repository link: [insert GitHub/Colab link].