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Autonomous Delivery Robots for Last-Mile Logistics: A Comprehensive Review of Navigation, Optimization, and Human Acceptance

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Abstract. Last-mile delivery is one of the most expensive and challenging stages of the supply chain due to increasing e-commerce demand, urban congestion, and rising labour costs. Autonomous Delivery Robots (ADRs) have emerged as a promising solution by enabling efficient, contactless, and sustainable package delivery. This review examines recent advancements in ADR technologies, focusing on navigation and localization methods, routing and optimization techniques, operational delivery models, regulatory challenges, sustainability, and human acceptance. A systematic review of 41 publications published between 2018 and 2025 was conducted using major scientific databases. The reviewed studies indicate that technologies such as SLAM, reinforcement learning, and optimization algorithms significantly improve navigation accuracy and delivery efficiency. However, large-scale deployment remains constrained by battery limitations, infrastructure requirements, regulatory issues, and public acceptance. The review also identifies current research gaps and highlights future directions, including multi-robot coordination, artificial intelligence-driven decision-making, smart city integration, and energy-efficient delivery systems. Overall, ADRs have strong potential to transform last-mile logistics while supporting sustainable and intelligent transportation systems.

Keywords**:** Autonomous *delivery robots; Human acceptance; Last-mile logistics; Logistics optimization; SLAM localization.*

1. INTRODUCTION

The increasing number of consumers using the internet to shop online and moving into cities has led to a huge increase in the need for last-mile delivery. Last-mile logistics is the final stage of the supply chain that provides products from distribution centres to end customers. Due to heavy traffic congestions, higher labour costs, and other environmental issues, this can be the most costly and time-consuming segment of the delivery process. Logistics companies are turning to innovative technologies to better serve customers through faster deliveries at lower operational costs.

Autonomous Delivery Robots (ADRs) are emerging as a promising technology for improving delivery efficiency and reducing operational costs [1]. The use of autonomous delivery robots (ADRs) eliminates dependence on human operators, resulting in higher efficiency of delivering goods and services. Lowering operational costs provides logistics companies an advantage over competitors. Additionally, ADRs provide a high level of reliability when it comes to making on-time deliveries. Several industries have begun adopting the use of autonomous delivery technologies. Healthcare is among those industries that are now using ADRs to deliver medicines and other medical supplies to patients [2]. Additionally, retailers and

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restaurants are also using ADRs to make door-to-door deliveries of products ordered online.

In addition to developing new technologies that support autonomous delivery, researchers have also developed various methods to optimize delivery routes for ADRs [3]. Optimizing delivery routes can be broken down into two primary categories: static route optimization and dynamic route optimization. Static route optimization is concerned with optimizing routes before they are executed. This type of route optimization is based on historical data and may include information about traffic patterns, road closures, and weather conditions. Dynamic route optimization is primarily concerned with optimizing routes during execution. This type of route optimization considers variables such as traffic congestion, road closures, and changes in demand.

This review paper is intended to provide readers with a comprehensive overview of recent advancements related to the development of ADRs. Topics covered in this report include navigation, routing optimizations, operational models for ADRs, and studies related to the social acceptability of ADRs.

2. METHODOLOGY

This paper follows a standard structured literature review framework to assess recent progress in Autonomous Delivery Robots for last-mile logistics. Relevant publications were obtained via IEEE Xplore, ScienceDirect, SpringerLink, Scopus and Google Scholar utilizing SLAM, Route Planning, Optimizing and Human Acceptance. The author's preliminary database search returned all relevant academic research papers published between 2018-2025 regarding autonomous delivery systems. Duplicate records and non-last-mile delivery-related papers were excluded.

These papers were grouped into the five main categories,

(i) Navigation & Localization
(ii) Operational Models
(iii) Route Planning & Optimization Methods
(iv) Regulatory Barriers & Public Policies and
(v) Human Acceptance & Social Factors.

After identifying the five major themes within the literature, the authors comparatively evaluated the literature to determine key contributions to date, current shortfalls and avenues for future research.

As illustrated in Figure 1, the autonomous delivery process begins with customer order placement, followed by route planning and task scheduling. The robot performs localization and navigation using techniques such as SLAM, A*, and reinforcement learning while avoiding obstacles through multiple sensors. Finally, the package is delivered, and delivery confirmation and feedback are used to improve future operations through data-driven optimization.

3. LITERATURE REVIEW

The growing interest in autonomous delivery robots in recent years is due to their potential to transform last-mile delivery. There are existing works that cover a wide range of topics, including robot navigation, logistics optimization, sustainability, and human-robot interaction. Unfortunately, much of the literature does so in isolation, rather than looking at it from a global view. Within this section, we have provided an organized and critical look at the literature using common themes for organizing related studies. This comparative analysis provides a structured understanding of the current state of autonomous delivery robot research while identifying the major technological advancements, existing limitations, and future research opportunities.

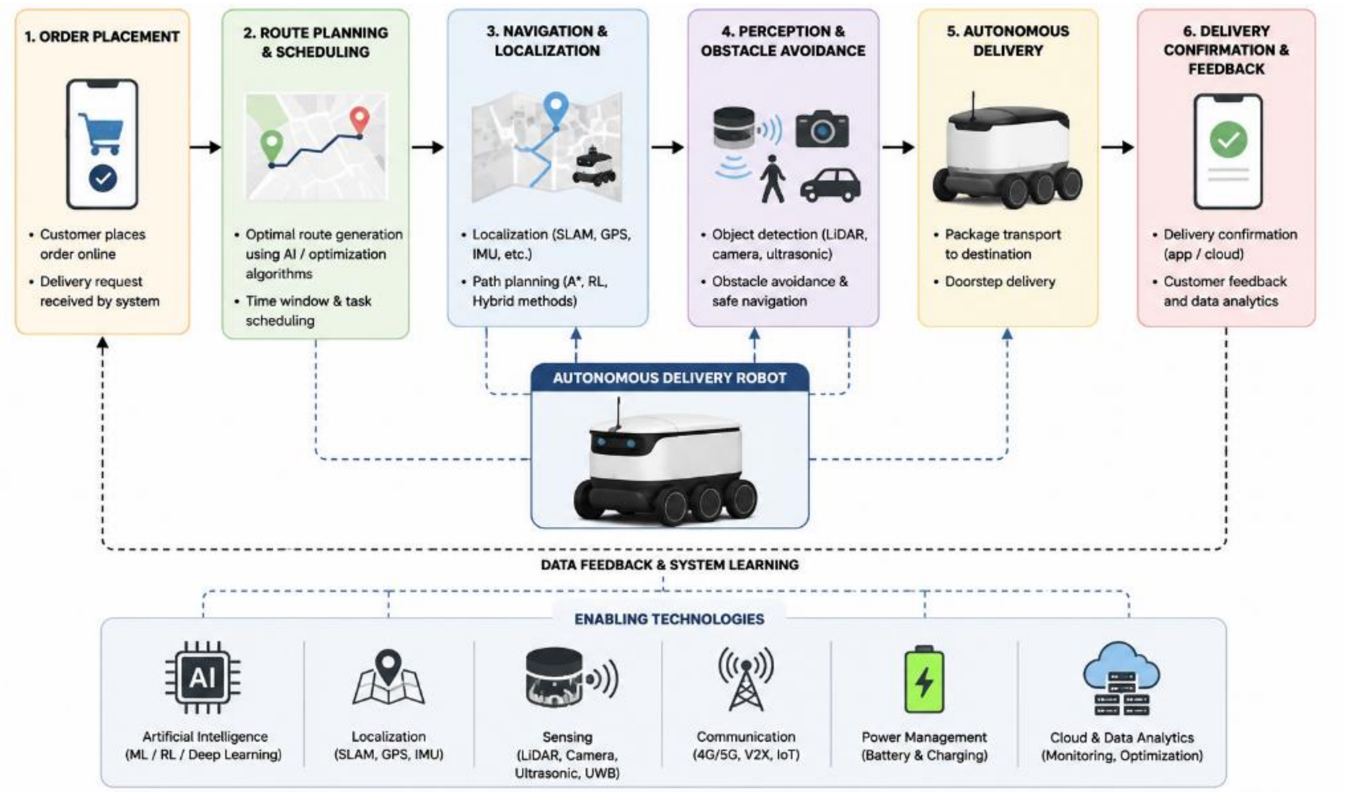

Fig. 1. Conceptual workflow of an autonomous delivery robot system for last-mile logistics.

3.1 Navigation and Localization in Autonomous Delivery Robots

Navigation and Localization is a key capability that autonomous delivery robots must have in order to effectively operate within dynamic and uncertain environments. They need to continuously determine their location, plan routes, avoid obstacles, and interact with their surroundings in a safe way. In general, the literature on navigation methods can be divided into three main categories: Classical methods, SLAM (Simultaneous Localization and Mapping) Based Methods, and Learning-Based Methods.

3.1.1 Classical and Graph-Based Methods

To overcome the mentioned issues, studies have looked into heuristic optimization approaches using Ant Colony Optimization (ACO), and hybrid ACO-based path planning approaches [4], [5] based on the ant's searching behaviour when looking for food, to find the best route through a probabilistic search process. Compared to traditional graph-based approaches, ACO has shown that it can be much more flexible within highly dynamic and uncertain environments, however at a high computational cost.

Many robotic navigation applications still apply classical path planning algorithms like A*, due to their ability to generate optimal paths in well-structured environments [6], [7]. This is done using a graph representation of an environment and heuristic functions to quickly find the shortest path possible. The two classical algorithms offer deterministic and optimal solutions; however, they perform poorly in dynamic environments where obstacles and conditions change frequently. Nevertheless, classical and heuristic approaches still struggle to handle highly dynamic unstructured environments; i.e., those typical of real-world delivery situations.

3.1.2 SLAM-Based Approaches

Simultaneous Localization and Mapping (SLAM), a major form of robotic navigation, allows robots to construct maps of unknown spaces while at the same time determining where they are in those spaces [8],

[9], [10]. Methods such as fast SLAM enhance this capability for real-time use through utilizing a combination of particle filters to address uncertainty and to track multiple possible locations of the robot [11].

Table 1 compares the major navigation algorithms used in autonomous delivery robots based on their working principles, advantages, limitations, and suitable operating environments. Classical graph-based algorithms such as A* provide optimal and computationally efficient path planning in structured environments but exhibit limited adaptability when unexpected obstacles or environmental changes occur. Ant Colony Optimization (ACO) offers improved adaptability through probabilistic search but requires higher computational resources. Reinforcement Learning (RL) enables robots to learn navigation policies directly from environmental interactions, making it highly suitable for dynamic and uncertain delivery scenarios. The comparison demonstrates that while no single algorithm is universally superior, hybrid approaches integrating classical planning with learning-based techniques are becoming increasingly important for reliable autonomous delivery systems. Conventional algorithms remain suitable for predictable environments, whereas learning-based approaches offer greater robustness in complex urban settings. This comparison also indicates the current research trend toward combining SLAM, artificial intelligence, and optimization algorithms to achieve accurate localization and efficient real-time navigation. Modern SLAM systems (e.g., ORB-SLAM2 [12], ORB-SLAM3 [13] and LOAM [14]) are able to improve the accuracy and scalability of modern SLAM systems. Visual SLAM uses camera(s) for real time localization; however, LiDAR based methods can be used to create reliable systems for outdoor applications. Even though there has been significant advancement in SLAM systems there continues to exist numerous obstacles with regards to lighting, cost, energy usage and computation for SLAM systems.

Table 1. Comparison of Navigation Algorithms.

Method	Principle	Advantages	Limitations	Environment
ACO [5]	Probabilistic search	Adaptive, flexible	High computation	Complex
A* [7]	Heuristic graph search	Optimal path, fast	Poor adaptability	Static
RL [16]	Reward-based learning	Learns dynamic behaviour	Requires training	Dynamic

3.1.3 Learning-Based Navigation

Deep reinforcement learning utilizes a Neural Network to analyze high-dimensional sensor data. This enables robots to function in complex and dynamic environments. Artificial Intelligence has recently improved the use of learning-based navigation techniques (including Reinforcement Learning). These methods allow robots to learn optimal navigation strategies through interaction with their environment rather than utilizing predefined models. Learning-based approaches have also been applied to obstacle avoidance, mapless navigation, motion planning, and hybrid path-planning systems [15], [16], [17],[18], [19], [20].

As summarized in Table 2, significant progress has been achieved in navigation, localization, optimization, and operational strategies for autonomous delivery robots. Nevertheless, there are many unresolved challenges. They include; scalable real time adaptive multi robot coordination, regulatory standardization for autonomous vehicles in urban environments, and longer-term public acceptability of autonomous vehicles. Therefore, these findings suggest that future research is needed to integrate artificial intelligence, advance sensing technology, logistics optimization (such as route planning), and smart city infrastructure to create reliable and sustainable autonomous delivery systems.

Table 2. Thematic Summary of Literature on Autonomous Delivery Robots

Theme	Methods / Technologies	Key Findings	Research Gap
Classical Navigation	A*, Hybrid ACO-DWA [4], [5], [6], [7]	Efficient and optimal path planning in structured environments with low computational complexity.	Limited adaptability to dynamic environments and unexpected obstacles.
SLAM-Based Navigation	FastSLAM, ORB-SLAM2, ORB-SLAM3, LOAM [8], [11]–[14]	Provides accurate real-time localization and mapping in unknown environments.	Performance is affected by sensor noise, lighting conditions, and high computational requirements.
Learning-Based Navigation	Reinforcement Learning (RL), Deep RL, AI-based Navigation [15]–[20]	Learns adaptive navigation policies and improves obstacle avoidance in dynamic environments.	Requires extensive training data, high computational resources, and real-world validation.
Operational Models	Truck-based, Hub-based, Hybrid Delivery Models [21], [22]	Improve delivery flexibility, operational efficiency, and service coverage.	Limited comparative evaluation under real-world operating conditions.
Multi-Robot Coordination	Task Allocation, Fleet Scheduling [23], [24]	Enhances productivity through cooperative task execution and resource utilization.	Communication reliability and coordination scalability remain significant challenges.
Regulations & Policy	Safety Standards, Privacy, Liability Frameworks [25], [26]	Regulatory frameworks are essential for safe and large-scale ADR deployment.	Lack of globally standardized regulations and legal frameworks.
Human Acceptance	Technology Acceptance Model (TAM), User Surveys [27]–[31]	Trust, perceived safety, and usefulness strongly influence public adoption of ADRs.	Limited long-term studies across diverse cultural and social environments.
Optimization & Routing	Dynamic Routing, Scheduling, Pickup and Delivery Problem (PDP) [36], [37]	Reduces travel distance, delivery time, and operational cost through optimized route planning.	Most models simplify traffic, weather, battery constraints, and demand uncertainty.

3.2 Operational Models for Last-Mile Delivery

Autonomous delivery vehicles utilize various models of operation in order to increase the overall efficiency of the vehicle as well as decrease the amount of time required for completion of each delivery [21], [22]. Truck based, Hub based, and Hybrid delivery models are examples of the primary types of models being utilized. In the case of the truck-based model delivery trucks are used along with autonomous robots. These robots then make the final portion of the delivery route to the customer. The Hub based model uses an autonomous robot that deploys from a local distribution center or "Hub" and delivers packages to the customer's location within a predetermined service area. Because this type of environment is typically found in a city or metropolitan area, it provides excellent opportunities for autonomous delivery robots to be used due to their ability to deliver within a relatively small geographic area.

3.3 Optimization and Routing Techniques

Optimization is a key element to autonomous delivery robot's success. The complexity of last-mile logistics calls for sophisticated algorithms in order to determine optimal paths, allocate tasks appropriately, and coordinate large numbers of ADRs. In this space, there are many publications that deal with the solution to route optimization and scheduling problems under numerous constraints including those related to time-windows and capacity limitations along with dynamic environmental conditions.

3.3.1 Pickup and Delivery Problems

The Pickup and Delivery Problem is an important logistics optimization problem, and it is more difficult for autonomous delivery robots due to constraints such as limited battery life and operating range. To improve delivery efficiency, dynamic PDP models with time windows and real-time updates are proposed [3]. However, it is still challenging to implement these models in real-world scenarios due to demand uncertainty, environmental changes, and simplified assumptions in many existing models.

3.3.2 Scheduling and Multi-Robot Coordination

In terms of developing a model that represents how efficiently pickup and delivery can be completed by autonomous delivery robots (as opposed to traditional delivery vehicles), the PDP becomes even more complicated by two factors: 1) the limitations on how long or far autonomous delivery robots can travel based on their batteries; and 2) the challenges of creating new routes to make deliveries while considering these limitations. Recent studies on multi-robot task allocation and distributed coordination have demonstrated improved fleet efficiency and resource utilization [23], [24].

3.4 Regulations and Policy Challenges

The greatest obstacle for large-scale use of autonomous delivery robots is the absence of standardized rules. Standardized rules would help resolve issues such as speed limits, weight restrictions and permits to operate that vary from one region to another [25]. Standards for pedestrian and other traffic users, along with safety and liability standards are needed to allow for the safe deployment of robots. Additionally, standards and regulations for the collection, storage and use of data collected by these robots will be necessary to address the issue of private and public acceptance of robots and their ability to provide security in this area [26].

3.5 Human Acceptance and Social Factors

Issues regarding the reliability and trustworthiness of Autonomous Delivery Robot (ADRs) will affect how well the general public accepts them. Because of COVID-19, there is an increasing amount of interest in alternative delivery routes because of the desire to reduce contact during delivery [27]; however, concerns exist related to the replacement of jobs, the reliability of ADs, barriers to adoption, and societal issues with regard to urban planning, cultural views on technology and other large-scale issues (i.e., regulations) continue to be major concerns [28], [29], [30], [31]. Research has also been conducted by several researchers into the willingness of consumers to adopt Autonomous Delivery Robots (ADRs), and they found that trust, perceived usefulness, and safety were key elements influencing consumer willingness to adopt ADRS [32], [33], [34].

4. DISCUSSION

The papers analyzed in this report demonstrate that Autonomous Delivery Robots (ADRs) have significant promise to increase the efficiency of Last-Mile Logistics. Since they are able to make deliveries without the need for extensive human interaction, ADRs may help decrease operational costs while improving delivery speed and supporting contactless delivery in urban and suburban areas.

Of all of the features of an ADR, Navigation is likely its most important feature. As a result of their low computation requirements and ability to produce an optimal path through a well-defined and static environment [6], [7] classical navigation methods including A* remain popular. Nonetheless, literature consistently shows a conflict between the high degree of deterministic reliability provided by classical algorithms and their poor performance in both dynamic and unstructured environments common in real-world delivery situation such as busy pedestrian walkways and unpredictable traffic [4], [5].

Beginning with SLAM-based and Reinforcement Learning-based methodologies, these types of approaches have seen wider use due to increased flexibility at an increased computational cost [16], [17] and researchers are currently using hybrids, like Hybrid A*, Classical Methods combined with the flexibility of the Learning-based Methodologies [20]. In terms of operational models Truck-based Systems will limit the Robot's operating area, but they still suffer from all the problems associated with traditional delivery methods including costs and traffic. Hub-based systems may reduce dependence on conventional delivery trucks but will be proven itself to be clearly better than another; instead, the decision for what type of methodology is best suited for each specific application is highly dependent upon the city density, regulation and existing infrastructure. Additionally, research on human acceptance of ADRs is inconsistent and varies by study: some studies indicate that trust in the system and perceived usefulness are the primary factors influencing adoption of ADRs while other studies suggest that safety concerns regarding the robots themselves, job-security fears based upon the introduction of ADRs, as well as demographic differences greatly influence attitudes towards ADRs suggesting that acceptance can vary based on local culture and demographics.

5. CHALLENGES AND LIMITATIONS

Despite significant progress, several challenges continue to limit the large-scale deployment of autonomous delivery robots. Table 3 ranks the major challenges according to their impact on the practical deployment of autonomous delivery robots.

Table 3. Major Challenges in Autonomous Delivery Robots

Priority	Challenge	Impact
High	Reliable navigation in dynamic environments	Affects delivery safety and operational reliability.
High	Regulatory and legal compliance	Delays commercial deployment due to lack of standardized policies.
Medium	Battery life and charging infrastructure	Limits operating range and delivery efficiency.
Medium	Traffic, weather, and environmental uncertainty	Reduces routing accuracy and scheduling performance.
Low	Public acceptance and trust	Influences adoption but improves as technology matures.

6. FUTURE RESEARCH DIRECTIONS

Concrete avenues that would benefit from additional study include: Navigation – development of hybrid approaches that combine classical reliability with adaptive reinforcement learning for the tradeoff between computational resources and performance in dynamic environments such as crowded sidewalks or traffic, which is tightly related to battery research – studies should focus on extending range of ADR batteries; reducing time spent charging; and lowering lifecycle environmental impact of production and disposal of current battery systems [35]. Multimodal robot coordination will be an important area as fleets grow – researchers must develop task allocation algorithms that account for real-world variations in demand and traffic patterns rather than idealized assumptions commonly used in today's simulations [23], [24]. Policy – additional research is needed to identify regulatory frameworks that address liability, data privacy, safety across jurisdictions, allowing ADRs to operate uniformly across regions instead of under today's fragmented, region-specific rules.

Finally, given mixed findings regarding adoption drivers, future work should identify the combination of trust, usability, safety, demographic factors most predictive of ADR acceptance cross-culturally and urban contextually and develop standardized metrics for comparing acceptance studies cross-regionally.

7. CONCLUSION

Autonomous delivery robots (ADR) may be an attractive option for addressing the growing challenge of last-mile logistics that is associated with increased demand due to e-commerce growth, traffic congestions in urban areas, labor shortages, and need for more sustainable logistics operations. This study evaluated four main aspects of ADR use: autonomous navigation, route optimization, operational models, regulatory issues related to ADR use, environmental impact of ADR use, and social acceptance of ADR use. There have been many improvements in autonomous navigation. The classical path-planning method was followed by SLAM based localization. There have also been many innovations in optimizing routes and developing hybrid operational models to improve efficiency, reduce costs, and increase sustainability. Recent life-cycle and sustainability assessments further indicate that ADR-based delivery systems have the potential to reduce environmental impacts and support sustainable urban logistics when compared with conventional delivery methods [38]-[40]. Studies on social acceptance indicate that building trust, demonstrating safe operation, and showing users how useful ADRs could lead to a successful deployment. Despite these advances in ADR technology, there are many challenges in achieving high levels of reliability in dynamic environments, battery limitations, the ability to process and store large amounts of data .

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