

Review

Planning of Logistic Networks with Automated Transport Drones: A Systematic Review of Application Areas, Planning Approaches, and System Performance

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Abstract

Background: The increasing integration of automated transport drones into logistics networks presents transformative potential for addressing contemporary logistics challenges, particularly in last-mile delivery, healthcare, disaster response, urban mobility, and postal services. However, their effective integration into varied logistics contexts remains hindered by infrastructure, regulatory, and operational limitations. This study aims to explore how drone-based logistics systems can be systematically planned and evaluated across diverse operational environments. **Methods:** A structured literature review was conducted, employing thematic synthesis to analyze current research on drone logistics. The analysis focused on identifying the key planning dimensions and interrelated components that influence the deployment of drone-based transport systems. **Results:** The review identified seven central planning dimensions: areas of application, system components, transport configuration, geographic areas, optimization and analysis methods, logistical planning, and performance assessment. These dimensions inform a conceptual framework designed to guide the planning and assessment of drone logistics networks. **Conclusions:** While existing studies contribute valuable insights into route optimization and drone deployment strategies, they often overlook integrative approaches that account for societal and environmental factors. The study emphasizes the need for interdisciplinary collaboration and context-specific planning frameworks to enhance the sustainable and effective implementation of drone-based logistics systems.

Keywords: logistics planning; drones; last-mile; delivery; air mobility; healthcare logistics; optimization



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1. Introduction

The logistics industry is undergoing a fundamental shift, fueled by the convergence of digitalization, automation, and the global push for more sustainable and customer-centric delivery solutions [1,2]. Within this transformation, unmanned aerial vehicles (UAVs), commonly referred to as drones, have emerged as a highly promising innovation. When enhanced with advanced automation capabilities such as autonomous flight control, obstacle detection, and dynamic decision-making, these systems are classified as highly automated transport drones. Their ability to operate independently over a wide range of distances positions them as a flexible solution for both traditional and emerging logistics demands [3].

These drones offer substantial benefits in terms of delivery speed, geographic accessibility, and environmental impact [3]. Unlike conventional delivery methods that rely on congested road infrastructure, drones are not constrained by surface conditions and can access hard-to-reach areas with minimal delay. Consequently, their applications have rapidly expanded beyond early experimental use cases. In urban environments, they support last-mile parcel delivery services, offering rapid fulfillment of e-commerce orders. In rural and remote regions, they enable reliable and timely transport of essential supplies, such as blood, vaccines, and medicines [4]. Disaster relief efforts and humanitarian logistics have also benefited from drone capabilities, especially when conventional logistics infrastructure is compromised [4].

Major logistics providers, retailers, and start-ups alike are investing in drone delivery systems. High-profile pilot projects in both developed and developing regions illustrate the growing momentum behind this technology [5]. These projects demonstrate not only improvements in service quality and operational efficiency but also notable reductions in greenhouse gas emissions when compared to fossil-fuel-based delivery modes [6]. However, integrating drones into logistics networks on a large scale is not without its challenges.

Several barriers impede the widespread adoption of highly automated drones. From a regulatory perspective, airspace integration, certification requirements, and privacy concerns must be addressed to ensure safe and compliant operations [7,8]. Technically, drones face operational limitations related to battery endurance, payload capacity, adverse weather conditions, and the need for landing or charging infrastructure. Social acceptance and safety concerns, particularly in shared urban airspace further complicate deployment scenarios [7,8]. These challenges demand advanced planning, supported by robust algorithms, infrastructure investments, and interdisciplinary collaboration.

Despite the growing body of research addressing individual aspects of drone logistics such as routing algorithms, flight control, or network architecture, there is a lack of comprehensive, systematic guidance for integrating highly automated drones into larger logistics systems [7]. Current studies often focus on isolated technical problems or single-case pilot implementations, limiting the transferability and scalability of proposed solutions [4]. Moreover, the literature spans multiple disciplines, including operations research, transportation science, robotics, and urban planning, making it difficult to consolidate knowledge and extract overarching strategies.

To address this gap, the present study conducts a systematic literature review (SLR) that synthesizes current research on planning logistics networks with highly automated transport drones. By identifying and analyzing contributions from various domains, the study aims to develop a structured overview of the state of the art, highlighting application areas, methodological approaches, system configurations, and performance metrics. For this purpose, the following research questions are formulated:

- *RQ1:* What types of planning problems are addressed in the design of drone-based logistics networks, and how are these problems formulated across different application domains?
- *RQ2:* Which use cases are considered in the literature for the planning of drone-based logistics problems?
- *RQ3:* What methodological approaches are employed in the literature to solve logistics planning problems involving drones?
- *RQ4:* How are the key components of drone-based logistics systems represented and integrated into planning models?
- *RQ5:* How are drone-based logistics systems evaluated in the literature, and what performance criteria are commonly used?

The remainder of this paper is structured as follows: Section 2 describes the systematic review methodology, including the search strategy, inclusion and exclusion criteria, and classification procedure. Section 3 presents the descriptive and thematic results of the review. Section 4 introduces a conceptual framework for planning drone logistics networks based on the identified categories. Section 5 provides a discussion of key findings, challenges, and research directions. Finally, Section 6 concludes the study with a summary of contributions and recommendations for future work.

2. Methodology

This section outlines the methodology applied in conducting a systematic literature review (SLR) on the planning of logistics networks with highly automated transport drones. A systematic approach enables a transparent, replicable, and comprehensive analysis of the current state of research [9,10]. The process includes defining the scope of the study, selecting appropriate databases, developing a search strategy, applying inclusion and exclusion criteria, and extracting relevant data for thematic analysis [11,12]. By adopting this structured method, potential biases in study selection are minimized, while key research themes, trends, and gaps can be effectively identified.

2.1. Research Scope and Focus

The review focuses on planning tasks within logistics networks that incorporate highly automated transport drones. The scope includes studies that examine logistical applications (e.g., last-mile delivery, healthcare supply chains, postal services), planning problems (e.g., network design, routing, location planning), and system components (e.g., hubs, drones, multimodal configurations). Studies are analyzed based on their geographical focus (urban, suburban, rural, remote) and methodological orientation (e.g., optimization models, simulations). Only peer-reviewed literature published within the past decade was considered, to ensure relevance given the recent acceleration in drone technology and regulatory development.

2.2. Database Selection

Two databases were chosen for the literature search: Scopus and Web of Science. These platforms were selected for their broad interdisciplinary coverage, especially in the fields of logistics, transportation, and aviation [13]. Both databases are widely used in SLRs and ensure a high standard of source quality. Preliminary explorations confirmed that other databases offered little added value and largely overlapped with the results from Scopus and Web of Science. Duplicate entries identified during the search were removed during the screening stage.

2.3. Search Strategy

The search strategy followed an iterative process to ensure relevance and completeness. The development of the final search string involved identifying core concepts and relevant keywords related to drone logistics, such as “transport drone”, “autonomous UAV”, “logistics network”, “delivery”, and “planning”. Synonyms and application-specific terms (e.g., “healthcare logistics”, “urban mobility”, “postal delivery”) were also considered. The refinement of the search string was conducted over nine iterations, aiming to strike a balance between comprehensiveness and manageability. As recommended by [14], each iteration was assessed for sensitivity and specificity. Table 1 presents the finalized search string used in both databases.

Table 1. Search strings.

<i>Database</i>	<i>Search Strings</i>
Scopus	TITLE-ABS-KEY = ("logistic*" OR "network") AND ("plan*" OR "design*") AND ("goods" OR "transport" OR "material*") AND ("drone*" OR "autonomous transport*" OR "uas" OR "aerial systems" OR "quadcopter") NOT ("military" OR "marine" OR "deep learning" OR "forest*")
Web of Science	TS = ("logistic*" OR "network") AND ("plan*" OR "design*") AND ("goods" OR "transport" OR "material*") AND ("drone*" OR "autonomous transport*" OR "uas" OR "aerial systems" OR "quadcopter") NOT ("military" OR "marine" OR "deep learning" OR "forest*")

The goal was to retrieve between 400 and 800 publications in the initial search phase, prior to filtering and deduplication. The strategy deliberately excluded application domains unrelated to transport logistics, such as agriculture, construction, and surveying, as these fields involve distinct regulatory, technical, and operational characteristics [15]. For instance, agricultural drones are primarily used for data collection or environmental monitoring, and thus fall outside the scope of drone-based logistics planning.

2.4. Inclusion and Exclusion Criteria

To ensure quality and consistency, only English-language publications were included. Eligible sources consisted of journal articles, peer-reviewed conference proceedings, and book chapters. Studies were included if they explicitly addressed the use of drones in planning or designing logistics networks. Papers focusing solely on drone technology without a logistics or planning context were excluded. Moreover, studies needed to provide generalized insights or applicable findings beyond a single case study, as well as address real-world implementations or theoretical models relevant to logistics.

Additional selection criteria included the geographical relevance and methodological clarity of the papers. Studies that illustrated planning strategies across different spatial settings such as urban, rural, remote were prioritized to support comparative analysis.

2.5. Screening and Data Extraction

The systematic workflow is outlined using the PRISMA framework, as illustrated in Figure 1. The process begins with a comprehensive database search, followed by the removal of duplicate records. Subsequently, titles and abstracts were screened for relevance to the research scope. In the final screening phase, full-text articles were assessed in accordance with the predefined inclusion criteria, leading to the final selection of studies for analysis.

The resulting dataset of selected publications was coded based on predefined thematic categories: planning tasks, application areas, methodological approaches, logistics system elements, geographic scope, performance evaluation, and transport modes, which serve as the analytical foundation for the review. These categories reflect the research questions and structure the findings presented in the following sections.

The initial search yielded a total of 608 results: 340 from Scopus and 268 from Web of Science. All records were exported and imported into a literature management tool designed for systematic reviews. This tool enabled efficient handling of duplicates and facilitated the multi-stage screening process using customizable inclusion and exclusion filters [16].

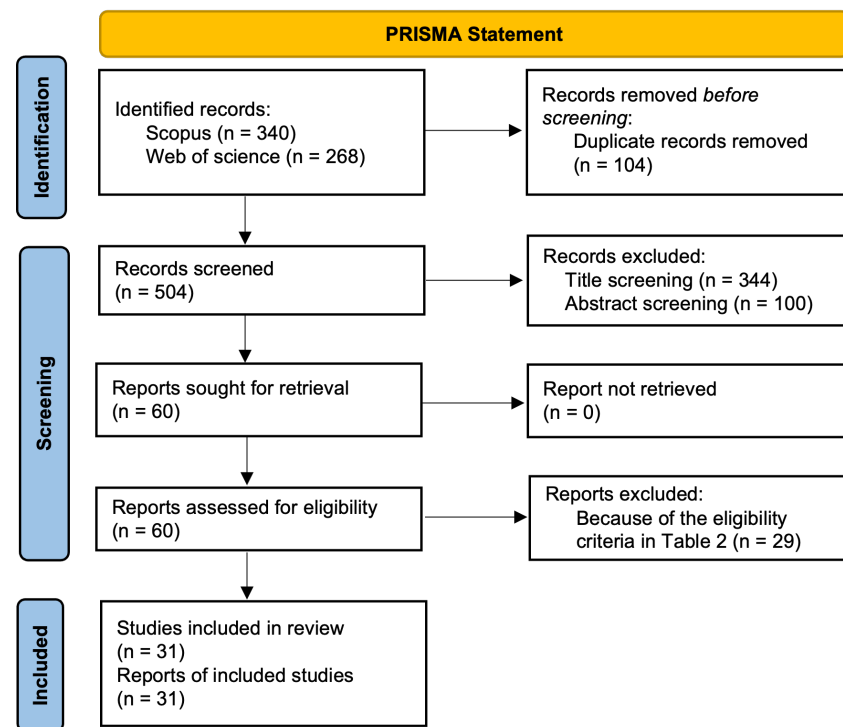


Figure 1. The Prisma flowcharts followed in the literature review.

Duplicate detection was the first step in data cleaning. Publications with matching titles, DOIs, authors, or keywords were flagged as potential duplicates. Of the 206 matches identified, 104 were removed, resulting in a consolidated dataset of 504 unique entries for further screening.

Screening was carried out in three stages: title screening, abstract screening, and full-text screening. During title screening, all entries were manually reviewed based on their titles to determine initial relevance. Despite the filtering built into the search string, a considerable number of irrelevant studies remained, often due to ambiguous or broad terminology. Titles were evaluated against defined inclusion and exclusion criteria, shown in Table 2, with decisions made to include, exclude, or flag publications as “maybe” if further review was needed.

Table 2. Inclusion and exclusion criteria applied during title screening (Author’s own presentation).

Inclusion Criteria		Exclusion Criteria	
Commercial transport	Civil drones	Military applications	Armed drones
Intermodal transport	Urban logistics	Forestry applications	Defense logistics
Distribution networks	Supply planning	Passenger drones	Combat operations
Resource allocation	Business logistics	Weaponized drones	Agricultural uses
Operational logistics	Route optimization	Military training	Autopilot systems
Economic operations	Last mile logistics	Sensor technology	
Multimodal transport	Rural transport	Trajectory analysis	
Tactical analysis		Warfare logistics	

Combinations of the above criteria were also applied to identify false positives. Publications from unrelated disciplines, such as computer science or medical imaging with no link to transport drones, were excluded. This process led to the exclusion of 344 records. Of the remaining studies, 102 were marked as “maybe” and 58 were retained for abstract screening.

In the abstract screening phase, the 160 retained publications (58 included and 102 maybe) underwent a detailed review of their abstracts. This step assessed whether the study content aligned with the research scope. The literature management tool's tagging features were used to apply predefined filters to each abstract. At this stage, 100 publications were excluded, 38 were tagged as “maybe”, and 22 were retained for full-text screening.

The final screening stage involved a full-text review of the remaining 60 publications (22 included and 38 maybe). Where available, full-text versions were retrieved electronically. Each publication was read in full, and a final decision on inclusion was made based on the original criteria. Studies that passed this stage were entered into a structured literature review matrix for detailed thematic analysis. A total of 31 publications successfully passed all three screening layers and were included in the final literature review for detailed qualitative analysis. These studies form the basis for the synthesis presented in the following section.

To facilitate the synthesis of results, the following analytical dimensions were used to categorize each study: Application Context (Areas of application and Geographical setting), System Components, Optimization & Analysis Methods, Transport Configuration, Logistical Planning, and Performance Assessment. These dimensions reflect critical perspectives drawn from the literature on smart logistics and drone-based transport systems as discussed in the research works of [17–19]. Table 3 presents descriptions for each dimension used in the review.

Table 3. Description of parameters included in the review.

Component	Description
Areas of application	Use cases: last-mile, emergency/medical, urban mobility, postal services
Geographic area	Application setting: urban, suburban, rural, island/remote)
System Components	Logistics building blocks: nodes, edges, routes, vehicles, payload
Optimization & Analysis Methods	Tools like heuristics, mathematical models, simulations, case studies
Transport Configuration	Delivery architecture: UAS-only, Drone + X, Truck-drone systems
Logistical Planning	Strategic planning: route optimization, location of hubs, network structure
Performance Assessment	Evaluation criteria: scalability, efficiency, reliability, speed, safety

3. Results and Analysis

3.1. Bibliometric Analysis

The bibliometric analysis is organized into two main areas. The first focuses on relevant and related topics analysis, mapping the frequency and the co-occurrence of specific topics. The second examines the geographical distribution of key reviewed publications.

3.1.1. Related Topic Analysis

The first part of the bibliometric analysis is focused on the most relevant and related topics of the reviewed publications. The following Figure 2 is a network visualization map generated from VOSviewer version 1.6.20 software and depicts the average timeline showing when the various key points appeared in a weighted chronological order across all connecting papers.

3.2. Thematic Analysis

This subsection presents the findings of the systematic literature review, focusing on the 31 publications that passed the final full-text screening stage. Each study is examined using the analytical framework introduced in the methodology section, encompassing key dimensions such as planning tasks, application areas, methodological approaches, system components, geographical contexts, assessment criteria, and transport configurations. These dimensions provide a structured basis for analyzing the literature and enable a comparative evaluation across diverse studies.

The results are organized into seven thematic tables, each aligned with one of the aforementioned dimensions. These tables offer a synthesized overview of how each study addresses the respective aspect, supplemented by narrative explanations that interpret emerging patterns and contextualize the findings.

Logistical Planning Approaches

The first dimension examined in the review is the type of logistical planning problem addressed by each study, as summarized in Table 4. This analysis considers whether the study explicitly engages with a logistical planning task, and if so, classifies it into one or more of four commonly recognized categories in the logistics literature:

- *Route Planning*: This operational task involves determining the most efficient paths for transportation, taking into account factors such as distance, travel time, delivery time windows, traffic conditions, and vehicle capacity. The primary objective is typically to minimize travel costs or delivery times while meeting operational constraints [20].
- *Network Planning*: This involves the strategic design and optimization of the overall transportation or distribution network. It includes decisions on the structure of the logistics system—such as how nodes (e.g., facilities or hubs) and links (e.g., transport routes) are connected—and aims to ensure cost-efficiency, scalability, and service quality across the entire network [21].
- *Location Planning*: This focuses on selecting optimal sites for logistics facilities, such as warehouses, distribution centers, or micro-hubs. The decision-making process considers factors such as proximity to customers, cost of land or infrastructure, and accessibility. The goal is to minimize logistics costs while maximizing service efficiency [21].
- *Allocation Planning*: Allocation planning addresses how key resources—such as vehicles, staff, or inventory—should be distributed across the logistics network. This includes determining how many units of a resource should be assigned to which location to ensure balanced workload distribution, cost-effectiveness, and high service levels [22].

Each reviewed study is classified into one or more of these planning categories based on its core focus. This classification sheds light on which logistical challenges are most frequently explored in the context of drone-based logistics and helps identify underrepresented areas that may warrant further research.

Table 4. Logistical planning task.

Logistical Planning Tasks	
Route planning	
1. Bogyrbayeva, A.; Yoon, T.; Ko, H. B.; Lim, S.; Yun, H. Y.K.; Kwon, C. (2023) [23]	Bogyrbayeva et al. (2023) [23] describe a route planning problem using artificial intelligence in relation to the TSP-D, the travelling salesman problem with drones.
2. Bruni, M. E.; Khodaparasti, S.; Perboli, G. (2023) [24]	Bruni et al. (2023) [24] presents selection of fulfillment centers to use and determines drone trips serving multiple customers.
3. Chiang, W. C.; Li, Y. Y.; Shang, J.; Urban, T. L. (2019) [25]	Chiang et al. (2019) [25] uses a mixed-integer (0–1 linear) green routing model in relation to sustainability aspects.
4. Hamid R. Sayarshad (2025) [26]	In the optimization model by Sayarshad (2025) [26], optimized delivery routes are developed to ensure timely vaccine distribution.
5. Gao, J. J.; Zhen, L.; Wang, S. A. (2023) [27]	Gao et al. (2023) [27] assigns customers to truck groups; schedules both vehicle trips and drone flights. The study covers both pickup and delivery within one integrated model, under time/window constraints.
6. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28]	Eberhardt et al. (2025) [28] considers routes optimization to prioritize supply delivery and minimize deprivation time.
7. Hong, F.; Wu, G.; Luo, Q.; Liu, H.; Fang, X.; Pedrycz, W. (2023) [29]	Hong et al. (2023) [29] present a two-phase optimization approach for drone-based package delivery, where the first phase addresses location planning for distribution points, and the second phase focuses on detailed route optimization.
8. Hu, Z. C.; Chen, H.; Lyons, E.; Solak, S.; Zink, M. (2024) [30]	Hu et al. (2024) [30] developing a decision support system for UAV path planning under the consideration of stochastic weather evolution.
9. Peng, Y.; Ren, Z.; Yu, D.Z.; Zhang, Y. (2025) [31]	Peng et al. (2025) [31] developed an optimization model to ensure time-efficient delivery paths for both trucks and drones.
10. Lin, M.; Lyu, J.-Y.; Gao, J.-J.; Li, L.-Y. (2020) [32]	A work by Lin et al. (2020) [32], determines coordinated paths for truck and drones; drones serve designated customer clusters while truck stops at planned points.
11. Patchou, M.; Sliwa, B.; Wietfeld, C. (2021) [33]	Patchou et al. (2021) [33] addresses the hybrid routing problem with drones and a dynamic pickup and delivery approach, allowing aerial vehicles to pick up packets from a moving truck.
12. Pina-Pardo, J. C.; Silva, D. F.; Smith, A. E. (2021) [34]	Pina-Pardo et al. (2021) [34] presents joint determination of truck route and drone resupply timing/locations, adjusting dynamically to order release times.
13. Lu, J.; Liu, Y.; Jiang, C.; Wu, W. (2025) [35]	Lu et al. (2025) [35] develops a Truck-UAV delivery route for truck drone joint delivery in rural China, considering both Truck and single drone, and truck multiple drone combinations.

Table 4. Cont.

Logistical Planning Tasks	
Network planning	
14. Gao, C.-F.; Hu, Z.-H.; Wang, Y.-Z. (2023) [36]	Gao, C.-F. et al. (2023) [36] analyses the TSP-D in terms of the development of the entire network. Here, both locations and the entire routes are included in the optimization of a hub-and-spoke network.
15. Hong, I.; Kuby, M.; Murray, A. T. (2018) [37]	The model of Hong et al. (2018) [37] „combines elements [...] to locate stations and construct a feasible and efficient delivery network in order to serve a region efficiently“.
16. Pinto, R.; Lagorio, A. (2022) [38]	Pinto & Lagorio (2022) [38] identifies optimal locations for charging stations and integrates them into point-to-point delivery routes.
17. Ulmer, M. W.; Streng, S. (2019) [39]	Ulmer & Streng (2019) [39] address the delivery of goods to pick-up parcel stations and the related planning and development of a logistics network.
18. Lu, J.; Liu, Y.; Jiang, C.; Wu, W. (2025) [35]	Lu et al. (2025) [35] designs a coordinated network topology that ensures efficient delivery across rural areas.
19. Peng, Y.; Ren, Z.; Yu, D.Z.; Zhang, Y. (2025) [31]	Peng et al. (2025) [31] focuses on designing an efficient delivery infrastructure.
Location planning	
20. Cokyasar, T. (2021) [40]	Cokyasar, T. (2021) [40] focusses on the e-commerce drone delivery problem (E-CDD) in his study. This problem describes the use of automated battery swapping machines to be able to use drones in the delivery process on a permanent basis.
21. Dhote, J.; Limbourg, S. (2020) [41]	In their research, Dhote & Limbourg (2020) [41] focus on the planning of locations with regard to the places where the UAVs are on standby to carry out a transport mission, where they can be recharged and where their maintenance is performed.
22. Enayati, S.; Campbell, J. F.; Li, H. (2023) [42]	In their study, Enayati et al. (2023) [42] focuses on the planning of a network with the help of optimize the facility locations.
23. Feng, X.; Murray, A. T.; Church, R. L. (2021) [43]	Feng et al. (2021) [43] determines optimal placement of EMS drone stations and allocates spatial areas to each station over time windows, forming dynamic service zones.
24. Petit, V.; Ribeiro, M. (2025) [44]	Petit & Ribeiro (2025) [44] focuses on identifying optimal vertiport locations to enhance the efficiency of the delivery network.
25. Guo, Y.; He, L.; Yang, H.; Wang, S.; Liu, K. (2025) [45]	Guo et al. (2025) [45] proposes a location-allocation based stochastic programming model for the relief aid supplies to the earthquake affected areas.

Table 4. Cont.

Logistical Planning Tasks	
Route planning	
Allocation planning	
26. Rave, A.; Fontaine, P.; Kuhn, H. (2023) [46]	Rave et al. (2023) [46] considers a tactical planning problem that aims to find the cost-optimal last-mile delivery system. This includes deciding on locations for dedicated drone stations (microdepots).
27. Lu, J.; Liu, Y.; Jiang, C.; Wu, W. (2025) [35]	A research work by Lu et al. (2025) [35] focuses on designing a network model for truck-drone delivery system. Customer locations are allocated to either of truck only, truck-single drone, or truck-multiple drone deliveries.
28. Guo, Y.; He, L.; Yand, H.; Wang, S.; Liu, K. (2025) [45]	In their study, Guo et al. (2025) [45] relief supplies allocated dynamically based on demand and supply uncertainties.
29. Hamid R. Sayarshad (2025) [26]	Sayarshad (2025) [26] optimized vaccine allocation based on regional infection rates and demand.
30. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28]	In the work by Eberhardt et al. (2025) [28], relief supplies are allocated dynamically based on demand and resource availability.

Route planning emerges as a central focus in many studies, emphasizing the optimization of drone delivery paths under various operational constraints such as limited range, time sensitivity, or sustainability objectives. Advanced computational techniques are widely employed, including artificial intelligence [23], mixed-integer linear programming [25], two-phase optimization models [29], and decision support systems [30]. For instance, Bogyrbayeva et al. approach the problem through the classic TSP-D framework, while Patchou et al. [33] introduce dynamic drone-truck coordination for in-motion pickups. Chiang et al. [25] develop a green routing model focused on minimizing emissions, whereas Hong et al. [29] integrate facility location and route planning in a two-stage process. Sayarshad [26] optimizes routing for vaccine delivery, prioritizing timely distribution in public health contexts. Hu et al. [30] incorporate stochastic weather forecasts into UAV path planning, enhancing adaptability. Eberhardt et al. [28] prioritize routes based on urgency and deprivation time, relevant to equitable relief logistics. Lu et al. [35] and Peng et al. [31] both propose hybrid truck-drone configurations, addressing coordination and synchronization in rural settings. Despite differing approaches, these studies collectively underscore the operational importance of route efficiency in drone logistics.

Network planning adopts a broader, system-level perspective. Studies in this category aim to design delivery networks that ensure efficient service coverage and infrastructure integration. Gao et al. [36] extend the TSP-D into a hub-and-spoke structure, combining location and routing decisions. Hong et al. [37] focus on station-based networks, while Ulmer and Streng [39] explore customer accessibility within parcel station systems. Lu et al. [35] develop network topologies for rural drone operations, and Peng et al. [31] propose integrated aerial-ground delivery infrastructures. These studies share a strategic outlook, focusing on the scalability, robustness, and connectivity of drone-enabled logistics systems.

Location planning centers on the siting of key infrastructure such as drone stations or vertiports. Although all studies highlight the importance of facility placement, their objectives vary. Cokyasar [40] proposes automated battery swapping stations for uninterrupted operations, while Dhote and Limbourg [41] emphasize multifunctional drone bases. Enayati et al. [42] address the problem from a high-level optimization perspective, seeking cost-effective facility configurations. Petit and Ribeiro [44] introduce a framework for identifying vertiport locations for middle-mile and long-range drone services. Guo et al. [45] integrate demand uncertainty into a stochastic location-allocation model for disaster logistics. Though varying in focus, these studies underline the strategic role of infrastructure placement in supporting drone operations.

Allocation planning addresses how resources such as drones, depots, or supplies are distributed across a delivery system. Rave et al. [46] focus on cost-optimized microdepot placement and customer assignment. Lu et al. [35] propose dynamic allocation schemes where customers are assigned to different delivery modes based on situational constraints. Guo et al. [45] present a real-time resource allocation model for post-disaster relief logistics, while Sayarshad [26] prioritizes vaccine distribution based on infection hotspots. Eberhardt et al. [28] similarly use dynamic allocation for critical relief supplies. Rave et al.'s work stands out by integrating location and allocation planning, addressing a notable research gap in coordinating multi-facility operations and resource scheduling.

A key observation across the literature is the frequent overlap of planning categories. Studies such as those by Hong et al. [29] and Gao et al. [36] combine multiple planning dimensions, reflecting the complexity and interconnectedness of real-world drone logistics systems. These hybrid approaches point toward a growing recognition that solving drone-based delivery problems requires integrated, multi-layered strategies.

3.3. Areas of Application in Logistics

This section presents the second criterion of the literature review, as summarized in Table 5. The focus here is on identifying the primary areas of application addressed in the reviewed studies. Based on a synthesis of the literature, four major categories of application are commonly explored in the context of drone-assisted logistics:

- *Last-mile delivery*: This category encompasses the final segment of the supply chain, where goods are transported from a distribution center or terminal directly to end customers. According to Bogyrbayeva et al. (2023) [23] and Jazairy et al. (2025) [47], last-mile delivery plays a critical role in customer satisfaction and operational efficiency. Various transportation modes and configurations have been explored to optimize this phase, particularly for parcel deliveries. UAVs are increasingly deployed in this domain to enhance delivery speed and reach, especially in areas with limited infrastructure or high congestion.
- *Healthcare and disaster logistics*: The rise in both natural and human-made disasters has heightened the demand for reliable, rapid, and flexible distribution of essential goods, particularly in last-mile contexts where infrastructure may be severely compromised [48,49]. UAVs have emerged as a viable solution to bridge logistical gaps during emergencies, offering agility and accessibility in challenging environments [50]. Beyond disaster response, drones are also gaining traction in healthcare logistics for delivering medical supplies, vaccines, and urgent pharmaceutical goods [51]. This subcategory reviews studies that highlight the effectiveness of drones in enhancing logistics resilience in critical scenarios.
- *Urban mobility*: Increasing urbanization has led to significant challenges in transportation, including congestion, pollution, and strained infrastructure [52,53]. UAVs are being recognized as a disruptive innovation with potential to support both freight and passenger transport in cities. Their capacity for vertical takeoff and landing, coupled with flexible routing, makes them a promising solution for urban logistics and mobility services such as air taxis and drone-based parcel delivery [47,54,55]. Nonetheless, integrating UAVs into urban environments poses challenges, including regulatory compliance, public safety, noise concerns, and airspace coordination. This subcategory explores the evolving role of drones in urban transportation systems.
- *Postal services*: The evolution of e-commerce and rising expectations for rapid, reliable delivery have placed growing pressure on traditional postal systems [56]. In response, postal service providers are increasingly exploring drone technologies to address inefficiencies in last-mile delivery, particularly in rural or densely populated areas where conventional methods are less effective [51,57]. Drones offer potential benefits such as reduced delivery times, lower operational costs, and improved accessibility. Pilot initiatives by postal services—such as Swiss Post and Deutsche Post DHL—reflect an industry-wide shift toward automation and digital transformation. This subcategory reviews literature that examines the integration of UAVs into postal logistics, focusing on implementation experiences, benefits, and limitations.

Table 5. Areas of application.

Areas of Application	
Last-mile deliver logistics	
1. Bogyrbayeva, A.; Yoon, T.; Ko, H. B.; Lim, S.; Yun, H. Y.K.; Kwon, C. (2023) [23]	Bogyrbayeva et al. (2023) [23] targets e-commerce, specifically improving cost-effectiveness and efficiency of last-mile delivery through drones.
2. Bruni, M. E.; Khodaparasti, S.; Perboli, G. (2023) [24]	A research by Bruni et al. (2023) [24] focuses on last-mile parcel delivery from fulfillment centers to multiple customers.
3. Chiang, W. C.; Li, Y. Y.; Shang, J.; Urban, T. L. (2019) [25]	Chiang et al (2019) [25] directly pertains to e-commerce delivery, examining how UAVs can optimize the delivery process by reducing delivery times.
4. Cokyasar, T. (2021) [40]	Cokyasar (2021) [40] presents E-commerce last-mile delivery with battery-swapping support, assessed via cost reduction (20%) compared to truck-only delivery.
5. Gao, J. J.; Zhen, L.; Wang, S. A. (2023) [27]	In their study, Gao et al. (2023) [27] address both pickup and delivery jobs handled by a fleet of truck–drone groups in urban context.
6. Hong, F.; Wu, G.; Luo, Q.; Liu, H.; Fang, X.; Pedrycz, W. (2023) [29]	Hong et al. (2023) [29] present last-mile pickup and delivery using multiple drones deploying to rooftop automated lockers on residential buildings.
7. Hong, I.; Kuby, M.; Murray, A. T. (2018) [37]	Hong et al. (2023) [37] aimed at enhancing e-commerce delivery through a stand-alone drone delivery service, particularly enhancing Amazon’s Prime Air service, which promises rapid package delivery.
8. Hu, Z. C.; Chen, H.; Lyons, E.; Solak, S.; Zink, M. (2024) [30]	Hu et al. (2024) [30] discusses the potential of UAVs to enhance urban mobility by serving as an alternative to traditional ground transportation.
9. Peng, Y.; Ren, Z.; Yu, D.Z.; Zhang, Y. (2025) [31]	Peng et al. (2025) [31] addresses last-mile logistics by integrating drones into traditional vehicles routing to enhance delivery efficiency.
10. Kouretas, K.; Kepaptsoglou, K. (2023) [58]	Kouretas & Kepaptsoglou (2023) [58] consider integrated last-mile parcel delivery combining drones and conventional vehicles, aimed at replacing or supplementing traditional fuel-based deliveries.
11. Pachayappan, M.; Sudhakar, V. (2021) [59]	Pachayappan & Sudhakar (2021) [59] show the advantages of drones, which do not face issues like traffic and pollution like traditional vehicles.
12. Patchou, M.; Sliwa, B.; Wietfeld, C. (2021) [33]	Patchou et al. (2021) [33] offers parcel delivery with prioritized medical goods during COVID-19, aiming to reduce human transmission and improve delivery capacity.
13. Pina-Pardo, J. C.; Silva, D. F.; Smith, A. E. (2021) [34]	Pina-Pardo et al. (2021) [34] addresses last-mile delivery where new customer orders (with release dates) arrive during the truck’s route and can be delivered via a drone resupplying the truck mid-route.
14. Pinto, R.; Lagorio, A. (2022) [38]	Pinto & Lagorio (2022) [38] designed for last-mile delivery via drones, aiming to overcome range limitations by introducing intermediate charging stations along flight corridors.

Table 5. Cont.

Areas of Application	
15. Ulmer, M. W.; Streng, S. (2019) [39]	Ulmer & Streng (2019) [39] discuss last-mile delivery as a possibility for same-day delivery for e-commerce.
16. Lu, J.; Liu, Y.; Jiang, C.; Wu, W. (2025) [35]	Lu et al. (2025) [35] proposes the combination of truck -drone parcel delivery from the distribution center to customers.
17. Gao, C.-F.; Hu, Z.-H.; Wang, Y.-Z. (2023) [36]	Gao et al. (2023) [36] present last-mile parcel consolidation in a hub-and-spoke network, where trucks connect hubs and drones serve spoke-level deliveries.
Healthcare/distaster logistics	
18. Dhote, J.; Limbourg, S. (2020) [41]	Dhote & Limbourg (2020) [41] report that UAVs are used in the sector of healthcare logistics, especially for the transport of biomedical materials such as blood products and medical samples between hospitals, laboratories and blood transfusion centers.
19. Enayati, S.; Campbell, J. F.; Li, H. (2023) [42]	Enayati et al. (2023) [42] focus on the vaccine distribution chain in Vanuatu, addressing challenges due to the region's geography and limited infrastructure.
20. Feng, X.; Murray, A. T.; Church, R. L. (2021) [43]	Feng et al. (2021) [43] consider locating drone-equipped emergency medical service (EMS) stations to optimize response times over space and time.
21. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F. K.; Schultmann, F. (2025) [28]	The study by Eberhardt et al. (2025) [28] focuses on optimizing last-mile distribution in disaster relief scenarios, addressing the challenges of emergency logistics.
22. Kunovjanek, M.; Wankmüller, C. (2021) [60]	Kunovjanek, M.; Wankmüller, C. (2021) [60] consider distribution of COVID-19 test kits to potentially infected individuals as part of a backup transport system during the pandemic.
23. La Haidari; Brown, S. T.; Ferguson, M.; Bancroft, E.; Spiker, M.; Wilcox, A. et al. (2016) [61]	La Haidari et al. (2016) [61] address routine vaccine delivery in low- and middle-income countries, especially in challenging terrains like Gaza Province, Mozambique.
24. Silvestri, S. de; Capasso, P. J.; Gargiulo, A.; Molinari, S.; Sanna, A. (2023) [62]	Silvestri et al. (2023) [62] utilize the use of drones to transport critical medical supplies in emergencies, which is crucial for disaster logistics and improves response capabilities in remote or affected areas.
25. Sayarshad H. R. (2025) [26]	The study by Sayarshad (2025) [26] introduces a methodology for drone based vaccine delivery to enhance equity in vaccine access across different regions including rural areas and small cities.
26. Guo, Y.; He, L.; Yang, H.; Wang, S.; Liu, K. (2025) [45]	Guo et al. (2025) [45] focuses on humanitarian logistics, specifically optimizing the delivery of relief supplies in disaster-affected areas.

Table 5. Cont.

Areas of Application	
Urban mobility	
27. Doole, M.; Ellerbroek, J.; Knoop, V. L.; Hoekstra, J. M. (2021) [63]	Doole et al. (2021) [63] Discusses drone-based delivery and flying taxis within urban mobility and highlights the potential environmental monitoring benefits through reduced pollution and better traffic management in urban areas.
28. Roesing, J.; Lima, I.; Feldhoff, E.; Hoenen, S.; Kuehnel, F.; Theissen, A. (2023) [64]	Roesing et al. (2023) [64] present conceptual design of “airborne-supplied city hubs”—urban logistic hubs that support drone operations like curbside delivery, reloads, or battery swaps.
29. Petit, V.; Ribeiro, M. (2025) [44]	Petit & Ribeiro (2025) [44] focuses on optimizing vertiport locations to support urban air mobility (UAM) for middle-mile package delivery.
30. Peng, Y.; Ren, Z.; Yu, D.Z.; Zhang, Y. (2025) [31]	Peng et al. (2025) [31] integrates truck–drone collaborative parcel delivery in urban environments, considering dynamic truck travel times and drone deployment from rendezvous points.
Postal services	
31. Rave, A.; Fontaine, P.; Kuhn, H. (2023) [46]	Rave et al. (2023) [46] targets improvements in postal and courier services by integrating drones for faster delivery.

The reviewed literature illustrates a dynamic and growing interest in the diverse application areas of drone-based logistics, spanning sectors such as e-commerce, healthcare, urban mobility, and postal services. Many studies draw upon real-world projects from the commercial sphere such as Amazon's Prime Air underscoring the practical relevance of UAVs (Unmanned Aerial Vehicles) in contemporary logistics. The integration of drones across these domains demonstrates their potential to increase efficiency, reduce costs, mitigate congestion, and enhance service accessibility.

A significant portion of the literature concentrates on e-commerce and last-mile delivery, reflecting the early and enthusiastic adoption of UAVs in commercial logistics. Studies by Bogyrbayeva et al. (2023) [23], Chiang et al. (2019) [25], and Hong et al. (2018) [37] explore different dimensions of UAV integration in online retail logistics. Bogyrbayeva emphasizes cost reductions, Chiang highlights improvements in delivery speed, and Hong focuses on drone-only delivery systems, such as those pioneered by Amazon. Additional contributions, including Hu et al. (2024) [30], Peng et al. (2025) [31], and Pachayappan and Sudhakar (2021) [59], expand the scope by proposing hybrid drone-vehicle models and stressing environmental benefits. Similarly, Ulmer and Streng (2019) [39] and Lu et al. (2025) [35] address the growing demand for same-day delivery through integrated truck-drone networks, particularly targeting suburban and rural areas. Collectively, these studies affirm the pivotal role of drones in reshaping last-mile logistics to meet the fast-evolving demands of e-commerce.

In contrast, a second cluster of studies focuses on healthcare and humanitarian logistics, where the emphasis shifts from commercial gains to public welfare and equitable access. UAVs are increasingly utilized to overcome transportation infrastructure deficits, particularly in remote or disaster-stricken regions. Dhote and Limbourg (2020) [41] investigate the transport of biomedical materials, such as blood and diagnostic samples, showcasing UAVs' capabilities for time-critical deliveries. Enayati et al. (2023) [42] and Sayarshad (2025) [26] delve into vaccine distribution in hard-to-reach regions, including island nations and underserved urban fringes. Silvestri et al. (2023) [62] and Eberhardt et al. (2025) [28] explore drone deployment in emergency response, emphasizing rapid distribution of medical supplies in post-disaster settings. Guo et al. (2025) [45] contribute a model for adaptive humanitarian supply chains, where drones respond dynamically to shifting needs. These studies underscore the unique value of UAVs in enhancing the reach, reliability, and responsiveness of critical health logistics, particularly where conventional methods fall short.

Another emerging domain is urban mobility, where UAVs are viewed as integral components of future smart transportation systems. Studies such as Hu et al. (2024) [30], Doole et al. (2021) [63], and Petit and Ribeiro (2025) [44] examine the role of drones in alleviating traffic congestion and facilitating efficient urban transport. Hu et al. investigates routing strategies under uncertain weather, while Doole et al. consider applications such as air taxis and environmental monitoring. Petit and Ribeiro propose optimized placement of vertiports for drone takeoff and landing, envisioning a more structured integration of UAVs within multimodal transport ecosystems. Unlike e-commerce or humanitarian logistics, studies in this category emphasize systemic urban challenges such as sustainability, infrastructure planning, and regulatory alignment.

Lastly, postal and courier services have begun to explore UAV applications as part of broader modernization efforts. Rave et al. (2023) [46] examine drone-assisted last-mile systems in the public postal sector, focusing on improving service quality and reducing delivery times. While thematically aligned with e-commerce logistics, these efforts are driven by public service mandates and often aim to extend delivery reach into underserved or high-cost areas.

In summary, the reviewed literature highlights the versatility of UAVs across multiple sectors. E-commerce remains the dominant application area, driven by commercial imperatives and technological readiness. However, healthcare and humanitarian applications emphasize drones' societal value, focusing on equity, access, and resilience. Meanwhile, urban mobility and postal services illustrate expanding horizons for UAV integration within broader logistics and transportation infrastructures. A common thread across all domains is the ability of drones to bypass ground-based limitations: whether related to traffic, infrastructure gaps, or emergency inaccessibility. Nonetheless, the success criteria such as cost-efficiency, speed, reliability, or sustainability vary according to the specific context, reflecting the distinct priorities and constraints of each application area.

3.4. Optimization and Analysis Methods

Table 6 summarizes the methodological approaches employed in the reviewed literature to tackle challenges in drone-based logistics networks. These approaches include mathematical modeling, heuristic algorithms, simulation methods, and case study analyses. Collectively, they reflect the diverse strategies researchers use to address the inherent complexity, uncertainty, and scalability issues associated with UAV logistics systems. This section provides an overview of how each methodological category contributes to the analysis and optimization of drone-based logistics.

- *Heuristic methods:* Solving complex logistics and drone delivery problems often involves large-scale, nonlinear, and combinatorial models that are difficult to solve optimally within reasonable time [65]. Heuristic methods such as Genetic Algorithms, Simulated Annealing, and Ant Colony Optimization provide practical approaches for generating high-quality solutions efficiently [66,67]. This subsection reviews literature where heuristics have been applied to optimize UAV-based logistics networks, including routing, scheduling, and facility placement.
- *Mathematical modeling:* Mathematical models offer a structured and rigorous way to represent complex decision-making problems in drone logistics, such as facility location, vehicle routing, and resource allocation [68,69]. These models support optimization under various operational constraints and provide theoretical foundations for system design. This part reviews literature that applies mathematical modeling to structure UAV logistics challenges and solve logistics problems involving UAVs.
- *Simulation:* Simulation techniques enable the evaluation of UAV logistics operations in dynamic, uncertain, and realistic environments, without the need for costly real-world deployment [70,71]. They are especially valuable for testing policy scenarios, system behaviors, and performance metrics under uncertainty. This subsection highlights research that utilizes simulation to analyze drone delivery strategies and operational effectiveness across different contexts.
- *Case study analysis:* Case studies offer empirical insights into how UAV-based logistics solutions are applied in practice. They provide context-specific evaluations of implementation challenges, feasibility, and scalability, helping to bridge the gap between theoretical models and real-world deployment [72,73]. This subsection discusses studies that investigate drone logistics through detailed analyses of real-life applications and pilot projects.

Table 6. Optimization and analysis methods (own presentation).

Optimization and Analysis Methods	
Heuristic methods	
1. Bogyrbayeva, A.; Yoon, T.; Ko, H. B.; Lim, S.; Yun, H. Y.K.; Kwon, C. (2023) [23]	Bogyrbayeva et al. (2023) [23] employs heuristic methods to find scalable solutions for the complex TSP-D and uses MDP for mathematical representation.
2. Chiang, W. C.; Li, Y. Y.; Shang, J.; Urban, T. L. (2019) [25]	In a research by Chiang et al. (2019) [25] Genetic Algorithm is applied to large instances; when exact solutions only feasible for small cases via MILP.
3. Hong, F.; Wu, G.; Luo, Q.; Liu, H.; Fang, X.; Pedrycz, W. (2023) [29]	Hong et al. (2023) [29] utilizes heuristic methods through the SATO-IVND algorithm, combining task allocation and route planning.
4. Petit, V.; Ribeiro, M. (2025) [44]	In the research by Petit & Ribeiro, M. (2025) [44] a Tabu search based heuristic algorithm is employed to solve the complex optimization problem.
5. Hong, I.; Kuby, M.; Murray, A. T. (2018) [37]	Hong et al. (2018) [37] develop custom heuristic algorithm integrating spatial reasoning with greedy and simulated annealing techniques.
6. Pachayappan, M.; Sudhakar, V. (2021) [59]	Heuristic approaches (Drone Neighbor Search Heuristic) are applied to develop and evaluate drone routing strategies, with a focus on optimizing delivery routes and schedules, in the research of Pachayappan & Sudhakar (2021) [59].
7. Pinto, R.; Lagorio, A. (2022) [38]	The research of Pinto & Lagorio (2022) [38] utilizes a mixed-integer optimization model and heuristic approaches to design a network of drone delivery paths and charging stations. It aims to optimize the placement and number of charging stations to efficiently cover all potential delivery points, employing bi-objective optimization for balancing service costs and infrastructure investments.
8. Peng, Y.; Ren, Z.; Yu, D.Z.; Zhang, Y. (2025) [31]	Peng et al. (2025) [31] develops a mixed integer programming model for the vehicle routing problems involving drones and proposes a metaheuristic algorithm based on variable neighborhood search approach to solve the problem.
Mathematical modeling	
9. Bogyrbayeva, A.; Yoon, T.; Ko, H. B.; Lim, S.; Yun, H. Y.K.; Kwon, C. (2023) [23]	Bogyrbayeva et al. (2023) [23] develop deep Reinforcement Learning (DRL) using an attention-based encoder and LSTM-decoder model enables stateful coordination between truck and drone.
10. Bruni, M. E.; Khodaparasti, S.; Perboli, G. (2023) [24]	Bruni et al. (2023) [24] employ Nonlinear mixed-integer robust optimization model, exact branch-and-check method with customized cut algorithm is used as a solution approach, and computational experiments and real world case study are used for validation.
11. Chiang, W. C.; Li, Y. Y.; Shang, J.; Urban, T. L. (2019) [25]	Chiang et al. (2019) [25] propose Mixed-integer linear programming (MILP) green-routing model to minimize combined energy use and emissions.

Table 6. Cont.

Optimization and Analysis Methods

12. Cokyasar, T. (2021) [40]	Cokyasar (2021) [40] employs mathematical modeling to formulate a Mixed-Integer Nonlinear Program (MINLP), later converted to a Mixed-Integer Quadratically-Constrained Program (MIQCP).
13. Dhote, J.; Limbourg, S. (2020) [41]	Dhote & Limbourg (2020) [41] present rigorous strategic planning combining qualitative analysis with quantitative location models. PESTEL and SWOT analyses to identify scenario drivers. Four MILP location-allocation models solved via IBM CPLEX for strategic base placement under different scenarios.
14. Feng, X.; Murray, A. T.; Church, R. L. (2021) [43]	Feng et al. (2021) [43] Employs mathematical modeling and optimization to address the location-allocation problem, adapting the p-median problem for spatial and temporal variability.
15. Gao, C.-F.; Hu, Z.-H.; Wang, Y.-Z. (2023) [36]	Gao et al. (2023) [36] develop a novel three-stage decomposition combining hub location, truck routing, and drone routing (TSP-D).
16. Gao, J. J.; Zhen, L.; Wang, S. A. (2023) [27]	The research work of Gao, J.J. (2023) [27] uses mathematical modeling, especially mixed-integer linear programming (MILP), to optimize routes. A novel hybrid algorithm combines column generation and logic-based Benders decomposition to solve the model efficiently.
17. Hong, I.; Kuby, M.; Murray, A. T. (2018) [37]	Hong et al. (2018) [37] develop Mixed-integer programming combining maximal coverage and flow-refueling location models with ESP for path planning.
18. Hu, Z. C.; Chen, H.; Lyons, E.; Solak, S.; Zink, M. (2024) [30]	Hu et al. (2024) [30] use mathematical modeling and simulation to propose a two-stage stochastic programming framework. This approach allows for adaptive UAV path planning that incorporates real-time environmental data, enhancing decision-making processes under uncertain conditions.
19. Petit, V.; Ribeiro, M. (2025) [44]	Petit & Ribeiro (2025) [44] developed a multi-objective optimization model to determine optimal vertiport locations, considering factors like capacity, safety, and noise impact.
20. Kouretas, K.; Kepaptsoglou, K. (2023) [58]	Kouretas & Kepaptsoglou (2023) [58] develop Mode-assignment and route optimization modeled via nested Genetic Algorithms, tailored for assignment and routing subproblems.

Table 6. Cont.

Optimization and Analysis Methods	
21. Hamid R. Sayarshad (2025) [26]	Sayarshad (2025) [26] employs optimization techniques to minimize travel and healthcare costs while ensuring equitable vaccine distribution. The have also developed a region-specific dynamic disease model to forecast vaccine demand based on infection and vaccination rates.
22. Kunovjanek, M.; Wankmüller, C. (2021) [60]	Kunovjanek & Wankmüller (2021) [60] utilizes mathematical modeling to compare traditional vehicle-based testing with drone-enabled testing, evaluating cost and time effectiveness.
23. Pachayappan, M.; Sudhakar, V. (2021) [59]	Pachayappan & Sudhakar (2021) [59] using Mixed-Integer Linear Programming (MILP) captures sequence constraints and battery-‘safe-return’ policies for a UAS-only logistics paradigm.
24. Pina-Pardo, J. C.; Silva, D. F.; Smith, A. E. (2021) [34]	Pina-Pardo et al. (2021) [34] develop a MILP formulation named TSPRD-DR, capturing release dates and drone resupply options.
25. Rave, A.; Fontaine, P.; Kuhn, H. (2023) [46]	Rave et al. (2023) [46] develop Mixed-integer linear program selecting fleet size, micro-depot locations, and delivery mode assignments. Scalable solution method and rigorous validation is also presented.
26. Peng, Y.; Ren, Z.; Yu, D.Z.; Zhang, Y. (2025) [31]	Peng, et al. (2025) [31] use Mixed-integer programming (MIP) formulation for time-dependent VRP with drones (TDVRP-D) minimizing combined transportation and carbon emission costs.
27. Ulmer, M. W.; Streng, S. (2019) [39]	Ulmer & Streng (2019) [39] formulated dynamic optimization as a Markov Decision Process (MDP), the SDDPSAV to dynamically dispatch AVs in real time.
28. Lu, J.; Liu, Y.; Jiang, C.; Wu, W. (2025) [35]	Lu et al. (2025) [35] develop an optimization model to calculate cost-effective and efficient delivery routes for trucks and drones. Their model includes variables like trajectory coordination and demand distribution.
29. Guo, Y.; He, L.; Yang, H.; Wang, S.; Liu, K. (2025) [45]	Guo et al. (2025) [45] developed a stochastic programming model to handle uncertainties in supply and demand. The model incorporates chance constraints to address dynamic uncertainties.
30. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28]	Eberhardt et al. (2025) [28] formulated a fleet size and mix vehicle routing problem for disaster management (FSMVRP-DM) to optimize fleet composition and routing.
Simulation	
31. Chiang, W. C.; Li, Y. Y.; Shang, J.; Urban, T. L. (2019) [25]	To solve a complex model, a genetic algorithm is used in the study by Chiang et al. (2019) [25], which is accompanied by extensive numerical simulations to test the effectiveness of the model in practice.

Table 6. Cont.

Optimization and Analysis Methods	
32. Doole, M.; Ellerbroek, J.; Knoop, V. L.; Hoekstra, J. M. (2021) [63]	Doole et al. (2021) [63] utilizes simulation techniques to design and compare two urban airspace concepts, evaluating their impact on traffic safety, stability, and efficiency.
33. Hong, F.; Wu, G.; Luo, Q.; Liu, H.; Fang, X.; Pedrycz, W. (2023) [29]	Hong et al. (2023) [29] employe two-phase heuristic: depot-level task allocation (simulated annealing + IVND), then per-depot drone routing (local search).
34. Hu, Z. C.; Chen, H.; Lyons, E.; Solak, S.; Zink, M. (2024) [30]	Hu et al. (2024) [30] use simulation to validate their model based on real-world data.
35. La Haidari; Brown, S. T.; Ferguson, M.; Bancroft, E.; Spiker, M.; Wilcox, A. et al. (2016) [61]	La Haidari et al. (2016) [61] using the HERMES software platform to develop a discrete-event simulation model of the vaccine supply chain.
36. Patchou, M.; Sliwa, B.; Wietfeld, C. (2021) [33]	Patchou et al. (2021) [33] employs simulation and mathematical modeling to design and evaluate a hybrid delivery system that includes UAVs to solve complex logistics problems like the Flying Sidekick Traveling Salesman Problem (FSTSP).
37. Ulmer, M. W.; Streng, S. (2019) [39]	Ulmer & Streng (2019) [39] present large-scale simulations (1000 orders/day, up to 10 vehicles), using real-world network.
38. Lu, J.; Liu, Y.; Jiang, C.; Wu, W. (2025) [35]	Lu et al. (2025) [35] simulates scenarios to test the performance of the truck-drone network under varying conditions, such as different demand levels and drone capacities.
39. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28]	In their study, Eberhardt et al. (2025) [28] have tested their FSMVRP-DM model through simulations to evaluate its performance om real-world distaster scenarios.
Case study analysis	
41. Enayati, S.; Campbell, J. F.; Li, H. (2023) [42]	Kunovjanek & Wankmüller's (2021) [60] study is based on a case study method in collaboration with the Red Cross and a manufacturer of supply drones.
42. Kunovjanek, M.; Wankmüller, C. (2021) [60]	Roesing et al. (2023) [64] utilizes real-world evaluations and mathematical approaches to refine the integration of drones into urban freight systems, ensuring effective distribution.
43. Sayarshad, H. (2025) [26]	Silvestri et al. (2023) [62] reviews literature systematically to assess drone applications in healthcare, analyzes data to evaluate effectiveness, challenges, and research needs.

Table 6. Cont.

Optimization and Analysis Methods	
44. Roesing, J.; Lima, I.; Feldhoff, E.; Hoenen, S.; Kuehnel, F.; Theissen, A. (2023) [64]	For the study by Petit & Ribeiro (2025) [44] the South Holland region is used as a case study to validate the proposed framework.
45. Silvestri, S. de; Capasso, P. J.; Gargiulo, A.; Molinari, S.; Sanna, A. (2023) [62]	Guo et al. (2025) [45] validated their framework using a case study of Mianyang city post-Wenchuan earthquake.
46. Petit, V.; Ribeiro, M. (2025) [44]	Eberhardt et al. (2025) [28] applied their FSMVRP-DM model to a case study in Baden-Württemberg to validate the model’s applicability.
47. Guo, Y.; He, L.; Yang, H.; Wang, S.; Liu, K. (2025) [45]	
48. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28]	

The findings presented in Table 6 reflect the methodological diversity and complexity inherent in UAV-based logistics research. Across the reviewed literature, four main methodological streams—heuristics, mathematical modeling, simulation, and case study analysis—emerge as foundational tools for tackling the multifaceted challenges of drone logistics. Each method is applied based on its specific strengths, yet their combined use in hybrid frameworks highlights the interdisciplinary and problem-driven nature of the field.

Heuristic methods are consistently adopted to address the computational challenges posed by large-scale, combinatorial problems, particularly those involving routing, such as the Traveling Salesman Problem with Drones (TSP-D) and its many variants. A common pattern among these studies is the development or customization of heuristic strategies to enhance scalability and generate high-quality solutions in reasonable time. For example, Bogyrbayeva et al. (2023) [23] integrate heuristic reasoning with Markov Decision Processes to manage routing complexity, while Hong et al. (2023) [29] propose the SATO-IVND algorithm to jointly optimize task allocation and drone routing. Similarly, Pachayappan and Sudhakar (2021) [59] introduce a drone-adapted neighbor search algorithm, demonstrating how tailored heuristics can efficiently handle domain-specific constraints. A noticeable trend is the hybridization of heuristics with mathematical optimization models. Peng et al. (2025) [31] embed a metaheuristic based on Variable Neighborhood Search into a Mixed Integer Programming (MIP) framework to solve a vehicle routing problem with drones. Pinto and Lagorio (2022) [38] extend this logic by incorporating a bi-objective model for both routing and charging station placement, using heuristics to manage trade-offs between cost and service coverage. Petit and Ribeiro (2025) [44] apply Tabu Search to a complex vertiport location problem, further illustrating how heuristic solvers enable tractability for problems that are otherwise computationally intensive. While these approaches effectively balance solution quality and runtime, they inherently involve a trade-off—sacrificing optimality guarantees for scalability and responsiveness.

Mathematical modeling remains the dominant approach for structuring decision problems and deriving optimal or near-optimal solutions. The reviewed literature frequently utilizes Mixed Integer Linear Programming (MILP), Mixed Integer Nonlinear Programming (MINLP), and Mixed Integer Quadratically Constrained Programming (MIQCP) to model location, routing, and scheduling problems. For instance, Cokyasar (2021) [40] and Gao (2023) [36] employ MILP formulations with decomposition techniques to optimize delivery systems, particularly in strategic planning contexts where exact solutions are feasible and desirable. These models are valued for their precision and theoretical rigor, making them suitable for benchmarking and foundational design. A consistent pattern across these works is the extension of classical models to better reflect real-world complexities. Feng et al. (2021) [43] adapt the p -median problem to include spatial-temporal dynamics, while Hu et al. (2024) [30] introduce a two-stage stochastic programming model to incorporate real-time environmental data. Similarly, Guo et al. (2025) [45] apply chance-constrained programming to address uncertainty in supply and demand, and Sayarshad (2025) [26] integrates epidemiological modeling into a vaccine delivery optimization problem. These examples demonstrate how mathematical modeling continues to evolve to meet domain-specific challenges. However, the scalability limitations of exact models remain a key contradiction; many studies resort to hybrid methods or decomposition strategies to bridge the gap between theoretical optimality and practical applicability.

Simulation methods are widely used to validate optimization models and explore system performance under uncertainty. Rather than solving optimization problems directly, simulation provides insights into how drone logistics systems behave under varying conditions and assumptions. Chiang et al. (2019) [25] and Doole et al. (2021) [63], for example, simulate urban airspace configurations to assess operational safety and traffic

flow. These studies illustrate the role of simulation as a decision-support tool, especially in early-stage planning or policy testing. A shared feature among simulation-based studies is their use for robustness analysis and sensitivity testing. Lu et al. (2025) [35] simulate a truck-drone delivery system to evaluate how changes in drone capacity and demand affect performance. Patchou et al. (2021) [33] combine simulation with optimization to assess the Flying Sidekick TSP, while Eberhardt et al. (2025) [28] use simulations to evaluate disaster response strategies in realistic emergency scenarios. These approaches highlight simulation’s value in bridging theory and practice, though they lack optimization guarantees and are highly dependent on the validity of input assumptions.

Case study analysis plays a critical role in contextualizing theoretical models and testing their applicability in real-world settings. Several studies incorporate case-specific data to validate their approaches. Kunovjanek and Wankmüller (2021) [60] use field trials with the Red Cross to compare traditional and drone-based delivery systems. Roesing et al. (2023) [64] examine urban freight integration in Germany, and Silvestri et al. (2023) [62] conduct a comprehensive review of healthcare drone applications to identify gaps and best practices. Other works, such as those by Petit and Ribeiro (2025) [44] and Guo et al. (2025) [45], apply their optimization models to specific geographic contexts (e.g., South Holland and Mianyang, respectively), enabling more grounded assessments of performance and feasibility. Eberhardt et al. (2025) [28] validate their FSMVRP-DM model using a disaster scenario in Baden-Württemberg, showcasing the operational potential of their framework. Despite the varied depth of analysis, the overarching trend is clear: case studies are essential for ensuring practical relevance, offering empirical support for theoretical claims and surfacing real-world constraints like regulation, infrastructure, and stakeholder behavior.

In summary, the reviewed studies reveal a strong trend toward methodological integration, where heuristics, mathematical models, simulations, and case studies are not used in isolation but rather in complementary roles. Heuristics offer scalability; mathematical models provide precision; simulations support robustness testing; and case studies ensure real-world applicability (the summary is given in Table 7). This blended approach reflects a nuanced understanding of the trade-offs and complexities in drone logistics planning. A further consistency lies in the shared optimization objectives across methods: minimizing cost and delivery time, while maximizing efficiency, coverage, or reliability. Whether applied to urban freight, emergency response, or healthcare logistics, these goals underpin most studies, allowing for cross-method comparisons and a cohesive body of knowledge. However, contradictions persist, particularly between scalability and optimality. Heuristics are fast but lack guarantees. Mathematical models are exact but computationally intensive. Simulations yield valuable insights but are non-optimizing. These tensions do not diminish the value of any single approach; instead, they highlight the importance of methodological diversity and context-aware application. The most promising research directions appear to be those that strategically combine methods to leverage their respective strengths while mitigating limitations.

Table 7. Summary of optimization methods and analysis (Author’s own presentation).

Method	Key Traits	Stengths	Limitations	Common Objectives	Representative Studies
Heuristc	Rule-based, fast, adaptable	Scalable for large problems	May miss global optima	Route/time optimization	[32,58]

Table 7. Cont.

Method	Key Traits	Strengths	Limitations	Common Objectives	Representative Studies
Mathematical Model	Structured, exact	Guarantees optimality (in small instances)	High complexity	Cost, route, coverage	[24,37]
Simulation	Empirical, dynamic	Tests robustness in variable conditions	Doesn't optimize	Validate performance	[62,63]
Case Study	Real-world validation	Ensures practical relevance	May lack generalizability	Confirm applicability	[42,61]

3.5. System Components

Table 8 summarizes how each study conceptualizes the core elements of a drone-enabled logistics network. Because logistics systems rely on multiple interdependent components, many studies address several of these elements simultaneously. The following discussion clarifies the role and modeling of each component across the literature:

- **Nodes:** Nodes are the physical or virtual points where goods are stored, processed, or exchanged such as warehouses, micro-hubs, landing pads, and customer locations. Their placement and capacity directly impact network performance, influencing travel distances and service coverage. Studies by Snyder and Daskin [68,69] emphasize that optimal node distribution is fundamental to feasibility and cost-efficiency. In UAV contexts, researchers model nodes to reflect drone-specific requirements, such as micro-hubs, battery-swap (charging) stations or vertiports.
- **Edges:** Edges represent the viable connections between nodes, corresponding to flight corridors or mixed-mode links. Modeling edges requires integration of geographic constraints (e.g., no-fly zones), regulatory limits (e.g., altitude restrictions), and energy considerations (battery endurance, wind) [51].
- **Routes:** Route planning focuses on sequencing node visits to meet service objectives—minimizing time, energy, or cost while respecting payload and range limits [57]. Efficient routes maximize coverage and mission success rates. The literature presents a variety of route-optimization algorithms, from classical TSP-D formulations to adaptive, real-time pathing under uncertain conditions.
- **Vehicles:** The characteristics of the drone fleet such as flight range, cruising speed, battery capacity, and recharge time define operational capabilities. Studies by Li et al. [74] and Liu et al. [75] demonstrate how differing UAV profiles affect network design and scheduling. Accurate vehicle models ensure realistic planning outputs and feasible operational parameters.
- **Payload:** Payload constraints (maximum weight or volume) influence not only vehicle choice but also route feasibility and service frequency. Rave et al. [46] highlight trade-offs between payload capacity and flight endurance, particularly critical for medical or relief logistics. Properly accounting for payload limitations is essential to avoid mission failures and guarantee reliability.
- **Network topology:** Network topology refers to the overall structure of nodes and edges: whether a hub-and-spoke, grid, or decentralized mesh configuration. Crainic and Liao [76,77] show that topology choices affect scalability, resilience, and cost. In drone logistics, researchers explore hybrid topologies that combine central hubs with localized micro-hubs to balance efficiency and adaptability.

Table 8. System components.

System Components	
Nodes	
1. Bogyrbayeva, A.; Yoon, T.; Ko, H. B.; Lim, S.; Yun, H. Y.K.; Kwon, C. (2023) [23] 2. Bruni, M. E.; Khodaparasti, S.; Perboli, G. (2023) [24] 3. Cokyasar, T. (2021) [40] 4. Dhote, J.; Limbourg, S. (2020) [41] 5. Guo, Y.; He, L.; Yang, H.; Wang, S.; Liu, K. (2025) [45] 6. Enayati, S.; Campbell, J. F.; Li, H. (2023) [42] 7. Feng, X.; Murray, A. T.; Church, R. L. (2021) [43] 8. Hong, F.; Wu, G.; Luo, Q.; Liu, H.; Fang, X.; Pedrycz, W. (2023) [29] 9. Sayarshad, H. (2025) [26] 10. Hong, I.; Kubby, M.; Murray, A. T. (2018) [37] 11. Kouretas, K.; Kepaptsoglou, K. (2023) [58] 12. Kunovjanek, M.; Wankmüller, C. (2021) [60] 13. La Haidari; Brown, S. T.; Ferguson, M.; Bancroft, E.; Spiker, M.; Wilcox, A. et al. (2016) [61] 14. Pachayappan, M.; Sudhakar, V. (2021) [59] 15. Pinto, R.; Lagorio, A. (2022) [38] 16. Ulmer, M. W.; Streng, S. (2019) [39] 17. Petit, V. & Ribeiro, M. (2025) [44] 18. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28] 19. Peng, Y.; Ren, Z.; Yu, D.Z.; Zhang, Y. (2025) [31]	Bogyrbayeva et al. (2023) [23] consider delivery points, such as customer locations where packages need to be delivered as nodes. By incorporating these nodes, they developed a model that ensures effective coordination between the delivery units to minimize time and costs. Dhote & Limbourg (2020) [41] use potential UAV base stations (“launch bases”), hospitals, labs, and blood banks as nodes. On the other hand, Enayati et al. (2023) [42] use central medical depots, drone bases, and remote vaccination points (villages, clinics) as nodes. Feng et al. (2021) [43] consider potential drone base/station locations and continuously distributed demand points. Nodes are represented as demand points for relief supplies by Eberhardt et al. (2025) [28] while Guo et al. (2025) [45] represents emergency supply distribution centers and disaster affected areas as nodes. Sayarshad (2025) [26] also represents nodes as regional vaccine demand points while Petit & Ribeiro (2025) [44] represents potential vertiport locations and demand points as nodes. In a work of Peng et al. (2025) [31], delivery points are represented as nodes within the network while Hong et al. (2023) [29] represented nodes as delivery and pick-up points, such as rooftops and depots. And Pachayappan & Sudhakar (2021) [59] represented pickup and delivery points as well as docking stations. Bruni et al. (2023) [24] used fulfillment centers and customer locations as nodes, while fulfillment centers, demand points, candidate automated battery swapping machines (ABSM) are considered as nodes by Cokyasar (2021) [40]. The research of Pinto & Lagorio (2022) [38] utilizes a mixed-integer optimization model and heuristic approaches to design a network of drone delivery paths and charging stations. It aims to optimize the placement and number of charging stations to efficiently cover all potential delivery points, employing bi-objective optimization for balancing service costs and infrastructure investments.
Edge	
20. Hong, I.; Kubby, M.; Murray, A. T. (2018) [37]	Hong et al. (2018) [37] describes edges in terms of transportation with drones as potential flight paths between nodes.

Table 8. Cont.

System Components	
21. La Haidari; Brown, S. T.; Ferguson, M.; Bancroft, E.; Spiker, M.; Wilcox, A. et al. (2016) [61]	Pinto & Lagorio (2022) [38] show edges that indicate feasible paths for drones.
22. Pinto, R.; Lagorio, A. (2022) [38]	In a research works by Eberhardt et al. (2025) [28], Guo et al. (2025) [45] and Sayarshad (2025) [26] connections between nodes are optimized for efficient delivery. Petit & Ribeiro (2025) [44] analyses connection between nodes for efficient cargo movement while connection between locations are optimized for better coordination between ground vehicles and drones by Peng et al. (2025) [31].On the other hand, La Haidari et al. (2016) [61] implicitly modeled flight routes connecting vaccine storage sites within simulation.
23. Petit, V.; Ribeiro, M. (2025) [44]	
24. Sayarshad, H. (2025) [26]	
25. Guo, Y.; He, L.; Yang, H.; Wang, S.; Liu, K. (2025) [45]	
26. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28]	
Routes	
27. Each of the 31 full texts selected in the last step of the (systematic literature review) SLR.	The sources describe routes in their explanations as (optimized) paths for vehicles, i.e., the distance they travel on the ground or in the air during delivery. Specifically, Enayati et al. (2023) describe it in simplified terms as routes connecting nodes while Eberhardt et al. (2025) [28] adjusted delivery routes dynamically to minimize deprivation time. Additionally, Guo et al. (2025) [45] adjusted delivery routes dynamically based on road network conditions. Peng et al. (2025) [31] modeled routes with time dependency to ensure efficiency in delivery.
Vehicles	
28. Bogyrbayeva, A.; Yoon, T.; Ko, H. B.; Lim, S.; Yun, H. Y.K.; Kwon, C. (2023) [23]	Each of these sources uses the term vehicles to describe a type of means of transportation, for example drones, UAVs, trucks, transport modes in general, ground vehicles, cargo pedelecs, autonomous verhicles. For example, papers like Hong et al. (2023) [29] includes the efficient interaction between vehicles and other elements of the network for drone transport and Eberhardt et al. (2025) [28] proposed a heterogeneous fleet, including trucks and drones. Guo et al. (2025) [45] and Peng et al. (2025) [31] integrates trucks and drones into the delivery system while Sayarshad (2025) [26] employes drones as the primary transportation units in the system.
29. Bruni, M. E.; Khodaparasti, S.; Perboli, G. (2023) [24]	
30. Chiang, W. C.; Li, Y. Y.; Shang, J.; Urban, T. L. (2019) [25]	
31. Cokyasar, T. (2021) [40]	
32. Enayati, S.; Campbell, J. F.; Li, H. (2023) [42]	
33. Hong, F.; Wu, G.; Luo, Q.; Liu, H.; Fang, X.; Pedrycz, W. (2023) [29]	
34. Hu, Z. C.; Chen, H.; Lyons, E.; Solak, S.; Zink, M. (2024) [30]	
35. Lin, M.; Lyu, J.-Y.; Gao, J.-J.; Li, L.-Y. (2020) [32]	
36. Patchou, M.; Sliwa, B.; Wietfeld, C. (2021) [33]	

Table 8. Cont.

System Components	
37. Pina-Pardo, J. C.; Silva, D. F.; Smith, A. E. (2021) [34] 38. Pinto, R.; Lagorio, A. (2022) [38] 39. Rave, A.; Fontaine, P.; Kuhn, H. (2023) [46] 40. Roesing, J.; Lima, I.; Feldhoff, E.; Hoenen, S.; Kuehnel, F.; Theissen, A. (2023) [64] 41. Silvestri, S. de; Capasso, P. J.; Gargiulo, A.; Molinari, S.; Sanna, A. (2023) [62] 42. Ulmer, M. W.; Streng, S. (2019) [39] 43. Lu, J.; Liu, Y.; Jiang, C.; Wu, W. (2025) [35] 44. Peng, Y.; Ren, Z.; Yu, D.Z.; Zhang, Y. (2025) [31] 45. Sayarshad, H. (2025) [26] 46. Guo, Y.; He, L.; Yang, H.; Wang, S.; Liu, K. (2025) [45] 47. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28]	
Payload	
48. Chiang, W. C.; Li, Y. Y.; Shang, J.; Urban, T. L. (2019) [25] 49. Sayarshad, H. (2025) [26] 50. Peng, Y.; Ren, Z.; Yu, D.Z.; Zhang, Y. (2025) [31]	
Chiang et al. (2019) [25] explains payloads and their capacity and weight limitations for both UAVs and traditional vehicles as an important consideration. Sayarshad (2025) [26] and Peng et al. (2025) [31] considers drone payload capacity to address operational constraints.	
Network topology	
51. Patchou, M.; Sliwa, B.; Wietfeld, C. (2021) [33] 52. Petit, V.; Ribeiro, M. (2025) [44] 53. Sayarshad, H. (2025) [26] 54. Guo, Y.; He, L.; Yang, H.; Wang, S.; Liu, K. (2025) [45] 55. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28]	
Patchou et al. (2021) [33] describe the interaction of the logistics infrastructure, as network topology, required to coordinate and operate a hybrid delivery system. Petit & Ribeiro (2025) [44] designs a network of vertiports to support middle-mile delivery operations. Sayarshad (2025) [26] designed a structured delivery network to ensure equitable access. Guo et al. (2025) [45] designed a dynamic network to adapt to changing conditions. Eberhardt et al. (2025) [28] designs a flexible network to adapt to resource constraints and demand fluctuations.	

The reviewed literature highlights six core system components: nodes, edges, routes, vehicles, payloads, and network topology each playing a distinct but interrelated role in drone-enabled logistics networks.

In the reviewed literature, nodes serve as fundamental components within drone-based logistics networks, often representing critical points such as demand locations, delivery destinations, or strategic infrastructure. For example, Bogyrbayeva et al. (2023) [23] and Pachayappan & Sudhakar (2021) [59] treat each delivery address as a node in their routing heuristics. Similarly, Hong et al. (2023) [29] employ a heuristic method, specifically the SATO-IVND algorithm, that integrates task allocation with route planning to handle node interactions efficiently. Pachayappan and Sudhakar (2021) [59] apply a drone neighbor search heuristic to design and evaluate routing strategies, conceptualizing nodes as delivery or service locations to optimize routes and schedules. In humanitarian and emergency logistics, Eberhardt et al. (2025) [28] define nodes as relief supply demand points, while Guo et al. (2025) [45] model both emergency supply distribution centers and disaster-affected zones as nodes. Furthermore, Sayarshad (2025) [26] presents regional vaccine demand points as nodes within a public health delivery context. Petit and Ribeiro (2025) [44] identify potential vertiport locations alongside demand points as key nodes in middle-mile cargo operations. In addition, Peng et al. (2025) [31] represent delivery locations as nodes and build a network around them. Meanwhile, Pinto and Lagorio (2022) [38] combine mixed-integer optimization with heuristic techniques to design drone delivery networks, treating delivery points and charging stations as nodes and optimizing their configuration to reduce service costs and infrastructure investments. These varied interpretations underscore that node selection must align with each application's objectives such as commercial, humanitarian, or public health.

Edges are the links connecting nodes and are modeled as feasible flight or transport pathways subject to regulatory, geographic, and energy constraints. Hong et al. (2018) [37] and Pinto & Lagorio (2022) [38] define edges based on permissible drone corridors, while in humanitarian contexts, Eberhardt et al. (2025) [28], Guo et al. (2025) [45], and Sayarshad (2025) [26] optimize these connections to ensure rapid, reliable links between supply and demand nodes. Peng et al. (2025) [31] extend this by modeling edges that govern coordination between drones and ground vehicles. Collectively, these studies demonstrate that the structure and weighting of edges critically shape network efficiency and system resilience.

Route design is a recurring focus, with several studies presenting routes as optimized or dynamic paths for vehicle movement across the logistics network. Enayati et al. (2023) [42] describe routes simply as paths linking nodes, emphasizing spatial connectivity. More advanced routing logic is seen in Eberhardt et al. (2025) [28] and Guo et al. (2025) [45], both of whom propose dynamically adaptable delivery routes that respond to real-time data such as resource availability or road network status, with the aim of minimizing deprivation time or optimizing delivery timing. Peng et al. (2025) [31] further integrate time-dependent modeling into route planning, ensuring operational efficiency by considering varying travel times and coordination between multimodal transport units. Across all cases, optimized routing remains central to meeting service level objectives under capacity, time, and regulatory constraints.

The concept of vehicles spans a variety of transport modes across the reviewed studies, including drones, trucks, cargo pedelecs, and autonomous vehicles. These vehicles play a critical role in both last-mile and middle-mile delivery contexts. Hong et al. (2023) [29] emphasize the coordination between multiple vehicle types within the network, ensuring efficient interaction and task allocation. Eberhardt et al. (2025) [28] model a heterogeneous fleet comprising both drones and trucks to meet different logistical needs. Similarly, Guo et al. (2025) [45] and Peng et al. (2025) [31] integrate ground and aerial vehicles into unified delivery systems, demonstrating the growing importance of hybrid transportation

strategies. Sayarshad (2025) [26] focuses on drones as the primary vehicle in a structured delivery network, reflecting the potential of UAVs to serve specialized missions, such as vaccine delivery. These analyses reveal that vehicle selection and fleet composition must reflect application requirements, coverage areas, and operational objectives.

Payload capacity and constraints are addressed in a few key studies as operational limitations that impact route design and vehicle choice. Chiang et al. (2019) [25] discusses the weight and capacity limitations of both UAVs and traditional vehicles, noting the necessity of matching vehicle capabilities with delivery requirements. Sayarshad (2025) [26] and Peng et al. (2025) [31] incorporate payload considerations directly into their models, optimizing delivery operations based on drones' carrying capacities and ensuring feasibility within system constraints. These studies underscore that payload constraints are a pivotal factor in balancing mission requirements with vehicle capabilities.

Network topology emerges as a strategic component that shapes the overall structure and adaptability of drone logistics systems. Patchou et al. (2021) [33] describe network topology in terms of infrastructure interactions necessary to support hybrid delivery systems, emphasizing coordination across modes. Petit and Ribeiro (2025) [44] focus on the design of vertiport networks to enable efficient middle-mile delivery, while Sayarshad (2025) [26] proposes a structured network aimed at promoting equitable access to medical supplies. Guo et al. (2025) [45] advocate for a dynamic network topology that adapts in real time to shifting environmental and logistical conditions. Meanwhile, Eberhardt et al. (2025) [28] model a flexible, resource-sensitive network that responds to demand fluctuations and system constraints, highlighting the need for resilience in drone-based logistics planning. Across these works, the chosen topology influences both strategic decisions (location planning, fleet sizing) and operational performance (routing efficiency, response time).

In summary, effective drone logistics requires an integrated perspective that simultaneously considers nodes, edges, routes, vehicles, payloads, and topology. While many studies focus on one or two elements in depth, the most robust approaches model their interplay capturing how infrastructure placement, fleet capabilities, and routing algorithms combine to meet diverse application objectives. This holistic view is essential for designing systems that are both efficient and adaptable to real-world complexities.

3.6. Geographic Setting

Table 9 categorizes the studies by their geographic focus, as urban, suburban, rural, and remote/island regions highlighting how different environments shape UAV logistics research and application.

- *Urban areas:* Dense cities pose distinctive challenges for drone operations, including high population density, complex airspace regulations, building obstructions, and limited landing space [78,79]. At the same time, UAVs promise to alleviate road congestion and accelerate last-mile deliveries. This subsection reviews research examining drone deployment in metropolitan logistics, focusing on strategies for navigating urban constraints while maximizing efficiency.
- *Suburban areas:* Suburban zones, characterized by intermediate population density and more flexible airspace, offer a valuable testing ground for scalable UAV networks [74]. These areas blend the infrastructure complexity of cities with the open spaces of rural regions, requiring adaptable routing and hub placement. Here, we synthesize studies that evaluate drone delivery solutions tailored to suburban delivery corridors.
- *Rural areas:* Rural regions often face limited infrastructure and longer travel distances, making traditional delivery inefficient. UAVs offer an opportunity to overcome ge-

ographic isolation and enhance service access by providing direct, aerial transport routes [46,51]. This subsection surveys studies applying drone logistics in rural settings to improve access, delivery efficiency and equity.

- *Remote areas and Island regions:* Isolated locations such as remote villages or island communities face acute logistics challenges due to geographical barriers and transport delays. Drones have been piloted to deliver vital supplies, including medical goods, at reduced time and expense [42]. We review studies that deploy UAVs in these hard-to-reach areas, illustrating how aerial delivery can transform service provision where traditional transport is impractical.

The geographic focus of the reviewed studies underscores how environment-specific challenges and opportunities shape drone-based logistics. Across all contexts of urban, suburban, rural, and remote, UAVs demonstrate remarkable adaptability, yet each setting demands tailored solutions.

Several studies explicitly focus on the challenges and opportunities associated with logistics operations in urban environments. Chiang et al. (2019) [25] emphasizes the importance of emissions reduction and logistical efficiency in densely populated urban areas. The study underlines that such environments, due to high traffic congestion and environmental concerns, particularly benefit from drone-based delivery systems. Similarly, Doole et al. (2021) [63] frame their research in an urban context by conducting detailed simulations based on the street network of Manhattan, New York City. This area serves as a prototypical dense urban setting, allowing the authors to evaluate the system's effectiveness in navigating constrained environments. Gao J.J. (2023) [27] also focuses on urban areas, presenting a detailed case study centered in Hangzhou, China, a city known for its vibrant e-commerce sector. The study showcases how drone logistics can enhance delivery speed and efficiency in such economically dynamic and high-demand regions. Likewise, Hong et al. (2023) [29] discusses the deployment of drones in urban settings, emphasizing the advantage of using vertical space and bypassing surface-level traffic congestion to improve delivery operations. Ulmer and Streng (2019) [39] base their computational experiments on the infrastructure of Braunschweig, Germany, which provides insights into delivery systems in a medium-sized European city with urban characteristics. Peng et al. (2025) [31] direct their work toward dense, time-sensitive urban environments. Their model focuses on optimizing last-mile delivery by integrating drones with ground vehicles in a hybrid logistics system tailored for city operations.

In terms of suburban logistics, Rave et al. (2023) [46] present a flexible and adaptive model designed to handle delivery challenges across various geographical settings, including urban, suburban, and rural areas. Their approach supports the scalability of logistics networks, accounting for differences in population density, infrastructure, and accessibility. In a more region-specific study, Petit and Ribeiro (2025) [44] apply their proposed methodology to both urban and suburban regions within South Holland. Their work particularly addresses the complexity of middle-mile logistics across these zones, which often experience transitional characteristics between urban congestion and rural sparsity. The suburban context in their study plays a critical role in designing networks that can support both high-volume and spread-out delivery needs.

Table 9. Elements (own presentation).

Geographic Area	
Urban	
1. Bruni, M. E.; Khodaparasti, S.; Perboli, G. (2023) [24]	Bruni et al. (2023) [24] implement their last-mile parcel delivery method in urban setting.
2. Chiang, W. C.; Li, Y. Y.; Shang, J.; Urban, T. L. (2019) [25]	Chiang et al. (2019) [25] explicitly state that the context and implications of the study suggest an urban focus, where logistical efficiency and emissions reduction are particularly important due to high population density and environmental concerns.
3. Cokyasar, T. (2021) [40]	Cokyasar (2021) [40] develops E-commerce last-mile delivery with battery-swapping support at strategic level, and implemented it to a case study in Chicago region.
4. Dhote, J.; Limbourg, S. (2020) [41]	Dhote, J.; Limbourg, S. (2020) [41] formulate strategic design of UAV networks for transporting biomedical items (e.g., blood units, test samples) between hospitals, labs, and blood centers focused on Brussels and its periphery, considering urban/regional public-health logistics.
5. Doole, M.; Ellerbroek, J.; Knoop, V. L.; Hoekstra, J. M. (2021) [63]	Doole et al. (2020) [63] set in an urban context, with detailed simulations conducted using the urban street network of Manhattan, New York City, representing a typical dense urban environment.
6. Feng, X.; Murray, A. T.; Church, R. L. (2021) [43]	Feng et al. (2021) [43] use continuous-area modeling (e.g., urban terrain) accounting for terrain, obstacles, and environmental variability.
7. Gao, J. J.; Zhen, L.; Wang, S. A. (2023) [27]	Gao J. J. (2023) [27] targets urban areas, with a detailed case study and testing in Hangzhou, China, which is a major city known for its e-commerce activity.
8. Hong, F.; Wu, G.; Luo, Q.; Liu, H.; Fang, X.; Pedrycz, W. (2023) [29]	Hong et al. (2023) [29] focuses on urban environments, discussing drone benefits in avoiding ground traffic and utilizing vertical spaces for operations.
9. Hong, I.; Kuby, M.; Murray, A. T. (2018) [37]	Hong et al. (2018) [37] consider urban-scale case study in Phoenix, AZ, using real spatial and obstacle data.
10. Hu, Z. C.; Chen, H.; Lyons, E.; Solak, S.; Zink, M. (2024) [30]	Hu et al. (2024) [30] target urban and peri-urban areas, focusing on integrating UAVs into existing transportation networks.
11. Kunovjanek, M.; Wankmüller, C. (2021) [60]	Kunovjanek & Wankmüller (2021) [60] considers distribution of COVID-19 test kits to potentially infected individuals primarily located in Austria, with insights from field studies involving the Austrian Red Cross.
12. Lin, M.; Lyu, J.-Y.; Gao, J.-J.; Li, L.-Y. (2020) [32]	Lin et al. (2020) [32] develop coordinated last-mile distribution using a single truck with multiple drones based on actual urban road networks, though the specific city isn't disclosed.

Table 9. Cont.

Geographic Area	
13. Pachayappan, M.; Sudhakar, V. (2021) [59]	For their last mile pick-up and delivery tasks, Pachayappan & Sudhakar (2021) [59] conduct case study in Delhi, India, with routes generated within a 10km radius. Patchou et al. (2021) [33] propose parcel delivery with prioritized medical goods during COVID-19 which is applied in urban setting based on real-world hybrid delivery scenario, though specific city not named. Pina-Pardo et al. (2021) [34] address last-mile delivery modeled in a single-day delivery zone, akin to urban/suburban scenarios. Roesing et al. (2023) [64] apply their conceptual design of airborne-supplied city hubs to urban environment with integration into city public spaces and transport infrastructure. Ulmer & Streng (2019) [39] with computational studies conducted based on the city layout and infrastructure of Braunschweig, Germany, which represents a typical European urban environment. Peng et al. (2025) [31] primarily targets urban areas, focusing on optimizing delivery in dense, time-sensitive environments.
14. Patchou, M.; Sliwa, B.; Wietfeld, C. (2021) [33]	
15. Pina-Pardo, J. C.; Silva, D. F.; Smith, A. E. (2021) [34]	
16. Roesing, J.; Lima, I.; Feldhoff, E.; Hoenen, S.; Kuehnel, F.; Theissen, A. (2023) [64]	
17. Ulmer, M. W.; Streng, S. (2019) [39]	
18. Peng, Y.; Ren, Z.; Yu, D.Z.; Zhang, Y. (2025) [31]	
Suburban	
19. Dhote, J.; Limbourg, S. (2020) [41]	Dhote, J.; Limbourg, S. (2020) [41] formulate strategic design of UAV networks for transporting biomedical items (e.g., blood units, test samples) between hospitals, labs, and blood centers focused on Brussels and its periphery, considering urban/regional public-health logistics. Petit & Ribeiro (2025) [44] applied the proposed methodology to the urban and suburban areas of the South Holland region, addressing the challenge of urban and suburban logistics.
20. Petit, V.; Ribeiro, M. (2025) [44]	
Rural	
21. Gao, C.-F.; Hu, Z.-H.; Wang, Y.-Z. (2023) [36]	Gao et al. (2023) [36] propose last-mile parcel consolidation in a hub-and-spoke network which is not tied to a specific city, but tested on standard VRP datasets, implying general applicability across logistics contexts.

Table 9. Cont.

Geographic Area	
22. Kouretas, K.; Kepaptsoglou, K. (2023) [58]	In their work, Kouretas & Kepaptsoglou (2023) [58] focus on rural, under-connected, and inter-city corridors, with emphasis on avoiding restricted airspace (e.g., urban no-fly zones) for the proposed model of integrated last-mile parcel delivery combining drones and conventional vehicles.
23. La Haidari; Brown, S. T.; Ferguson, M.; Bancroft, E.; Spiker, M.; Wilcox, A. et al. (2016) [61]	While not explicitly categorized in traditional geographic terms, the application by La Haidari (2016) [61] implies a focus on rural areas or regions with poor infrastructure, as these are typical of many low and middle income countries.
24. Rave, A.; Fontaine, P.; Kuhn, H. (2023) [46]	Rave et al. (2023) [46] propose parcel delivery in rural or scattered settlement areas with drone deployment both from trucks and fixed micro-depots.
25. Lu, J.; Liu, Y.; Jiang, C.; Wu, W. (2025) [35]	Lu et al. (2025) [35] centered on rural locations, emphasizing the unique challenges these areas pose for delivery networks, such as longer distances, sparse populations, and limited accessibility. They propose solutions tailored to these specific conditions.
26. Sayarshad, H. (2025) [26]	Sayarshad (2025) [26] targets rural and small cities, emphasizing the challenges of vaccine distribution in these regions.
27. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28]	Eberhardt et al. (2025) [28] focuses on rural and disaster affected areas and their research is applied to disaster prone regions, with a case study in Baden-Württemberg, Germany.
Remote areas/Island regions	
28. Enayati, S.; Campbell, J. F.; Li, H. (2023) [42]	Enayati et al. (2023) [42] address planning of drone-supported vaccine distribution for remote, less developed regions.
29. Silvestri, S. de; Capasso, P. J.; Gargiulo, A.; Molinari, S.; Sanna, A. (2023) [62]	Silvestri et al (2023) [62] emphasizes drone benefits in remote areas where traditional delivery methods fail, enhancing healthcare reach and effectiveness.
30. Guo, Y.; He, L.; Yang, H.; Wang, S.; Liu, K. (2025) [45]	Guo et al. (2025) [45] targets earthquake affected regions, addressing challenges like road disruptions and supply-demand uncertainties.

Logistics in rural context often involves unique constraints such as limited infrastructure, long travel distances, and dispersed populations. La Haidari et al. (2016) [61], although not explicitly labeling the geography, focus on delivery challenges in low- and middle-income countries, areas commonly associated with rural and underdeveloped logistics networks. The research deals with vaccine distribution and emphasizes the critical need for reliable, autonomous delivery mechanisms in areas with limited road access. Along similar lines, Lu et al. (2025) [35] present a model tailored specifically for rural delivery systems. Their study addresses key logistical barriers such as road quality, sparse demand points, and the higher costs of delivery per unit due to low density. Sayarshad (2025) [26] focuses on small cities and rural regions where vaccine distribution is logistically challenging. The study proposes a drone-based delivery model that enhances equity by improving access to essential medical supplies in underserved regions. Eberhardt et al. (2025) [28] also address rural delivery but within the context of disaster-affected areas. Their case study in Baden-Württemberg, Germany, demonstrates how a logistics network can be designed to function under resource constraints and fluctuating demand, typical of rural or remote locations during emergencies.

Studies targeting remote or isolated areas, including disaster-affected or island regions, underline the strategic value of drone delivery in overcoming accessibility issues. Silvestri et al. (2023) [62] highlight how drones can play a transformative role in healthcare delivery in remote regions where traditional transport options are inadequate. Their work illustrates improved reach and effectiveness in delivering medical supplies to isolated populations. Guo et al. (2025) [45] extend this concept by focusing on earthquake-affected regions, where conventional logistics networks are severely disrupted. Their study models the dynamics of delivery under uncertainty, accounting for road closures and variable demand. The system proposed integrates emergency response planning with autonomous drone operations, offering a resilient logistics framework for critical situations.

Across all geographic contexts, drones excel at bypassing ground-based limitations, whether congestion in cities, infrastructure gaps in rural areas, or complete isolation in remote locales. However, success metrics vary: urban studies prioritize speed and emissions reduction; suburban research balances flexibility with scale; rural and remote applications emphasize coverage, equity, and resilience. Tailoring drone logistics to these diverse geographies is therefore essential, requiring adaptive network designs, hybrid transport configurations, and context-aware planning methodologies.

3.7. Performane Assessment

Table 10 presents the key metrics used to evaluate the effectiveness of drone-based logistics systems. Five primary performance dimensions emerge from the literature: scalability, efficiency, reliability, speed, and safety. Each offers a distinct perspective on system capabilities and limitations.

- *Scalability:* Scalability is a key performance criterion for UAV logistics, reflecting the system's ability to maintain performance when extended across larger networks or higher delivery volumes. Studies explore how drone-based systems can adapt to growing demand and geographic coverage [57,74]. This subsection reviews literature examining scalable drone delivery frameworks.
- *Efficiency:* Efficiency measures the optimal use of resources such as energy, time, and cost in UAV logistics. Researchers focus on routing strategies, fleet management, and energy consumption to improve system-wide performance [51,56]. Here, we highlight contributions that quantify gains in overall system efficiency via improved logistics algorithms and smart scheduling.

- *Reliability*: Reliability refers to a system's robustness in the face of uncertainty, including adverse weather, mechanical failures, or communication disruptions. Rave et al. [46] and others assess strategies such as redundant routing, predictive maintenance, and resilient communication networks to ensure consistent service quality. This subsection synthesizes methods designed to bolster UAV logistics against operational variabilities.
- *Speed*: The rapid delivery capability of drones is often cited as a major advantage over traditional ground transport. Metrics under this category include flight time, end-to-end latency, and comparative delivery speeds [78,79]. In this subsection, we review studies that benchmark drone performance in urgent or time-critical scenarios, highlighting demonstrated time savings.
- *Safety*: Safety remains a critical concern for UAV operations, particularly in populated areas or during emergencies. Research addresses collision avoidance, airspace management, and risk mitigation frameworks [42]. This subsection summarizes safety innovations and regulatory compliance measures aimed at minimizing hazards during drone-based delivery.

The performance assessment literature underscores that, although profit-driven returns vary by application, efficiency remains a cornerstone of drone logistics—and safety is nonnegotiable given the inherently risky domain of low-altitude flight.

Scalability is a critical performance criterion, particularly for logistics networks expected to evolve with increasing demand or expanding geographic coverage. Gao J. J. (2023) [27] examines scalability through the lens of system adaptability, illustrating how the proposed drone delivery network could be applied across different urban environments and scaled up for future needs. Similarly, Guo et al. (2025) [45] propose a flexible framework capable of being adapted to various disaster scenarios and geographic regions, ensuring its long-term applicability and responsiveness to emergencies. Hong et al. (2018) [37] demonstrates the scalability of their logistics model through successful application in a complex urban setting, highlighting how the system can handle diverse logistical challenges. Petit and Ribeiro (2025) [44] underscore scalability by designing a framework that can be adjusted to different regions and logistics scenarios, making it suitable for both current and future needs. In the case of La Haidari et al. (2016) [61], scalability is tested via sensitivity analyses, which help assess how the model performs under varying operational parameters and environmental conditions. Lu et al. (2025) [35] directly address scalability by modeling scenarios with multiple drones, allowing for increased demand coverage in rural and remote areas. Pinto and Lagorio (2022) [38] contribute to the scalability discourse by incorporating flexible infrastructure components such as additional charging stations and network expansions. Similarly, Peng et al. (2025) [31] demonstrate scalability through simulation and testing on increasingly large delivery networks, while Eberhardt et al. (2025) [28] present a logistics model adaptable to diverse fleet configurations and disaster conditions, further emphasizing scalability through robustness.

Table 10. Performande assessment.

Performance Assessment	
Scalability	
1. Bogyrbayeva, A.; Yoon, T.; Ko, H. B.; Lim, S.; Yun, H. Y.K.; Kwon, C. (2023) [23]	Scalability is discussed by Gao J. J. (2023) [27] in terms of the system's applicability to different urban environments and potential for future expansion.
2. Chiang, W. C.; Li, Y. Y.; Shang, J.; Urban, T. L. (2019) [25]	The framework by Guo et al. (2025) [45] is adaptable to various disaster scenarios and regions.
3. Guo, Y.; He, L.; Yang, H.; Wang, S.; Liu, K. (2025) [45]	Hong et al.'s (2018) [37] model scalability is demonstrated through its application to a large urban area with complex logistical demands.
4. Cokyasar, T. (2021) [40]	Petit & Ribeiro (2025) [44] developed an adaptable framework to other regions and scenarios, demonstrating scalability.
5. Gao, J. J.; Zhen, L.; Wang, S. A. (2023) [27]	In La Haidari et al. (2016) [61] scalability is considered through sensitivity analyses to ensure the model's applicability under various operational scenarios.
6. Petit, V.; Ribeiro, M. (2025) [44]	Lu et al. (2025) [35] addresses the analysis of scalability through addition of multiple drones in cases of increased demand.
7. Hong, F.; Wu, G.; Luo, Q.; Liu, H.; Fang, X.; Pedrycz, W. (2023) [29]	Scalability is considered through the flexible integration of additional charging stations and potential expansion of the network to cover more areas, in Pinto & Lagorio (2022) [38].
8. Hong, I.; Kuby, M.; Murray, A. T. (2018) [37]	Peng et al. (2025) [31] demonstrates scalability by testing the solution on larger delivery networks.
9. Kouretas, K.; Kepaptsoglou, K. (2023) [58]	Eberhardt et al. (2025) [28] developed a framework that is adaptable to various disaster scenarios and fleet compositions.
10. La Haidari; Brown, S. T.; Ferguson, M.; Bancroft, E.; Spiker, M.; Wilcox, A. et al. (2016) [61]	
11. Lu, J.; Liu, Y.; Jiang, C.; Wu, W. (2025) [35]	
12. Lin, M.; Lyu, J.-Y.; Gao, J.-J.; Li, L.-Y. (2020) [32]	
13. Pinto, R.; Lagorio, A. (2022) [38]	
14. Rave, A.; Fontaine, P.; Kuhn, H. (2023) [46]	
15. Peng, Y.; Ren, Z.; Yu, D.Z.; Zhang, Y. (2025) [31]	
16. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28]	
Efficiency	
17. Cokyasar, T. (2021) [40]	Cokyasar (2021) [40] evaluates the efficiency of the proposed delivery system by minimizing operational costs.
18. Dhote, J.; Limbourg, S. (2020) [41]	

Table 10. Cont.

Performance Assessment	
19. Guo, Y.; He, L.; Yang, H.; Wang, S.; Liu, K. (2025) [45]	In their study, Guo et al. (2025) [45] developed a model that aims to minimize total costs while ensuring effective delivery.
20. Doole, M.; Ellerbroek, J.; Knoop, V. L.; Hoekstra, J. M. (2021) [63]	Dhote & Limbourg (2020) [41] focus on improving the efficiency and speed of medical care, which is crucial in emergency health situations.
21. Feng, X.; Murray, A. T.; Church, R. L. (2021) [43]	Lin et al. (2020) [32] assess the efficiency of the proposed collaborative delivery system, emphasizing improvements in delivery times and cost-effectiveness.
22. Gao, C.-F.; Hu, Z.-H.; Wang, Y.-Z. (2023) [36]	In their work, Kunovjanek, M.; Wankmüller, C. (2021) [60] compare delivery time and cost against mobile testing teams; outcomes include estimated reduction in human contact.
23. Gao, J. J.; Zhen, L.; Wang, S. A. (2023) [27]	Sayarshad (2025) [26] develops the model that aims to minimize delivery costs and enhances operational efficiency.
24. Hu, Z. C.; Chen, H.; Lyons, E.; Solak, S.; Zink, M. (2024) [30]	The study by La Haidari et al. (2016) [61] assesses the efficiency of using UAVs compared to traditional transport methods, with a focus on improving vaccine availability and reducing logistics costs.
25. Peng, Y.; Ren, Z.; Yu, D.Z.; Zhang, Y. (2025) [31]	Pinto & Lagorio (2022) [38] aims to enhance the efficiency of the delivery network by reducing travel distances and operational costs.
26. Kunovjanek, M.; Wankmüller, C. (2021) [60]	Lu et al. (2025) [35] demonstrates efficiency in the reduction of time and cost associated with deliveries.
27. La Haidari; Brown, S. T.; Ferguson, M.; Bancroft, E.; Spiker, M.; Wilcox, A. et al. (2016) [61]	Roesing et al. (2023) [64] evaluate how drones can boost efficiency in delivery systems and considers the broader applicability of city hubs in addressing urban logistics challenges.
28. Lin, M.; Lyu, J.-Y.; Gao, J.-J.; Li, L.-Y. (2020) [32]	Peng et al. (2025) [31] achieves an efficiency improvements through route optimization and carbon emissions cost minimization.
29. Pachayappan, M.; Sudhakar, V. (2021) [59]	The study by Petit & Ribeiro (2025) [44] develops a model that aims to improve delivery efficiency by optimizing vertiport placement.
30. Patchou, M.; Sliwa, B.; Wietfeld, C. (2021) [33]	Eberhardt et al. (2025) [28] formulated a model that aimed to minimize operating costs and population deprivation costs.
31. Pina-Pardo, J. C.; Silva, D. F.; Smith, A. E. (2021) [34]	
32. Pinto, R.; Lagorio, A. (2022) [38]	
33. Rave, A.; Fontaine, P.; Kuhn, H. (2023) [46]	
34. Sayarshad, H. (2025) [26]	
35. Roesing, J.; Lima, I.; Feldhoff, E.; Hoenen, S.; Kuehnel, F.; Theissen, A. (2023) [64]	
36. Ulmer, M. W.; Streng, S. (2019) [39]	
37. Lu, J.; Liu, Y.; Jiang, C.; Wu, W. (2025) [35]	
38. Petit, V. & Ribeiro, M. (2025) [44]	
39. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28]	
Reliability	
40. Bruni, M. E.; Khodaparasti, S.; Perboli, G. (2023) [24]	In the Study by Dhote & Limbourg (2020) [41], reliability is a key focus, given the need for consistent and dependable delivery systems to handle sensitive medical payloads.
41. Dhote, J.; Limbourg, S. (2020) [41]	

Table 10. Cont.

Performance Assessment	
Scalability	
42. Lu, J.; Liu, Y.; Jiang, C.; Wu, W. (2025) [35]	In the research by Lu et al. (2025) [35] reliability is evaluated through the coordinated operation of trucks and drones, ensuring consistent deliveries. Pachayappan & Sudhakar (2021) [59] evaluate the reliability of drone use in logistics, considering factors like route optimization and battery management to ensure timely deliveries. Peng et al. (2025) [31] presents how reliability can be enhanced through coordinated operations between trucks and drones. Sayarshad (2025) [26] focuses on designing a system that is designed to provide consistent and dependable vaccine delivery. The model by Eberhardt et al. (2025) [28] ensures consistent delivery despite resource constraints and dynamic conditions.
43. Feng, X.; Murray, A. T.; Church, R. L. (2021) [43]	
44. Pachayappan, M.; Sudhakar, V. (2021) [59]	
45. Sayarshad, H. (2025) [26]	
46. Ulmer, M. W.; Streng, S. (2019) [39]	
47. Peng, Y.; Ren, Z.; Yu, D.Z.; Zhang, Y. (2025) [31]	
48. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28]	
Speed	
49. Pina-Pardo, J. C.; Silva, D. F.; Smith, A. E. (2021) [34]	Pina-Pardo et al. (2021) [34] evaluates the efficiency and speed of delivery processes, with an objective to minimize the total completion time of deliveries, enhancing overall operational speed. Ulmer & Streng (2019) [39] reducing the delivery time through immediate dispatch and strategic placement of pickup stations.
50. Ulmer, M. W.; Streng, S. (2019) [39]	
Safety	
51. Doole, M.; Ellerbroek, J.; Knoop, V. L.; Hoekstra, J. M. (2021) [63]	Doole et al. (2021) [63] assess how different airspace configurations can minimize conflicts and improve the flow of drone traffic. Hu et al. (2024) [30] focus on safety by developing UAV operational plans that mitigate risks associated with stochastic weather conditions. Kunovjanek & Wankmüller (2021) [60] discuss infection risk reduction and social distancing benefits, but lacks formal safety or reliability modeling. Lu et al. (2025) [35] implicitly addressed safety through payload limitations and route optimization for both trucks and drones. Petit & Ribeiro (2025) [44] incorporates safety considerations such as maximum safety distances into the optimization process.
52. Hu, Z. C.; Chen, H.; Lyons, E.; Solak, S.; Zink, M. (2024) [30]	
53. Kunovjanek, M.; Wankmüller, C. (2021) [60]	
54. Silvestri, S. de; Capasso, P. J.; Gargiulo, A.; Molinari, S.; Sanna, A. (2023) [62]	
55. Lu, J.; Liu, Y.; Jiang, C.; Wu, W. (2025) [35]	
56. Petit, V.; Ribeiro, M. (2025) [44]	

Efficiency remains a central concern in drone-based logistics systems, often measured through cost savings, delivery time, and resource utilization. Cokyasar (2021) [40] evaluates efficiency by aiming to reduce overall operational costs within the proposed logistics model. Guo et al. (2025) [45] also focus on cost efficiency, developing a delivery framework that ensures effective transportation while minimizing total costs which is a vital consideration in post-disaster contexts. Dhote and Limbourg (2020) [41] approach efficiency from a healthcare perspective, highlighting the importance of rapid and cost-effective delivery of medical supplies during emergencies. Lin et al. (2020) [32] assess a collaborative delivery system, showcasing efficiency gains through improved delivery times and optimized routing. Sayarshad (2025) [26] builds a cost-minimizing model that enhances operational efficiency, specifically tailored to critical vaccine distribution. La Haidari et al. (2016) [61] provide a comparative efficiency assessment between UAVs and traditional methods, demonstrating how drones can reduce both cost and delivery delays, particularly for vaccine supply chains. Pinto and Lagorio (2022) [38] focus on reducing delivery distances to lower fuel consumption and operational expenses. Similarly, Lu et al. (2025) [35] highlight how drone-truck coordination reduces delivery time and cost, particularly in rural settings. Roesing et al. (2023) [64] examine how drones improve the efficiency of last-mile deliveries and propose city hubs as scalable solutions for urban logistics. Peng et al. (2025) [31] incorporate both route optimization and carbon emission considerations into their efficiency metrics. In Petit and Ribeiro (2025) [44], delivery efficiency is enhanced by optimizing vertiport placement to reduce unnecessary detours and delays. Eberhardt et al. (2025) [28] formulate a cost-efficient model that also minimizes deprivation for affected populations, presenting a balance between cost and social value.

The reliability of drone logistics systems is essential for ensuring timely and consistent deliveries, especially in healthcare and emergency scenarios. Dhote and Limbourg (2020) [41] underscore reliability as a foundational requirement, especially for the transportation of sensitive medical supplies. Their model emphasizes the need for consistent performance across varied conditions. Lu et al. (2025) [35] further explore reliability through coordinated operations between drones and trucks, ensuring redundancy and continuity in the delivery chain. Pachayappan and Sudhakar (2021) [59] assess system reliability by analyzing battery management and route planning, both of which are essential for consistent performance in drone logistics. Peng et al. (2025) [31] enhance reliability through the integration of trucks and drones, enabling flexible and dependable operations even in complex networks. Sayarshad (2025) [26] builds reliability into their vaccine delivery system, ensuring that critical medical goods reach rural populations consistently. Eberhardt et al. (2025) [28] focus on maintaining reliability despite fluctuating demand and resource constraints, ensuring that essential goods are delivered even under adverse conditions.

Speed is another important dimension of performance, particularly in emergency logistics and time-sensitive deliveries. Pina-Pardo et al. (2021) [34] evaluate how their system reduces total delivery time, aiming to minimize the time between dispatch and delivery completion. Their model prioritizes swift execution of logistics tasks to enhance overall service responsiveness. Ulmer and Streng (2019) [39] address speed through immediate dispatch strategies and the optimal placement of pickup stations, both of which contribute to reduced delivery times and faster service cycles.

Safety in drone logistics encompasses airspace management, weather adaptability, and collision avoidance. Doole et al. (2021) [63] explore safety by simulating various airspace configurations, aiming to reduce conflicts and maintain orderly drone movement in dense areas. Hu et al. (2024) [30] develop UAV operational plans that factor in stochastic weather conditions, helping to avoid unsafe routes and delays due to unpredictable environments.

Lu et al. (2025) [35] implicitly address safety through route optimization and consideration of drone payload limitations, reducing risks associated with overloading and misrouting. Petit and Ribeiro (2025) [44] incorporate safety parameters such as minimum distance buffers into their optimization models, ensuring drones operate within safe margins. These approaches collectively highlight how safety can be systematically embedded into the planning and operation of drone logistics networks.

Across all performance dimensions: scalability, efficiency, reliability, speed, and safety, drone logistics studies share a common goal of optimizing delivery networks through modular designs, robust algorithms, and hybrid vehicle fleets. However, the emphasis placed on each criterion varies by application context: commercial e-commerce research prioritizes cost savings and rapid, same-day delivery; healthcare and humanitarian studies stress reliability and equitable access in time-critical scenarios; urban mobility work focuses on safety, airspace integration, and environmental benefits; and rural or remote logistics emphasize scalability and resilience under infrastructure constraints. This alignment on core objectives, paired with context-driven adaptations, underscores both the methodological unity and the tailored innovations that characterize the field of UAV-based logistics.

3.8. Transport Configuration

Table 11 classifies the reviewed studies by their chosen transport architectures namely, UAS only, Drone + X, and truck-drone systems each reflecting a different strategy for leveraging UAVs in delivery networks.

- *UAS only*: The UAS only configuration relies exclusively on unmanned aerial systems (UAS) for transport, offering end-to-end delivery via drones without integration with other transport modes. This model is particularly suitable for short-range, time-sensitive, or hard-to-access deliveries such as in disaster zones or medical emergencies [42,51]. This subsection reviews literature focused on fully aerial delivery systems using UAVs.
- *Drone + X*: Hybrid models combining drones with other transport modes (e.g., bikes, boats, or rail) aim to exploit the strengths of each. This Drone + X configuration allows flexible operations, particularly in environments with partial access or regulatory constraints [79]. Here, we discuss studies that investigate these multimodal configurations for increased adaptability and coverage.
- *Truck-drone system*: Here, drones are deployed from moving or stationary trucks to complete the last mile of delivery, while the trucks handle longer hauls. This approach synergizes the speed and direct routing of drones with the capacity and road network access of trucks [80,81]. Truck-drone systems have emerged as a leading solution for reducing delivery times and costs in urban and suburban settings. The literature reviewed below evaluates various implementations and optimization strategies for these integrated fleets.

Table 11. Transport configuration(own presentation)

Transport Configuration	
UAS only	
1. Doole, M.; Ellerbroek, J.; Knoop, V. L.; Hoekstra, J. M. (2021) [63] 2. Hu, Z. C.; Chen, H.; Lyons, E.; Solak, S.; Zink, M. (2024) [30] 3. La Haidari; Brown, S. T.; Ferguson, M.; Bancroft, E.; Spiker, M.; Wilcox, A. et al. (2016) [61] 4. Silvestri, S. de; Capasso, P. J.; Gargiulo, A.; Molinari, S.; Sanna, A. (2023) [62] 5. Roesing, J.; Lima, I.; Feldhoff, E.; Hoenen, S.; Kuehnel, F.; Theissen, A. (2023) [64] 6. Sayarshad, H. (2025) [26]	The study by Doole et al. (2021) [63] involves UAS, specifically focusing on drones and potentially flying taxis, within the context of urban mobility and delivery services. Considering constraints like energy consumption, no-fly zones, and weather conditions, Hu et al. (2024) [30] employ UAS only system. La Haidari et al. (2016) [61] model UAS-only system against a traditional multi-tiered land transport system (TMLTS), while Silvestri et al. (2023) [62] focus on UAS-only operations, often point-to-point. Roesing et al’s (2023) [64] study examines how drones and vertical take-off and landing (VTOL) systems can be integrated into urban delivery networks to replace or reduce reliance on traditional road transportation. The study by Sayarshad (2025) [26] focuses exclusively on drone-based vaccine delivery systems.
Drone + X	
7. Bruni, M. E.; Khodaparasti, S.; Perboli, G. (2023) [24] 8. Chiang, W. C.; Li, Y. Y.; Shang, J.; Urban, T. L. (2019) [25] 9. Enayati, S.; Campbell, J. F.; Li, H. (2023) [42] 10. Kunovjanek, M.; Wankmüller, C. (2021) [60]	Bruni et al. (2023) [24] discuss the integration of drones into city logistics for last-mile delivery, along with the use of other vehicles like Fuel-based Cargo Bikes (F-CBs) and Electric Cargo Bikes (E-CBs) in different fleet configurations. Chiang et al. (2019) [25] address hybrid truck–drone system; drones launched from trucks to take customers while trucks serve the rest. Enayati et al.’s (2023) [42] study names multi-modal transport options, including integration of drones with boats, trucks, and planes. Kunovjanek & Wankmüller (2021) [60] discussing an integrated transportation solution using drones in conjunction with the existing healthcare logistics infrastructure.

Table 11. Cont.

Transport Configuration	
11. Ulmer, M. W.; Streng, S. (2019) [39]	Ulmer & Streng (2019) [39] introduce autonomous vehicle (AV)-only ground-based system with fixed stations, no traditional delivery to customer door.
12. Petit, V.; Ribeiro, M. (2025) [44]	A framework by Petit & Ribeiro (2025) [44] supports middle-mile delivery using drones in conjunction with vertiports.
Truck-drone system	
13. Bogyrbayeva, A.; Yoon, T.; Ko, H. B.; Lim, S.; Yun, H. Y.K.; Kwon, C. (2023) [23]	Bogyrbayeva, A.; Yoon, T.; Ko, H. B.; Lim, S.; Yun, H. Y.K.; Kwon, C. (2023) [23] develop hybrid truck–drone system coordinating deliveries in tandem.
14. Cokyasar, T. (2021) [40]	Cokyasar (2021) considers drones as the primary delivery mechanism, with strategic integration of trucks for certain delivery tasks, forming a hybrid transportation model.
15. Gao, C.-F.; Hu, Z.-H.; Wang, Y.-Z. (2023) [36]	Gao et al. (2023) [36] present hybrid system—trucks for inter-hub travel and drones for spoke delivery tasks.
16. Gao, J. J.; Zhen, L.; Wang, S. A. (2023) [27]	Gao J. J. et al. (2023) [27] describes a hybrid transport system where trucks function as mobile hubs for drones, integrating aerial and ground logistics to optimize urban delivery.
17. Kouretas, K.; Kepaptsoglou, K. (2023) [58]	Kouretas & Kepaptsoglou (2023) [58] implement multimodal transport configuration with hybrid CV–UAV system where the conventional vehicle supports drone operations and acts as a mobile depot.
18. Guo, Y.; He, L.; Yang, H.; Wang, S.; Liu, K. (2025) [45]	Guo et al. (2025) [45] examines the collaborative operation of trucks and drones for relief delivery.
19. Lin, M.; Lyu, J.-Y.; Gao, J.-J.; Li, L.-Y. (2020) [32]	Lin et al. (2020) [32] address hybrid transport system with truck- multiple drone configuration.
20. Patchou, M.; Sliwa, B.; Wietfeld, C. (2021) [33]	Enabling capacity lift and prioritized medical dispatch, Patchou et al. (2021) [33] employ hybrid truck–drone system.
21. Pina-Pardo, J. C.; Silva, D. F.; Smith, A. E. (2021) [34]	Pina-Pardo et al. (2021) [34] consider truck with drone resupply, a hybrid configuration tailored for real-time order fulfillment.
22. Pinto, R.; Lagorio, A. (2022) [38]	The paper by Pinto & Lagorio (2022) [34] evaluate a hybrid delivery system combining drones with static and mobile hubs (trucks), leveraging drones for last-mile deliveries.
23. Rave, A.; Fontaine, P.; Kuhn, H. (2023) [46]	Rave et al. (2023) [46] address hybrid truck–drone system, supporting both station-based and truck-launched drone deliveries.
24. Lu, J.; Liu, Y.; Jiang, C.; Wu, W. (2025) [35]	The study by Lu et al. (2025) [35] specifically examines the coordinated operation of trucks and drones as a unified system.
25. Eberhardt, K.; Diehlmann, F.; Lüttenberg, M.; Kaiser, F.K.; Schultmann, F. (2025) [28]	In their research, Eberhardt et al. (2025) [28], incorporates diverse fleet types, including drones, for efficient last-mile delivery.

The transport configuration literature reveals three principal deployment models: UAS only, Drone + X, and Truck-drone systems each offering distinct advantages and trade-offs.

Several studies focused exclusively on the use of Unmanned Aerial Systems (UAS), particularly drones, without the integration of other transport modes. Doole et al. (2021) [63] investigate the role of drones and potentially flying taxis in urban mobility and delivery systems. Their study emphasizes the potential of UAS to independently operate within designated urban air corridors, reducing dependence on road infrastructure and offering new possibilities for rapid and flexible transportation. Similarly, Roesing et al. (2023) [64] explore the use of drones and Vertical Take-Off and Landing (VTOL) systems as a standalone solution for urban logistics. Their research highlights how UAS can be used to overcome congestion in city centers and how VTOL capabilities can allow operations in dense urban landscapes without requiring traditional infrastructure like runways. Sayarshad (2025) [26] provides another clear example of UAS-only transport, focusing specifically on a drone-based vaccine distribution model. This system is designed to serve remote or underserved regions, leveraging drones' autonomous flight capabilities to ensure timely and consistent vaccine delivery without reliance on conventional ground transport.

Other studies adopt a multimodal approach, where drones are integrated with different types of transport modes to enhance logistics efficiency. Bruni et al. (2023) [24] present a city logistics model that combines drones with Fuel-based Cargo Bikes (F-CBs) and Electric Cargo Bikes (E-CBs). This integrated approach supports last-mile delivery operations in urban areas and enables flexible fleet configurations that can be adapted based on environmental considerations and delivery density. Enayati et al. (2023) [42] take multimodality further by proposing a system where drones are coordinated with boats, trucks, and airplanes. Their study emphasizes the versatility of drone deployment in complex logistics chains, such as inter-island deliveries or disaster response operations that require multimodal reach. Kunovjanek and Wankmüller (2021) [60] investigate how drones can complement the existing healthcare logistics infrastructure. They propose a framework in which drones are integrated into established medical supply chains, increasing responsiveness and extending the reach of emergency healthcare services. Petit and Ribeiro (2025) [44] propose a framework that supports drone operations in the middle-mile segment. Their model incorporates the use of vertiports, enabling drones to function efficiently within a larger logistics ecosystem while bridging the gap between long-haul deliveries and the last mile.

A prominent transport configuration emerging in the literature is the hybrid truck-drone system, which combines the strengths of ground and aerial vehicles to create a more robust delivery network. Cokyasar (2021) [40] proposes a system where drones serve as the primary delivery method, but trucks are used strategically for supporting roles, such as transporting large payloads or covering areas where drones may face restrictions. This approach offers the flexibility of drones while maintaining the logistical power of trucks. Gao J. J. et al. (2023) [27] also explore a hybrid model, where trucks serve as mobile hubs for drones. In their system, trucks move through urban areas and launch drones to complete final deliveries. This method reduces the need for static infrastructure and enhances delivery reach. Lu et al. (2025) [35] focus on the synchronized operation of drones and trucks as a unified system. Their study demonstrates how such coordination can improve both delivery time and coverage while maintaining reliability. Pinto and Lagorio (2022) [38] take a similar approach by evaluating a delivery network that uses both static hubs and mobile truck depots to support drone operations. This configuration enables more agile last-mile delivery, especially in urban environments. Guo et al. (2025) [45] present a disaster-relief logistics framework that coordinates drones and trucks for efficient supply distribution. This collaboration ensures that urgent relief items can reach affected

regions even when infrastructure is compromised. Eberhardt et al. (2025) [28] develop a flexible logistics model that includes a diverse fleet of vehicles, including drones and trucks. Their focus is on optimizing last-mile delivery by leveraging the specific strengths of each vehicle type, adapting to different demand scenarios and geographical constraints.

Across all configurations, drones demonstrate remarkable adaptability: UAS Only systems are highly effective for lightweight, urgent deliveries, particularly in remote, disaster-prone, or medically underserved areas [42,51]. However, their dependence on battery life and payload limitations restricts their broader use in urban contexts. Drone + X configurations provide maximum flexibility by leveraging existing transport modes for part of the journey. They are particularly useful in geographically diverse regions, such as islands or mountainous zones, but they require careful planning and multi-modal coordination [79]. Truck-Drone Systems are most suitable for last-mile delivery in urban or suburban areas, combining the strength of traditional logistics with drone agility. Their real-world feasibility and growing commercial interest make them a promising choice for scalable applications, though synchronization and regulatory hurdles must be addressed [80,81]. The choice of configuration depends on operational priorities such as speed, reach, capacity, or resilience and on the availability of supporting infrastructure. Comparative analysis is presented in Table 12.

Table 12. Comparative analysis of drone-based transport configurations (Author’s own presentation).

Aspect	UAS Only	Drone + X	Truck-Drone System
Definition	Full delivery by UAVs without other modes	Drones combined with another mode (e.g., boat, rail, bike)	Drones launched from and return to trucks during delivery
Strengths	Quick deployment, full autonomy, ideal for remote/emergency delivery	High flexibility, adaptable to multi-modal environments	Efficient for last-mile, scalable in urban/suburban areas
Limitations	Limited range and payload, airspace constraints	Requires coordination and transfer infrastructure	Synchronization needed, affected by traffic and regulations
Use cases	Disaster relief, medical/pharmaceutical supplies, rural deliveries	Island logistics, mountainous regions, mixed terrain	Parcel delivery, e-commerce fulfillment, urban last-mile
Infrastructure needs	Minimal ground setup, charging/swap stations	Multi-modal hubs, integration interfaces	Trucks equipped for launch/retrieval, in-transit charging
Operational complexity	Low to medium	High	Medium to high
Scalability	Moderate (battery and range limitations)	High, but infrastructure-intensive	High with truck fleet expansion

4. Derivation of a Framework

Building on the systematic review, we propose a structured framework that captures the interconnected steps of planning drone-enabled logistics networks. The conceptual framework integrates all the review categories in a planning-oriented sequence to guide logistical decision-making for highly automated drone networks. The Application Context and Geographic Scope category combines the areas of application and geographic environments, as these factors are interdependent and jointly influence planning requirements. The framework is formulated as a generalizable structure to support planning, rather than to individually position each reviewed study within its components. It provides a high-level structure that illustrates how application needs, system components, optimization approaches, and performance considerations are combined into a cohesive planning process.

Specifically, the Application Context and Geographic Scope dimension reflects diverse use cases addressed in the literature, such as healthcare logistics (e.g., [42,60]) and last-mile parcel delivery (e.g., [25,33]), across urban, suburban, and remote regions. Within the

System Components dimension, studies such as [34] and [46] focus on nodes, routes, and vehicle interactions, while others like [37] emphasize infrastructure elements, including recharging stations. The Optimization and Analysis dimension includes diverse methodological approaches such as mathematical modeling (e.g., [24,31]), heuristic algorithms (e.g., [32,58]), and simulation-based analysis (e.g., [63]). The Logistical Planning component is addressed across multiple studies, including location planning (e.g., [36,37]), routing and scheduling problems (e.g., [23]), and network design (e.g., [38]). In the Performance Assessment dimension, scalability and efficiency are frequently evaluated (e.g., [30,39]), though fewer studies systematically assess safety or regulatory readiness. The feedback loop in the framework, which links performance assessment back to application scope definition, is informed by studies like [41,61], which emphasize the iterative improvement of drone logistics systems based on operational outcomes.

In planning drone-enabled logistics networks, the first step is to clearly define the application context and geographic scope. Whether the use case is last-mile e-commerce, urgent healthcare delivery, disaster relief, or urban air mobility, each scenario carries its own operational and regulatory constraints [23,26]. Likewise, the geographic setting: urban, suburban, rural, or remote affects airspace rules, infrastructure availability, and environmental risks [42,63]. Identifying these parameters upfront ensures that subsequent planning decisions align with the mission's core objectives, such as speed, equity, resilience, or sustainability.

Once the application context is established, identification of the key system components that form the network's backbone follows. This includes selecting physical and virtual nodes (e.g., vertiports, micro-hubs, or customer sites) and mapping edges (flight corridors and ground links) [38,68,69]. Another important task here is, to define the vehicles such as UAV types, trucks, cargo bikes, or multimodal combinations and to account for payload constraints that shape vehicle choice and route feasibility [25,46]. It is also important to decide on an overarching network topology (hub-and-spoke, mesh, or hybrid) to balance efficiency and resilience [76,77].

With components in place, decision-makers choose an appropriate transport configuration. Pure UAS only models suit short-range, time-critical missions such as medical supply drops where direct aerial routes confer maximum speed [26,42]. Drone + X configurations pair drones with bikes, boats, or rail to navigate partial infrastructures [24,60]. Truck-drone hybrids use trucks as mobile hubs for last-mile drone deployment, combining range and payload benefits or trucks can combine with drones for delivery [27,80]. Each configuration involves trade-offs in range, capacity, infrastructure needs, and regulatory complexity.

Next is the selection of optimization and analysis methods. For example, for route planning, heuristics or AI algorithms can be applied to solve large-scale routing problems efficiently [23,29]. Location and network design often rely on mathematical programming (MILP, MINLP, or stochastic models) to optimize hub placement and connectivity under uncertainty [27,30]. Allocation planning, which for example, is assigning vehicles and resources in real time requires dynamic algorithms to adjust to fluctuating demand [45,46]. Simulation and case study analyses then validate model assumptions and stress-test the network under variable conditions [44,63]. Hybrid approaches combining exact models, heuristics, and simulation strike a balance between precision, scalability, and robustness. Equipped with these tools, core logistical tasks can be executed: optimizing routes for minimal time or cost [33], siting facilities for maximum coverage [42], and dynamically allocating vehicles to meet delivery requirements [26,28]. These tasks translate strategic designs into operational schedules, ensuring efficient resource flows and service delivery. Ultimately, the network's performance is assessed against metrics such as scalability, efficiency, reliability, speed, and safety [32,63]. This evaluation provides feedback for refining

network design, transport configurations, and optimization parameters. Iterating this cycle allows adaptation to evolving demands, regulatory landscapes, and technological advances, resulting in efficient, resilient, and purpose-built drone logistics networks.

Together, these interconnected steps: defining context, modeling components, choosing configurations, selecting methods, executing plans, and assessing performance form a cohesive, repeatable framework for designing and operating drone-enabled logistics networks (see Figure 4). This structured approach ensures that each decision builds on the last, resulting in networks that are efficient, resilient, and fit for purpose in a wide range of real-world applications.

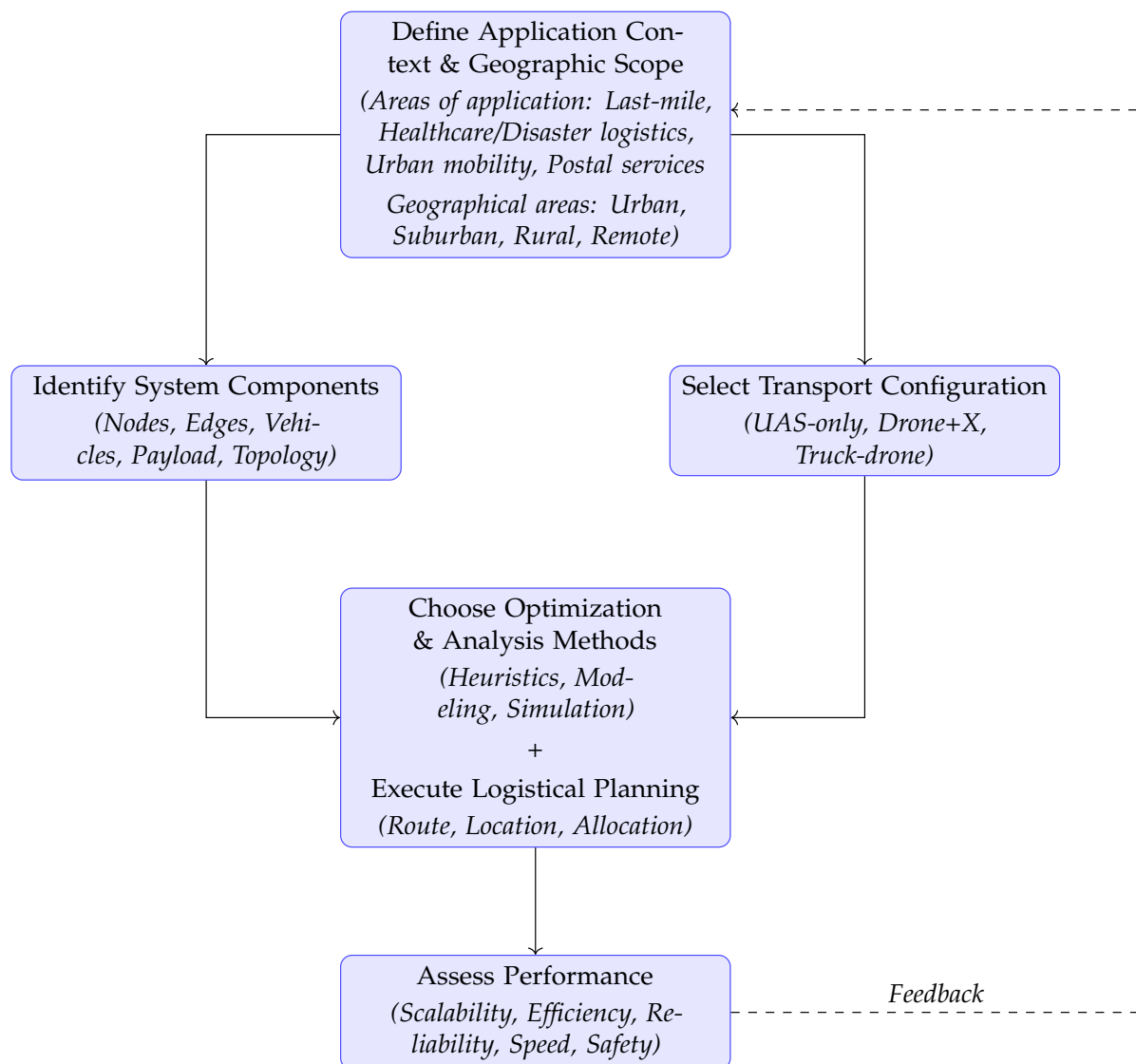


Figure 4. Framework for planning logistics networks with automated drones (Author’s own presentation).

5. Discussion

5.1. Key Findings

The review of existing literature reveals that the application context including specific use cases (e.g., last-mile delivery, emergency relief, healthcare logistics) and geographic settings (urban, suburban, rural, and remote) serves as the starting point for planning drone-based logistics networks. This context not only influences operational goals and challenges but also significantly shapes the design of the system components and the selection of planning and optimization methods. For instance, last-mile e-commerce delivery in urban

areas, as discussed by Boggyrbayeva et al. (2023) [23] and Chiang et al. (2019) [25], requires different configurations and planning approaches compared to remote healthcare delivery addressed by Dhote and Limbourg (2020) [41] or Sayarshad (2025) [26] which demands models resilient to infrastructural limitations and uncertainty.

Figure 5 provides an overview of how methodologies: mathematical models, heuristics, simulation, and case studies are distributed across planning domains and application areas. The visualization highlights a research concentration around last-mile and healthcare logistics using mathematical models, while case studies and simulations remain underutilized. Postal planning, in particular, appears under-represented, revealing opportunities for future empirical investigation.

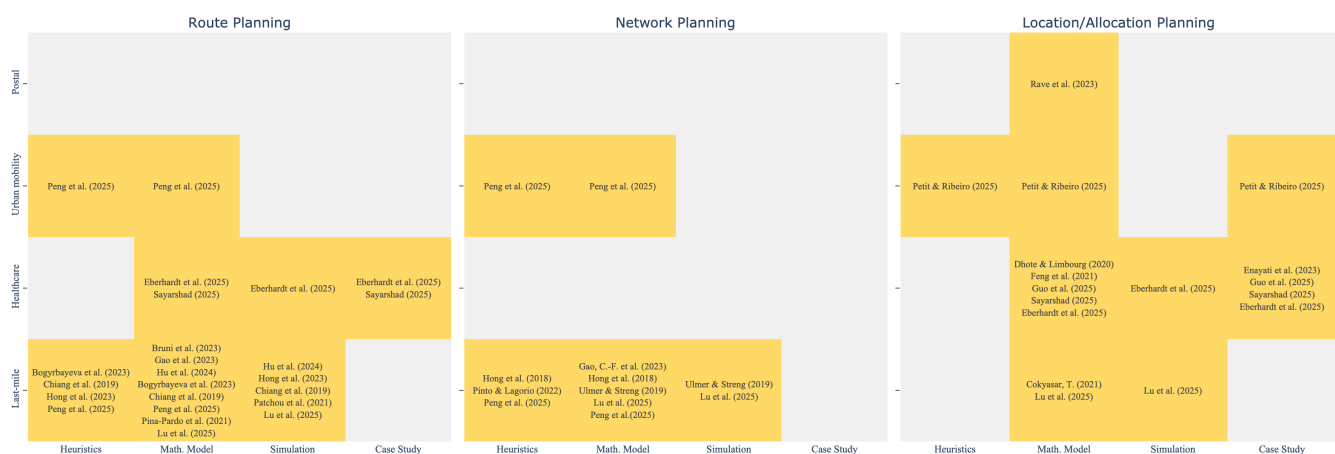


Figure 5. Methodologies applied across planning tasks and application areas. It visualizes the distribution of methodologies across planning domains and application areas, revealing how certain use cases (e.g., last-mile and healthcare) are dominated by mathematical models, while simulation and case study approaches remain underutilized.

Figure 6 complements this analysis by showing how planning domains intersect with transport configurations and geographic settings. It reveals the prominence of truck-drone systems in both urban and rural contexts, while UAS-only systems are largely absent from network planning. Research in suburban and remote areas remains sparse despite their strategic importance, suggesting future work should address unique constraints such as long-range flight operations and infrastructure scarcity.

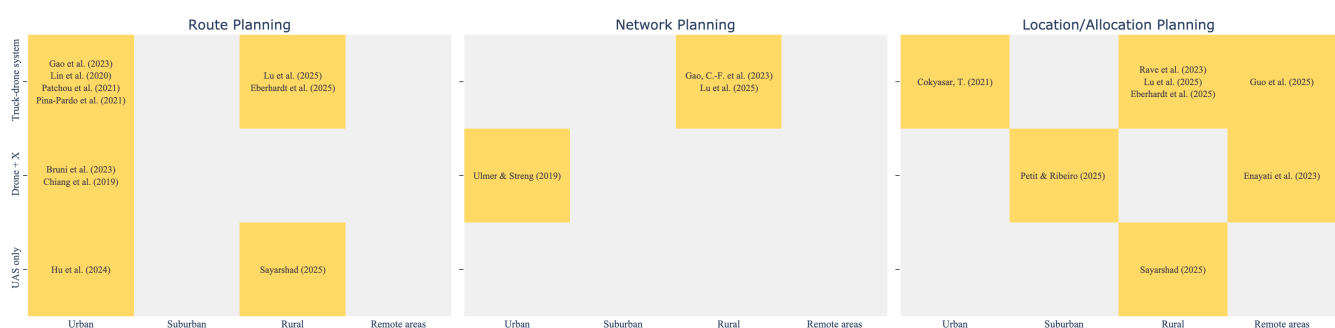


Figure 6. Transport configurations and geographic settings across planning tasks. It illustrates the distribution of cited studies across planning domains (Routing, Network, and Location/Allocation) intersected with drone transport configurations (UAS-only, Drone + X, and Truck-drone systems) and geographic deployment settings (Urban, Suburban, Rural, and Remote areas).

Across use cases, studies underscore the importance of co-designing the system components, namely, nodes, routes, and vehicle types in alignment with the transport configuration. Whether a logistics network is designed as UAS-only, hybrid truck-drone, or a more complex multi-modal system (Drone + X), this decision depends on contextual constraints such as terrain, payload, regulatory conditions, and infrastructure availability. Lu et al. (2025) [35] and Peng et al. (2025) [31] both emphasize how combining ground and aerial vehicles can improve delivery flexibility and efficiency, particularly in the last-mile segment. Nevertheless, comparative assessments across different transport configurations remain rare. Only a few studies systematically evaluate trade-offs in delivery speed, infrastructure dependence, or carbon impact. For instance, Chiang et al. (2019) [25] examine carbon emissions in drone vs. truck routes, and Hong et al. (2018) [37] study recharging infrastructure, but no unified benchmarking framework exists to inform mode selection in diverse operational scenarios.

Methodologically, the literature applies a diverse but fragmented set of optimization and simulation approaches. Depending on the scale and complexity of the logistics system, various mathematical models, heuristics, and simulations are employed to support decision-making. Simulation approaches, as shown by Doole et al. (2021) [63] and Silvestri et al. (2023) [62], allow for scenario testing and performance evaluation under uncertainty while optimization models, like those presented by Eberhardt et al. (2025) [28] and Guo et al. (2025) [45], support more structured decision-making in network design and resource allocation. From a methodological perspective, mathematical optimization models are praised for their precision and transparency (e.g., Bruni et al., 2023 [24]) but are often limited in scalability or flexibility to real-time constraints. Heuristic approaches (e.g., Lin et al., 2020 [32]; Kouretas and Kepaptsoglou, 2023 [58]) offer computational efficiency, yet rarely include formal validation or performance guarantees. Across all approaches, only a limited number of studies (e.g., Patchou et al., 2021 [33]; Gao et al., 2023 [36]) conduct sensitivity analysis or model validation raising concerns about robustness and transferability of results.

Notably absent from many studies is methodological triangulation combining different modeling approaches to validate robustness or explore edge cases. Similarly, few studies report on model sensitivity, input-data uncertainty, or computational performance, which raises concerns about the reliability of the proposed solutions in real-world implementation.

Performance assessment emerges as a critical but sometimes underutilized component in the literature. While several studies assess operational metrics such as cost efficiency and delivery speed (e.g., Ulmer and Streng (2019) [39]; Rave et al., 2023 [46]), fewer examine system-wide impacts, including scalability, equity of access, environmental sustainability, or safety. Studies like Petit and Ribeiro (2025) [44] and Sayarshad (2025) [26] begin to address these broader dimensions, suggesting a growing awareness of the need for holistic evaluation frameworks.

However, a comprehensive set of performance indicators is still lacking in most studies. In particular, trade-offs between environmental, economic, and social outcomes are rarely modeled jointly. While Hu et al. (2024) [30] propose sustainability-aware drone routing, and Kouretas and Kepaptsoglou (2023) [58] consider restricted airspace constraints, few studies provide integrated performance dashboards that align with policymaker and operator needs.

Lastly, it is evident that most studies focus on isolated planning aspects rather than pursuing integrated network planning. Few approaches consider the full chain from application context through transport configuration to final assessment. This fragmentation limits the development of comprehensive and scalable drone logistics solutions. A more integrated approach could foster more robust, adaptable, and context-sensitive drone

logistics systems. Rave et al. (2023) [46] and Pinto and Lagorio (2022) [38] begin to bridge these gaps, but overall, holistic frameworks remain rare.

5.2. Gaps and Future Directions

Given these findings, several directions for future research are evident. First, there is a strong need for holistic planning models that integrate multiple planning dimensions; from application context and system design to performance evaluation. Future research should aim to create comprehensive models that capture the interplay among transport modes, logistics configurations, and contextual constraints. Multi-layer optimization or hybrid simulation-optimization models may be particularly valuable in this regard.

On the other hand, underexplored use cases and geographies deserve greater attention. While urban and last-mile applications dominate the literature, there is a clear need for studies addressing rural, remote, and emergency scenarios. These contexts may benefit most from drone logistics due to lack of infrastructure or urgency of delivery, as demonstrated in the studies by Enayati et al. (2023) [42] and Guo et al. (2025) [45]. There is also an opportunity to develop dynamic and real-time decision-support tools. Most current models assume static inputs and environments. Future research should explore methods that account for uncertainties in demand, weather, and system disruptions, particularly in emergency logistics or rapidly changing urban settings.

Additionally, future research should expand the scope of performance metrics to include social and environmental considerations, such as equity, safety, emissions, and public acceptance. These aspects are crucial for the long-term viability and regulatory approval of drone-based systems and have only recently begun to enter mainstream research. Finally, more empirical validations are needed. While modeling and simulation are valuable, the assumptions behind them must be tested in real-world pilot studies.

6. Conclusions

This study systematically investigated the planning dimensions of logistics networks employing highly automated transport drones, based on a structured literature review across seven critical criteria: areas of application, system components, transport configuration, methodological approaches, geographic settings, planning tasks, and performance assessment. The analysis demonstrated that existing research often addresses these elements in isolation, with limited efforts toward developing unified and comprehensive planning approaches. Furthermore, essential considerations such as performance evaluation, environmental sustainability, and social equity are frequently underrepresented, despite their growing significance for both policy development and practical implementation. In response to these gaps, this study emphasizes the need for future research to adopt multidisciplinary, integrated frameworks capable of accommodating operational complexity while addressing broader societal impacts. For practitioners, the findings underscore the importance of tailoring system designs to specific use cases and geographic contexts, fostering stakeholder collaboration, and ensuring flexibility and scalability within system architectures. By bridging theoretical modeling with practical requirements, the study contributes to the advancement of more efficient, resilient, and equitable drone logistics networks. As drone technologies continue to evolve and regulatory environments adapt, the necessity for comprehensive and context-sensitive planning strategies will become increasingly critical, highlighting the timeliness and relevance of the proposed framework.

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