

ARTIFICIAL INTELLIGENCE IN LAST-MILE DELIVERY: A BIBLIOMETRIC REVIEW OF OPERATIONAL INNOVATION AND PERFORMANCE

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ABSTRACT

Artificial intelligence (AI) is increasingly applied to last-mile delivery (LMD) to address routing, forecasting, and operational challenges, yet research on the topic remains fragmented. This study examines the current state of AI research in LMD, identifies key research topics, and proposes a future research agenda. A bibliometric analysis was conducted on 523 publications retrieved from Scopus and Web of Science, and the data were analysed using the Bibliometrix R package. The findings reveal rapid growth in research, particularly after 2021, and a shift from traditional optimisation and routing towards advanced AI-enabled delivery systems, with IEEE Transactions on Intelligent Transportation Systems as the most influential journal. Three dominant research areas emerged: AI-based routing and optimisation, autonomous and drone delivery, and predictive and data-driven delivery planning. However, stochastic modelling, urban planning, customer satisfaction, policy, and developing-country contexts remain underexplored. The study provides a structured understanding of AI's evolution in LMD and identifies priority areas for future research.

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1. INTRODUCTION

Artificial intelligence (AI) has emerged as a transformative technology capable of reshaping how organisations process information, make decisions, automate operations, and respond to increasingly complex and dynamic environments (Prasanth et al., 2023; Wamba-Taguimdje et al., 2020; Omido et al., 2025). AI refers to computational systems that use data and algorithms to learn, predict, recognise patterns, solve problems, optimise processes, and support decision-making (Sarker, 2022). Its capabilities encompass technologies and computational approaches, including machine learning, deep learning, reinforcement learning,

computer vision, and intelligent decision support systems. These capabilities allow AI systems to analyse complex data and generate insights that support operational decisions (Mohamed, 2025; Razzaq & Shah, 2025; Shandilya et al., 2024). Such capabilities are particularly relevant to logistics and transportation operations characterised by uncertainty, time-sensitive decisions, complex routing and resource-allocation problems, especially found in last-mile delivery (LMD) (Sorooshian et al., 2022). These AI-enabled capabilities represent more than isolated technical improvements; they constitute a form of operational innovation, changing how delivery organisations plan, coordinate, and execute logistics activities. Such innovation is

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increasingly recognised as a driver of business and industrial performance more broadly, improving cost efficiency, service reliability, and competitiveness (Wamba-Taguimdje et al., 2020). Understanding how AI research in LMD has developed is, therefore, important not only for advancing academic knowledge but also for clarifying how AI-driven operational innovation translates into measurable performance gains for delivery organisations.

LMD is the final stage of transportation in which goods move from a fulfilment centre, store, or other distribution point to the end customer or a designated collection point (Mogire et al., 2023; Sorooshian et al., 2022; Wang & Alidaee, 2023). Although it represents a relatively short segment of the distribution chain, LMD is widely recognised as one of its most complex and costly stages (Boysen et al., 2021; Sorooshian et al., 2022). Delivery providers must coordinate numerous individual deliveries to geographically dispersed destinations while responding to uncertain, frequently changing operating conditions. Inefficient routing, unpredictable traffic and weather conditions, failed or delayed deliveries, fluctuating demand, tighter delivery windows, and increasing customer expectations for faster, reliable, and flexible delivery place considerable pressure on LMD operations (Sorooshian et al., 2022; Shuaibu et al., 2025). These challenges also have wider economic and environmental implications through increased operating costs, vehicle kilometres travelled, fuel consumption, urban congestion, and air and noise pollution (Mangiaracina et al., 2019; Mogire et al., 2023; Mogire et al., 2022; Puram et al., 2022). The continued growth of e-commerce has further intensified LMD's operational challenges by increasing parcel volumes and delivery frequency, thereby creating greater demand for efficient, responsive, and sustainable LMD systems (Kumar & Chidambara, 2024).

AI offers significant potential for addressing these challenges by enabling LMD systems to predict, optimise, and respond dynamically to changing delivery conditions. AI applications in LMD include demand forecasting, route optimisation, delivery-time prediction, fleet management, resource allocation, customer-demand prediction, predictive maintenance, and real-time operational decision-making (Sorooshian et al., 2022; Shuaibu et al., 2025). Machine-learning algorithms can learn from historical and real-time operational data to improve forecasting and routing decisions, while dynamic optimisation can adjust routes according to traffic, weather, order information, and customer requirements (Giuffrida et al., 2022; Sorooshian et al., 2022; Reis, 2025). Routing algorithms can also predict customer demand, optimise delivery routes according to customer requirements, and support personalised delivery options, thereby improving the responsiveness of LMD systems (Mogire, 2026). AI also supports logistics performance more broadly in e-commerce contexts, where machine learning is applied to improve routing, demand prediction, and service delivery outcomes (Malhotra & Kharub, 2025). AI provides

important capabilities for emerging physical delivery systems such as autonomous vehicles, delivery robots, and unmanned aerial vehicles by supporting perception, navigation, scheduling, and real-time decision-making (Sorooshian et al., 2022). More recent developments involving Edge Intelligence further extend these capabilities by enabling intelligent processing closer to where delivery data is generated, potentially supporting real-time route adjustment, predictive maintenance, fleet monitoring, and improved delivery reliability (Reis, 2025). AI, therefore, provides an important technological foundation for improving the efficiency, adaptability, and sustainability of LDM systems.

The operational significance of these applications can be traced through specific changes in the delivery of work. Machine-learning forecasts improve the information used to anticipate parcel volumes and delivery times; learning-based routing converts historical and real-time data into revised vehicle sequences; and reinforcement-learning models support routing and crowd-shipping decisions when demand and operating conditions change (Araujo & Etemad, 2021; Özark et al., 2023; Silva & Pedroso, 2022). These applications represent operational innovation because they alter the routines through which firms forecast demand, assign vehicles and drivers, sequence stops and respond to disruptions. Their expected business effects are correspondingly observable: more accurate forecasts can reduce under- or over-allocation of delivery capacity; better routes can reduce travel time, vehicle kilometres and fuel use; and improved delivery-time prediction can increase schedule reliability and customer service. AI, therefore, affects business and industrial performance through changes in operational processes rather than through technology adoption alone. The relevant performance outcomes include delivery cost per order, on-time delivery rates, vehicle and labour utilisation, energy use, failed delivery rates, and customer satisfaction.

Despite the growing application and potential of AI in LMD, research at the intersection of AI and LMD remains fragmented across specific technologies, applications, and operational problems. Existing studies have provided important insights into AI-enabled LMD. Rosendorff et al. (2021) explored the application of AI to LMD forecasting and proposed an AI-based procedure and information-system architecture for improving delivery predictions. Reis (2025) investigated the role of Edge Intelligence in enhancing last-mile logistics, whereas Sorooshian et al. (2022) classified AI-enabled LMD technologies into tangible and intangible applications. More recent studies have examined AI-driven optimisation strategies (Shuaibu et al., 2025) and intelligent routing and operational decision-making (Agatz et al., 2025). These studies illustrate how literature has evolved around distinct technological capabilities and operational applications; however, they do not discuss how AI research in LMD has developed into an integrated knowledge domain. A few bibliometric studies have begun to provide a broader perspective on AI and logistics. Purba and Hutabarat (2025) analysed

186 LMD publications from 2013 to 2024 and identified themes relating to sustainability, technological innovation, and consumer behaviour.

Kumar and Chidambara (2024) combined a systematic literature review with a bibliometric approach to examine last-mile e-commerce delivery in urban areas, emphasising its environmental, economic, social, and technological dimensions. Pourmohammadreza et al. (2025) examined 257 publications on last-mile logistics, with particular attention to alternative delivery locations, while Mogire et al. (2025) analysed 605 publications on LMD technologies and identified sustainability, delivery efficiency, and emerging technological innovations as dominant research themes. These studies have substantially advanced the understanding of the wider LMD research; however, AI is situated within a broader set of technological and operational themes rather than being examined as the primary analytical domain. The study, therefore, examines research trends and future directions in AI for LMD through a bibliometric analysis. The study contributes to the existing body of knowledge by providing researchers, practitioners, and policymakers with a structured understanding of AI's evolution in LMD and a roadmap for future research. Accordingly, the bibliometric analysis addresses the following research questions: (1) What is the current state of research on AI in LMD? (2) What are the most significant research topics within the domain of AI in LMD? (3) What should be the future research agenda for AI in LMD?

The remainder of the paper is structured as follows. Section 2 reviews the existing literature on AI and its applications in LMD. Section 3 describes the methodological approach employed for bibliometric analysis, including the search strategy, database selection, screening, and data analysis procedures. Section 4 presents the results of performance analysis, science mapping, and network analysis, including publication trends, influential research constituents, collaboration patterns, and major research themes. Section 5 discusses the findings and their implications and develops the future research agenda for AI in LMD. Finally, Section 6 concludes the paper by summarising the major findings and contributions, outlining the study's limitations, and identifying directions for future research..

2. LITERATURE REVIEW

AI is increasingly used to support prediction, routing, and optimisation in LMD, where fluctuating demand, traffic conditions, customer time windows, vehicle constraints, and service requirements create complex and dynamic decision-making environments (Sorooshian et al., 2022). Giuffrida et al. (2022) identify optimisation and machine learning as important approaches to addressing these challenges, particularly by leveraging operational data to improve delivery decisions. Özarık et al. (2023) demonstrated this potential by combining machine learning with conventional optimisation to learn

structural information from historical delivery routes, while Dieter et al. (2023) incorporated driver behaviour and contextual knowledge into route planning. Mo et al. (2023) similarly applied neural networks to learn delivery sequences from historical operational data, while James et al. (2019) combined neural combinatorial optimisation with deep reinforcement learning for online vehicle routing. AI has also been used to deliver-time prediction (Araujo & Etemad, 2021) and to dynamic crowd-shipping decisions under uncertainty using deep reinforcement learning (Silva & Pedroso, 2022; Silva et al., 2023). These developments reflect a shift from static optimisation towards predictive and adaptive delivery systems that learn from historical data and respond to changing operational conditions.

AI also provides the computational capabilities required for autonomous and intelligent delivery systems, including drones, delivery robots, autonomous vehicles, and hybrid truck-drones. Sorooshian et al. (2022) distinguish these tangible applications from intelligent decision-support systems, illustrating how AI connects digital intelligence with physical delivery automation. Arishi et al. (2022) applied machine learning and deep reinforcement learning to truck-drone delivery, while subsequent studies have extended learning-based approaches to increasingly complex collaborative truck-drone routing and scheduling problems. Similarly, Alyassi et al. (2022) applied machine learning to drone energy estimation and flight planning, while Salama & Srinivas (2020) developed drone-based routing optimisation integrated with customer-location clustering. Reviews by Garg et al. (2023) and Shuaibu et al. (2025) identify potential improvements in delivery efficiency, accessibility, routing, and service performance from AI-enabled and autonomous delivery technologies. Similar opportunities have been identified for autonomous delivery robots, although Alverhed et al. (2024) highlight operational, infrastructural, regulatory, and societal considerations affecting their implementation. The literature reflects a movement from AI supporting human delivery decisions towards intelligent systems capable of performing increasingly complex physical delivery functions.

The integration of AI with connected digital technologies represents another important development in LMD. AI-based delivery systems increasingly depend on real-time information concerning vehicle locations, traffic, orders, customer requirements, weather, equipment condition, and delivery status, making technologies such as the Internet of Things (IoT) and edge computing important complements to intelligent decision-making. Reis (2025) examined Edge Intelligence in last-mile logistics and identified opportunities to combine AI with real-time data processing to improve routing, operational efficiency, reliability, and customer service. Shuaibu et al. (2025) similarly highlight the integration of AI-driven decision-making, predictive analytics, IoT-supported monitoring, dynamic routing, and autonomous technologies in LMD optimisation. Such integration expands AI from an isolated analytical tool to an

intelligence layer that connects data collection, prediction, planning, and execution across delivery operations. Improved routing, demand prediction, fleet utilisation, and coordination may also reduce unnecessary vehicle movements, travel time, energy consumption, and emissions. Yet these operational and environmental benefits depend on the context in which AI is deployed. Garg et al. (2023), for example, show that the environmental performance of drone delivery varies with operational and technological conditions, while Chen et al. (2024) more broadly highlight sustainability criteria as an increasingly important consideration in AI-based logistics optimisation. The effectiveness of integrated AI-enabled LMD, therefore, depends on data quality, interoperability, digital infrastructure, organisational capabilities, energy systems, and the configuration of the delivery network.

Research on AI in LMD can therefore be understood through three closely related areas: predictive and adaptive optimisation, intelligent and autonomous delivery, and connected data-driven delivery systems. The literature shows a progression from applying machine learning to individual forecasting and routing problems towards learning from operational behaviour, responding dynamically to uncertainty, coordinating multiple delivery modes, and embedding intelligence within autonomous and connected delivery technologies. Important limitations remain across these areas. Algorithmic studies frequently rely on context-specific datasets and simulated environments, autonomous delivery faces unresolved infrastructural, regulatory, safety, and acceptance issues, and connected AI applications require substantial data and digital capabilities. Human expertise also remains relevant, particularly where experienced delivery personnel possess contextual knowledge that optimisation models may not adequately represent (Dieter et al., 2023; Mo et al., 2023). These developments indicate that AI functions not merely as a technical tool but as a driver of operational innovation in LMD. Predictive and adaptive optimisation reduces routing inefficiencies and operating costs; intelligent and autonomous delivery systems reshape service delivery models and capacity; and connected, data-driven delivery systems improve reliability and responsiveness to customer needs. Such operational innovations are consistent with broader evidence that AI adoption enhances business and industrial performance through improved efficiency, competitiveness, and customer value (Wamba-Taguimdje et al., 2020). AI-enabled LMD is therefore developing as both a technological and operational domain in which algorithms interact with delivery technologies, human decision-making, organisational capabilities, infrastructure, regulation, and sustainability objectives. This multidimensional development provides an important basis for examining the structure, major research themes, and emerging directions of the AI–LMD knowledge domain through bibliometric analysis.

The studies reviewed indicate three distinct mechanisms connecting AI with performance. First, predictive and adaptive decision support changes in planning routines. Delivery-time prediction, demand forecasting and learning from historical routes can improve capacity allocation and route selection (Araujo & Etemad, 2021; Giuffrida et al., 2022; Özark et al., 2023). The operational outcomes to be evaluated are forecast errors, route length, travel time, vehicle utilisation and on-time delivery; their business consequences include lower delivery costs, improved reliability and stronger customer retention. Second, AI enables process and service reconfiguration through truck-drone systems, delivery robots and autonomous vehicles. Machine-learning-based drone energy estimation and truck-drone scheduling can change how delivery capacity is deployed and how difficult locations are served (Alyassi et al., 2022; Arishi et al., 2022). Relevant performance measures include energy consumption, number of deliveries completed, fleet productivity, service coverage and cost per delivery. Third, integrating AI with IoT and edge computing supports continuous fleet monitoring and faster operational responses (Reis, 2025). This may reduce decision latency and service disruptions, but the gains depend on data quality, interoperability, digital infrastructure, staff capabilities and governance. Importantly, most existing studies demonstrate algorithmic or operational improvements; fewer directly test whether these improvements produce sustained firm-level profitability, productivity or competitive advantage.

3. METHODOLOGY

The study adopted a quantitative, bibliometric approach. Bibliometric analysis uses quantitative methods to systematically review large bodies of scholarly literature, identify patterns in existing knowledge, expose research gaps, and show how a research field has developed and where it is heading (Linnenluecke et al., 2020; Donthu et al., 2021). This approach was used to establish the current state of the research field, identify its dominant themes, and examine emerging areas of interest. Bibliometric analysis combines three techniques: performance analysis, science mapping, and network analysis. Performance analysis measures the productivity and influence of research constituents such as authors, institutions, journals, countries, and research areas (Donthu et al., 2020). Science mapping examines the intellectual relationships and connections among these constituents (Baker et al., 2020). Network analysis complements these approaches by examining the structural relationships among constituents such as authors, institutions, and countries, relationships that publication and citation counts alone may not fully capture (Andersen, 2021).

Bibliographic records were retrieved from Scopus and Web of Science (WoS). The two databases were selected for their extensive coverage of peer-reviewed scientific literature and widespread use in bibliometric research.

Combining the two databases was intended to provide broader coverage of the multidisciplinary literature on AI and LMD than reliance on a single bibliographic database. The database searches were conducted on 20 August 2026, covering publications from 2000 to 20 August 2026. Equivalent search terms were applied across both databases, with adjustments as needed to accommodate differences in database search syntax and bibliographic fields. The search strategy combined AI-related terms with LMD-related terms using the Boolean operators AND and OR. The following search string was used: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "natural language processing" OR "reinforcement learning" OR "AI-based" OR "AI-driven" OR "generative AI" OR "computer vision") AND ("last mile delivery" OR "last-mile delivery" OR "last mile logistics" OR "last-mile logistics" OR "last mile distribution" OR "last-mile distribution" OR "final mile delivery" OR "final-mile delivery" OR "home delivery" OR "door-to-door delivery"). Prior to the final search, a pilot search was conducted in both databases to assess the relevance and precision of the search records. The search string was refined based on this pilot phase to improve specificity and reduce irrelevant results.

Eligibility was assessed against explicit inclusion and exclusion criteria. Publications were included if they applied artificial intelligence or machine learning methods within a last-mile delivery or logistics context, were written in English, and were published as journal articles, conference papers, book chapters, or reviews. Publications were excluded if AI/ML was not core, if the study addressed a delivery stage other than the last-mile (e.g., first-mile or long-haul freight), or if the search terms matched an unrelated use of the word "delivery" (e.g., in a health or service-delivery context) rather than logistics. Title and abstract screening were conducted independently by both authors against these criteria, with disagreements resolved through discussion until consensus was reached.

In Scopus, the search was conducted within the title, abstract, and keywords, while the corresponding topic fields were searched in Web of Science. The initial search retrieved 570 records from Scopus and 252 from Web of Science, for a combined total of 822 records. Only English-language articles, conference papers, book chapters, and review publications were eligible for inclusion. These restrictions were applied to ensure that the publications included in the analysis were relevant and contained sufficient bibliographic information for subsequent analysis. The records retrieved from Scopus and Web of Science were exported, and the two datasets were subsequently combined into a single bibliographic dataset. As publications indexed in both databases may occur more than once in the combined dataset, duplicate records were identified and removed. A total of 222 duplicate records were removed, leaving 600 unique publications for screening. One publication was excluded because no abstract was available, leaving 599 publications. The titles and abstracts of the remaining

599 records were screened against the predefined eligibility criteria. A total of 76 publications were excluded because they did not examine AI or machine learning as a central methodological approach, did not address the last-mile stage of logistics or delivery, or used the search terms in a context unrelated to last-mile logistics. This resulted in a final dataset of 523 publications for bibliometric analysis. The final 523 publications were exported as a CSV file for further analysis using the Bibliometrix R package in RStudio. Performance analysis was conducted to assess publication output, while science mapping was used to identify research themes in the topic. To avoid query-induced bias during analysis, search-query keywords were excluded from science-mapping techniques that utilised keywords.

Table 1. Summary of research on AI for last-mile delivery research (2000 – 2026)

Description	Results
Timespan	2011:2026
Sources (Journals, Books, etc.)	330
Documents	523
Annual Growth Rate %	37.97
Document Average Age	1.92
Average citations per doc	11.93
References	20451
DOCUMENT CONTENTS	
Keywords Plus (ID)	3041
Author's Keywords (DE)	1537
AUTHORS	
Authors	1665
Authors of single-authored docs	38
AUTHORS COLLABORATION	
Single-authored docs	39
Co-Authors per Doc	3.93
International co-authorships %	30.59
DOCUMENT TYPES	
Article	248
Book chapter	45
Conference paper	212
Review	18

Table 1 summarises the 523 publications on ai for last-mile delivery, showing an annual growth rate of 37.97%. Most studies were articles (248) and conference papers (212). Only 18 review papers were published, thus a need for more reviews to consolidate existing findings.

4. RESULTS

This section presents the key findings: performance and scientific mapping of the 523 publications.

4.1 Performance Analysis

Figure 1 shows the publication trend research on AI for last-mile delivery from 2000 to 2026. No publications

from 2000 to 2010, as e-commerce was still growing. The first publication on the topic by Zhang et al. (2017) applied the Ant Colony Optimisation algorithm to improve vehicle routing for home delivery, reflecting the early focus on route optimisation. Research remained low from 2011 to 2017. The limited research activity during this period suggests that the application of AI to last-mile delivery was still at an early stage. From 2018 to 2021, publications increased gradually, reaching 20. The focus was on machine learning, electric vehicles, drones, crowdsourcing, and delivery time prediction. Growth accelerated from 2022 to 2024, with publications rising

from 48 to 81 in 2024. This rapid growth indicates increasing research interest in AI-based last-mile delivery solutions. Most research focused on AI, autonomous delivery, fleet management, and advanced route optimisation. Research output peaked at 163 publications in 2025, then fell to 125 in 2026 (not yet complete). Most studies are exploring deep reinforcement learning, generative AI, digital twins, autonomous vehicles, and drones in last-mile delivery.

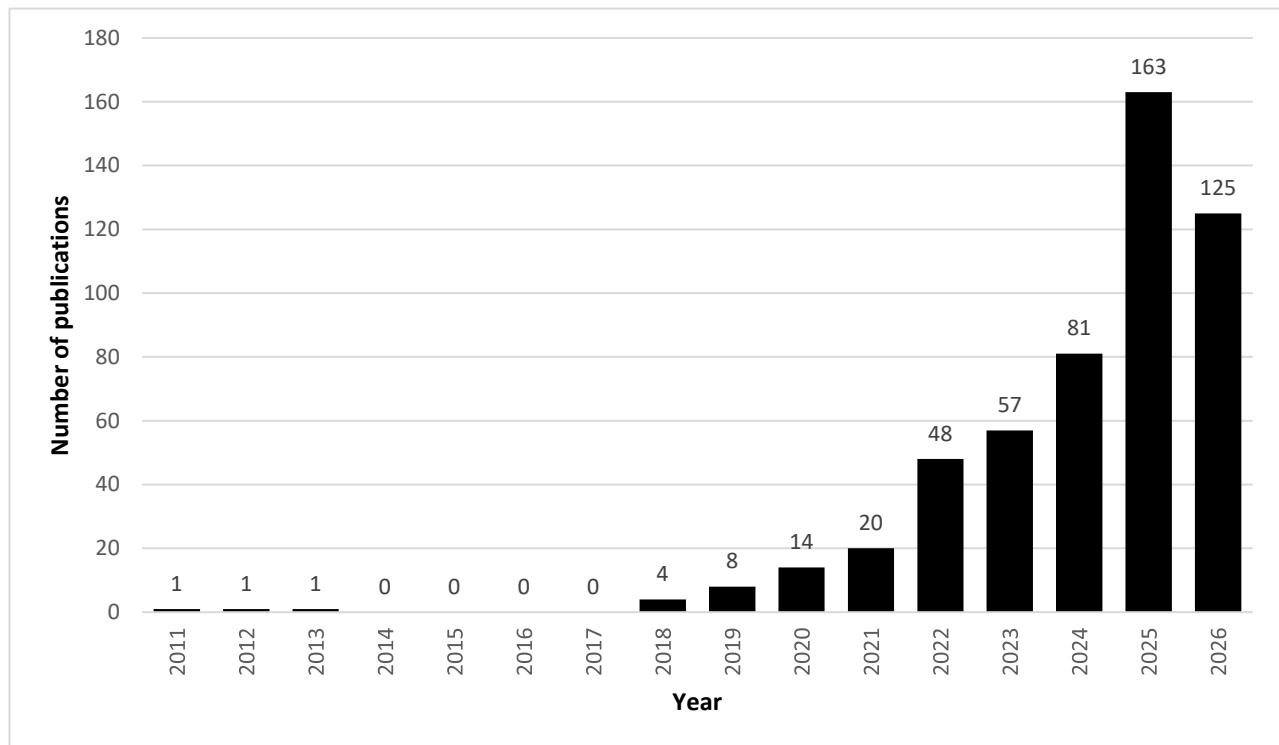


Figure 1. Publications per year on AI for last-mile delivery research (2000 – 2026)

4.1.1 Journal performance

Table 1 shows that 330 sources were used to publish research on AI in last-mile delivery. Among these sources, *IEEE Transactions on Intelligent Transportation Systems* is the most influential journal with 593 total citations (Table 2). The journal covers AI applications in transportation, including optimisation, data-driven approaches, freight transportation, autonomous vehicles, and electric mobility, which are directly relevant to AI-enabled last-mile delivery. *Expert Systems with Applications* and *Transportation Science* are emerging journals with an m-index of 1.667 based on 7 publications counted from 2024. The *Expert Systems with Applications* journal focuses on expert and intelligent systems, including their design, development, testing, implementation, and management in real-world applications. The journals can be grouped into four broad

thematic areas. *Transportation Research Part E*, *Transportation Review*, *Transportation Science*, and *Computers & Industrial Engineering* focus on logistics, routing, optimisation, and decision-making. *IEEE Transactions on Intelligent Transportation Systems*, *Applied Sciences*, and *IEEE Access* focus on AI, intelligent transportation, and digital technologies. *Drones* focus on drone-based and autonomous delivery systems. *Expert Systems with Applications* and *Lecture Notes in Computer Science* emphasise AI methods, expert systems, machine learning, and computational approaches. Thus, the journals mainly focus on logistics and route optimisation, intelligent transportation and digital technologies, autonomous delivery systems, and AI and machine learning methods. This distribution shows that AI for last-mile delivery is being studied across both logistics and computing-oriented journals.

Table 2. Top 10 journals on AI for last-mile delivery research (2000 – 2026)

Rank	Journal	h-Index	g-Index	m-Index	TC	NP	PY_Start
1	IEEE Transactions on Intelligent Transportation Systems	8	13	1	593	13	2019
2	Applied Sciences (Switzerland)	7	10	1.4	123	10	2022
3	Transportation Research Part E: Logistics and Transportation Review	6	12	1	167	15	2021
4	Drones	5	7	1.25	191	7	2023
5	Expert Systems with Applications	5	7	1.667	167	7	2024
6	Transportation Research Procedia	5	7	0.714	60	9	2020
7	Transportation Science	5	7	1.667	132	7	2024
8	Computers and Industrial Engineering	4	5	1	85	5	2023
9	IEEE Access	4	8	0.571	168	8	2020
10	Lecture Notes in Computer Science	4	5	0.667	30	9	2021

4.1.2 Author performance

Table 1 shows that 1665 authors contributed to research on AI in the last-mile delivery. Among these sources, *Wang, H.* is the most productive author, with 13 publications, the highest h-index (6), and the highest total citations (148) (Table 3). *Wang H.*'s research focuses on using AI to optimise courier routing, scheduling, and workload optimisation in last-mile delivery. *Wang, H.*, and *Zhang, D.* have co-authored most of their studies and are emerging authors, with an m-index of 1.5 computed

from 2023. *Li, Y.* has the longest research history on the topic among the top 10 authors, starting in 2019, and has 6 publications (Table 3). The 2019 study used reinforcement learning to improve the fuel efficiency of an electric vehicle for last-mile delivery. Thus, the top authors mainly focus on AI for route optimisation, delivery planning, vehicle efficiency, and operational decision-making.

Table 3. Top 10 authors on AI for last-mile delivery research (2000 – 2026)

Rank	Author	h-Index	g-Index	m-Index	TC	NP	PY_Start
1	Wang, H.	6	12	1.5	148	13	2023
2	Zhang, D.	6	10	1.5	125	10	2023
3	Liu, Y.	5	9	0.833	147	9	2021
4	Wang, S.	5	11	1	135	12	2022
5	Winkenbach, M.	5	5	0.714	147	5	2020
6	Chen, X.	4	6	1	47	6	2023
7	He, T.	4	8	0.8	117	8	2022
8	Jaeglerm, A.	4	4	0.8	74	4	2022
9	Li, X.	4	6	0.8	56	6	2022
10	Li, Y.	4	6	0.5	83	6	2019

4.1.3 Author affiliation performance

Author affiliations are the institutions where the lead authors are based, ranked by the number of publications they have. Table 4 shows that Rutgers University (USA) leads with 15 publications, followed by Southeast University (China) with 12. Most of the leading institutions are from Asia, including China, Saudi Arabia,

Singapore, India, and Hong Kong. This concentration indicates that Asian institutions are playing a major role in AI research on last-mile delivery. The USA represents North America, while Italy and Portugal represent Europe. There is no representation from Africa or South America.

Table 4. Top author affiliations on AI for last-mile delivery research (2000 – 2026)

Rank	Institution	Frequency
1	Rutgers University (USA)	15
2	Southeast University (China)	12
3	King Fahd University of Petroleum and Minerals (Saudi Arabia)	9
4	Massachusetts Institute of Technology (USA)	9
5	Tsinghua University (China)	9
6	Anhui University (China)	8
7	Deakin University (Australia)	8
8	University of Aveiro	8
9	Nanyang Technological University (Singapore)	7
10	Politecnico Di Torino (Italy)	7

11	Sun Yat-Sen University (China)	6
12	Tongji University (China)	6
13	University Of Electronic Science and Technology of China (China)	6
14	Amity University (India)	5
15	Nanjing University of Posts and Telecommunications (China)	5
16	Peking University (China)	5
17	Purdue University (USA)	5
18	SRM Institute of Science and Technology (India)	5
19	The Hong Kong Polytechnic University (Hong Kong)	5
20	Yildiz Technical University (Turkey)	5

4.2 Science Mapping

Table 1 shows an average of 3.93 co-authors per document. The highest research activity is concentrated in the USA and China (red colour) (Figure 2). Strong collaboration links are evident between China and the USA, primarily in AI-based route optimisation, delivery

scheduling, and delivery-time prediction. European countries show active collaboration within the region, while Australia has links with China, the USA, and France. Moderate research activity is evident across parts of Europe, Asia, North America, and Australia (orange colour).

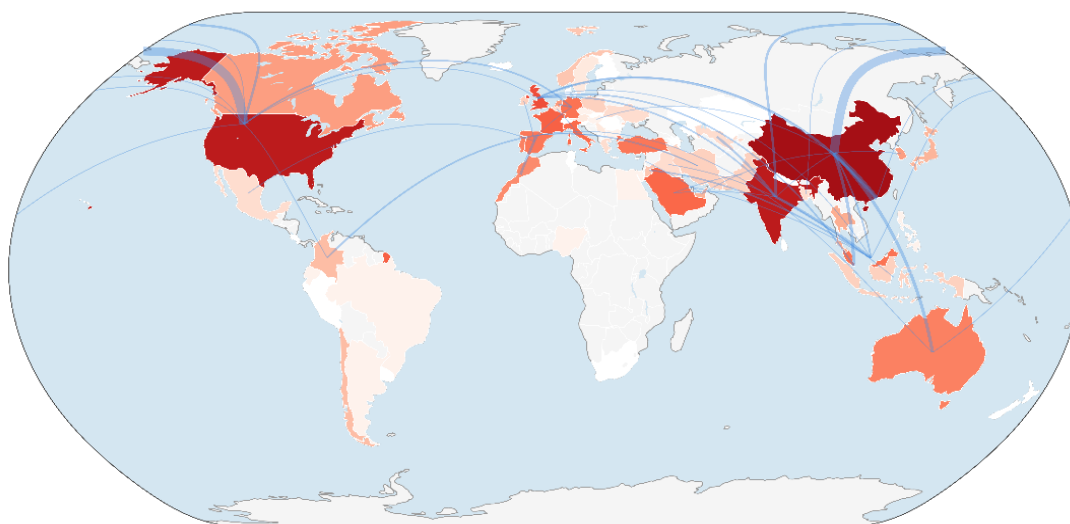


Figure 2. Countries' collaboration world map on AI for last-mile delivery research (2000 – 2026)

In contrast, many African and South American countries show limited research activity (grey colour). Overall, the map indicates that substantial research on AI in LMD comes from North America, Asia, and Europe, with limited participation from Africa and parts of South America. This uneven distribution highlights a geographical gap in AI research on last-mile delivery.

4.2.1 Word cloud

The word cloud shows the relative frequency of keywords through font size. Larger words indicate more frequent keywords. *Logistics*, *e-commerce*, *learning systems*, *vehicle routing*, and *optimisation* are the most prominent (Figure 3). This shows a strong focus on AI-enabled logistics, route planning, and optimisation. *Drones*, *unmanned aerial vehicle*, *learning algorithms*, and *decision-making* are also prominent. These highlight the use of AI for autonomous last-mile delivery and intelligent operational decision-making. Other visible keywords, such as *supply chains*, *sustainable*

development, traffic congestion, travel time, and customer satisfaction, show that AI also addresses wider delivery and sustainability concerns.



Figure 3. Word cloud on AI for last-mile delivery research (2000 – 2026)

The smaller terms, including *forecasting*, *data mining*, *multi-agent systems*, and *routing algorithms*, represent more specific research applications. Overall, research on AI for last-mile delivery focuses on logistics, routing, and optimisation. The prominence of logistics, routing, and optimisation indicates that operational efficiency remains a central concern in AI for last-mile delivery research. However, *forecasting*, *stochastic modelling*, *intelligent robots*, *urban planning*, *intelligent systems*, and *customer satisfaction* research remain underexplored. The less prominent keywords indicate opportunities to examine a wider range of AI applications in last-mile delivery.

4.2.2 Thematic map

Figure 4 displays the thematic map of AI for last-mile delivery research based on Keywords Plus. The map identifies four thematic clusters according to centrality (i.e., relevance) and density (i.e., development): motor, basic, niche, and emerging/declining themes (Figure 4). The motor themes are well-developed and highly relevant focusing on AI-driven optimisation and routing. This is reflected in keywords such as *vehicle routing*, *drones*, *learning algorithms*, *optimisation and routing*. It also covers *drone-based delivery* using *unmanned aerial vehicles* and *multi-agent systems*. The themes link AI

with operational activities such as routing and optimisation. The basic themes are highly relevant but less developed, focusing on logistics, supply chain, and sustainability challenges that AI seeks to address. This is reflected in keywords such as *logistics*, *supply chains*, *sustainable development*, *traffic congestion*, and *travel time*. Their high centrality but lower density suggests that they provide important foundations for the field but remain less developed. The niche themes are well-developed but more specialised, focusing on forecasting and data-driven delivery planning. This is represented by keywords such as *learning systems*, *forecasting*, *delivery routes*, *data mining*, and *delivery time*. The emerging/declining themes are less developed and less central. They focus on stochastic delivery modelling, reflected in keywords such as *stochastic systems*, *Markov processes*, *delivery service*, and *stochastic models*. They also focus on e-commerce and customer decisions, reflected in keywords such as *e-commerce*, *decision-making*, *optimisation*, *sales*, and *customer satisfaction*. Overall, the thematic map shows that research on AI for last-mile delivery is anchored in routing, logistics, and optimisation. At the same time, broader themes such as sustainability and customer satisfaction remain less developed.



Figure 4. Thematic map on AI for last-mile delivery research (2000 – 2026)

4.2.3 Thematic evolution

Figure 5 shows the thematic evolution of AI in the last-mile delivery research. The periods are consistent with the growth in publications shown in Figure 1. In 2011–2013, research centred on *decision support systems* and *optimisation* (Figure 5). This reflects an early focus on improving delivery decisions and operational efficiency.

The early themes indicate a focus on solving basic last-mile delivery problems. By 2018–2020, the focus broadened to *route optimisation*, *e-commerce*, *unmanned aerial vehicles*, and *learning systems*. This indicates wider use of AI in routing, online delivery, and autonomous last-mile delivery technologies. In 2021–2023, *learning systems* and *optimisations* became more

prominent. *E-commerce*, *unmanned aerial vehicles*, and *k-means clustering* also featured. This indicates greater use of data-driven approaches for last-mile delivery planning. During 2024–2025, attention shifted towards *routing* and *logistics*. *Aerial vehicles*, *convolutional neural networks*, and *optimisation* also gained prominence. This indicates greater emphasis on intelligent routing, logistics operations, and AI-based last-mile delivery solutions. In 2026, *learning systems*

have remained prominent. *Drones*, *logistics*, and *optimisation* have been joined by *supply chains*, *crowdsourcing*, and *predictive analytics* (Figure 5). This shows increasing diversification of AI applications in last-mile delivery. Overall, the research has progressed from decision support and optimisation towards broader applications in intelligent routing, autonomous delivery, and predictive analytics.

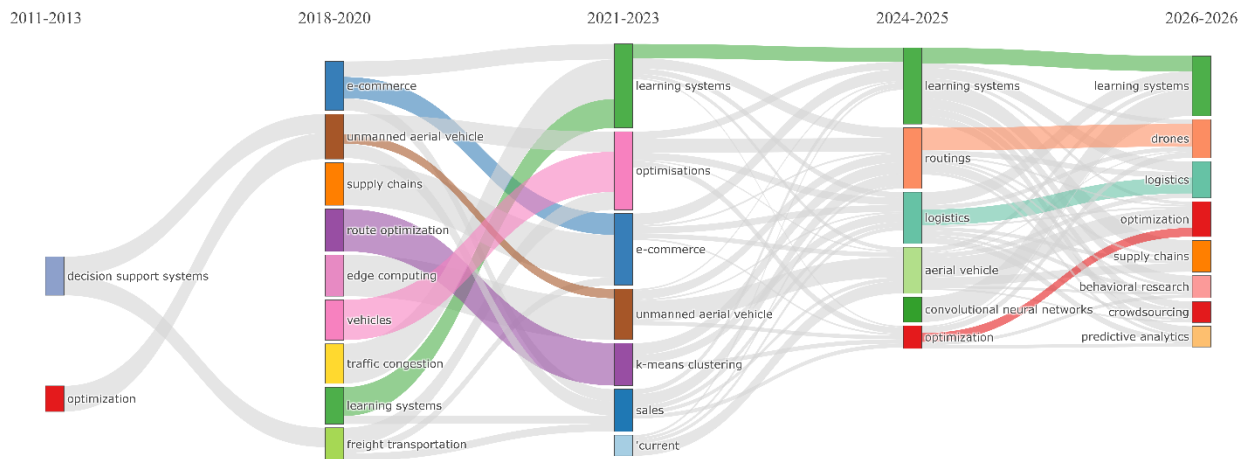


Figure 5. Thematic evolution on AI for last-mile delivery research (2000 – 2026)

4.2.4 Citation analysis

Table 5 presents the top 10 cited publications in AI for last-mile delivery research. Modgil et al. (2022) is the most influential, with 499 citations and 99.80 citations per year. The study examines the role of AI in strengthening supply chain resilience through predictive analysis, route planning, and workforce management. This highlights the importance of AI in improving delivery operations and responding to supply chain disruptions. Autonomous and drone-based delivery is another major research focus (Alyassi et al., 2022; Thomas et al., 2024). Whereas Alyassi et al. (2022) applied machine learning to drone energy estimation and flight planning, Thomas et al. (2024) examined truck–drone collaboration and delivery scheduling. The two studies show the growing use of AI to support autonomous delivery and coordinate different delivery modes. Predictive and data-driven delivery planning is also a prominent research focus. Giuffrida et al. (2022) examined machine learning applications in demand

forecasting and anomaly detection. This indicates that AI is increasingly being used to anticipate delivery requirements and improve operational decisions. The use of predictive methods extends AI applications beyond route optimisation. Malhotra and Kharub (2025) also linked AI use with logistics efficiency and last-mile delivery performance in e-commerce. Chen et al. (2024) examined AI-based optimisation for sustainable logistics. Sustainability is therefore becoming an additional consideration in AI-based logistics optimisation. The highly cited studies therefore cover both operational optimisation and emerging intelligent delivery technologies. However, some research areas remain underexplored. These include customer satisfaction, urban planning, policy, and research in developing countries. These areas provide opportunities for future research on the wider application of AI for last-mile delivery.

Table 5. Top 10 cited publications on AI for last-mile delivery research (2000 – 2026)

Author(s) and year	Title	Total Citations Per Year	Total Citations	Summary
Modgil et al. (2022)	AI for supply chain resilience: learning from Covid-19	99.80	499	The study examined the role of AI in strengthening supply chain resilience during the COVID-19 pandemic through interviews with 35 e-commerce experts. It was found that AI contributes to supply chain resilience by supporting timely and efficient last-mile

				delivery through predictive analytics, route planning, and smart workforce management..
Shuaibu et al. (2025)	A review of last-mile delivery optimisation: strategies, technologies, drone integration, and future trends	46.00	92	The study reviewed AI-based optimisation techniques for last-mile delivery decision-making. It found that AI and IoT support predictive analytics, better route planning, and fleet management. However, their wider use is limited by scalability and regulatory challenges.
Chen et al. (2024)	AI in logistics optimisation with sustainable criteria: a review	41.30	124	The study reviewed the integration of AI in sustainable logistics optimisation. The study proposed further research into AI-based solutions for sustainable last-mile delivery, such as autonomous vehicles, drones, and crowdsourced shipping.
James et al. (2019)	Online vehicle routing with neural combinatorial optimisation and deep reinforcement learning	38.50	308	The study developed a deep reinforcement learning-based neural optimisation strategy for online vehicle routing in last-mile delivery. Using a real transport network in Cologne, Germany, it was found that the approach generated better routes in less computation time than conventional mathematical programming methods.
Alyassi et al. (2022)	Autonomous recharging and flight mission planning for battery-operated autonomous drones	34.50	138	The study developed a machine learning model to estimate drone energy use under real-world and weather conditions. It used the model to optimise flight routes and recharging for energy-constrained drones, including parcel drop-off locations. The approach supported real-time flight planning and route adjustment.
Salama & Srinivas (2020)	Joint optimisation of customer location clustering and drone-based routing for last-mile deliveries	33.70	236	The study developed a machine-learning-based approach to optimise drone and truck routing for last-mile deliveries. It jointly considered customer locations, delivery routes, costs, and delivery time. The approach helped speed up the routing process and supported more efficient delivery decisions.
Singh et al. (2024)	Building AI enabled resilient supply chain: a multi-method approach	28.30	85	The study examined how AI can enable supply chain resilience. It was found that procurement strategy positively influences last-mile delivery. The right procurement strategies can reduce end-to-end supply chain cycle time. AI-enabled systems can facilitate access to last-mile delivery options and support capacity procurement.
Giuffrida et al. (2022)	Optimisation and machine learning applied to last-mile logistics: a review	23.20	116	The study reviewed traditional optimisation models, machine learning approaches, and mixed methods in last-mile logistics. It found that machine learning studies mainly focused on demand forecasting and anomaly detection. It suggested developing and testing innovative unsupervised learning techniques for last-mile logistics.
Malhotra & Kharub (2025)	Elevating logistics performance: harnessing the power of AI in e-commerce	22.50	45	The study examined AI usage and logistics efficiency in e-commerce firms in India. It was found that AI usage independently affects logistics efficiency, with supply chain consistency and last-mile delivery performance as mediating variables. Collaboration and coordination among logistics firms also strengthen AI's efficacy in logistics operations.
Thomas et al. (2024)	Collaborative truck multi-drone delivery system considering drone scheduling and en-route operations	21.70	65	The study introduced the collaborative truck-drone routing and scheduling problem with en-route operations for last-mile parcel delivery. It found that the proposed relax-and-fix with re-couple-refine-and-optimize heuristic achieved optimal or near-optimal solutions for small instances and was computationally efficient for large cases. En-route drone operations resulted in an average 30% reduction in delivery completion time and a 62% increase in drone utilisation.

5. DISCUSSION

The findings in the preceding subsection reveal that research on AI in last-mile delivery has grown rapidly in recent years, particularly after 2021. Early research was mainly concerned with decision support, optimisation, and vehicle routing. Over time, research on the topic expanded from traditional optimisation approaches to machine learning, electric vehicles, drones, crowdsourcing, and AI-based delivery-time prediction. More recent studies have examined deep reinforcement learning, autonomous vehicles, digital twins, generative AI, and predictive analytics. Journal performance also reflects this development, with leading journals focusing on intelligent transportation, logistics, routing, optimisation, autonomous delivery, and machine learning. The thematic evolution further shows a gradual shift from decision support systems and optimisation towards route optimisation, learning systems, unmanned aerial vehicles, and more recent applications involving predictive analytics and crowdsourcing. The findings show progression from conventional decision and routing problems towards learning-based and autonomous delivery applications.

The findings further show that research on AI in last-mile delivery focuses on three main areas: AI-based routing and optimisation, autonomous and drone delivery, and predictive and data-driven delivery planning. AI-based routing and optimisation is the most established research area. The word cloud shows vehicle routing and optimisation among the most prominent keywords, while the thematic map places vehicle routing, optimisation, routing, and learning algorithms within the motor themes. The top-cited studies support AI-based routing and optimisation, with Modgil et al. (2022) highlighting AI applications in route planning and James et al. (2019) applying deep reinforcement learning to online vehicle routing. Shuaibu et al. (2025) further identify AI-based route planning and optimisation as important applications in last-mile delivery. The thematic evolution further shows that research initially centered on decision support systems and optimisation, then shifted towards route optimisation and intelligent routing. This indicates that routing and optimisation are not only frequent research topics but also core areas where AI is being applied to last-mile delivery operations. The top-cited studies also provide evidence of how these AI applications translate into operational outcomes. James et al. (2019) reported better routes with less computation time, while Thomas et al. (2024) reported a 30% reduction in delivery completion time and a 62% increase in drone utilisation. Malhotra and Kharub (2025) further linked AI usage with logistics efficiency and last-mile delivery performance in e-commerce firms. These findings provide a direct connection between AI applications, operational improvements, and last-mile delivery performance. Autonomous and drone delivery has also become an important area. The word cloud highlights drones and unmanned aerial vehicles, while the thematic map places drones within the motor themes alongside multi-agent

systems. The top-cited studies reinforce the focus on autonomous and drone delivery (Alyassi et al., 2022; Thomas et al., 2024). Whereas Alyassi et al. (2022) applied machine learning to drone energy estimation and flight planning, Thomas et al. (2024) examined truck–drone collaboration and delivery scheduling. Predictive and data-driven delivery planning represents a more specialised research area. The thematic map identifies learning systems, forecasting, delivery routes, data mining, and delivery time as niche themes. The thematic evolution shows the more recent emergence of predictive analytics. At the same time, the top-cited publications by Giuffrida et al. (2022) identify demand forecasting and anomaly detection as key applications of machine learning in last-mile delivery.

Several underexplored areas are also evident from the results. The thematic map places stochastic systems, Markov processes, and stochastic models among the less developed themes. This suggests that greater attention is needed to how AI can support last-mile delivery under uncertain demand, travel times, traffic conditions, and other operational disruptions. The word cloud also shows relatively limited prominence of intelligent robots and urban planning, while customer satisfaction receives less attention. The top-cited publications further indicate limited research on policy and developing-country contexts. The countries' collaboration world map reinforces this gap, as research activity is concentrated mainly in the USA, China, Europe, and parts of Asia. In contrast, many African and South American countries remain less represented. The findings therefore point to both thematic and geographical gaps in the current research on AI for last-mile delivery research.

6. CONCLUSION

A bibliometric review was undertaken to understand the current state of research on AI in last-mile delivery, identify significant research topics, and propose future research agendas. The findings revealed that research has grown rapidly in recent years, particularly after 2021. Research has shifted from traditional optimisation and routing to advanced AI-driven delivery systems, focuses on three main areas: AI-based routing and optimisation, autonomous and drone delivery, and predictive and data-driven delivery planning. However, customer satisfaction, urban planning, policy, and developing-country contexts remain underexplored. Future research could explore these areas further.

- AI-based routing and optimisation emerged as the most established research focus. However, the thematic map shows that stochastic modeling remains underdeveloped, despite the inherent uncertainty in last-mile operations. Future research should therefore integrate AI with stochastic optimisation to address uncertainty in demand, travel times, traffic conditions, and delivery disruptions. Testing such models with real-time delivery data could provide stronger evidence of their robustness under changing operating conditions.

- Autonomous and drone delivery emerged as another significant research focus, particularly in routing, energy management, and delivery scheduling. However, the limited prominence of urban planning suggests that technological development has not been sufficiently connected to the spatial context in which these systems operate. Future research should examine how autonomous and drone delivery can be integrated with urban structure, delivery zones, transport networks, and infrastructure. Comparative studies across different urban contexts could identify the conditions under which these technologies are operationally and spatially viable.

- Predictive and data-driven delivery planning has emerged as a specialised yet growing research focus, particularly in learning systems, forecasting, and predictive analytics. In contrast, customer satisfaction remains less prominent in research. Future research should therefore examine whether improvements in AI-enabled planning translate into measurable service outcomes in last-mile delivery. Such studies could link AI-based predictions and delivery decisions with waiting time, failed deliveries, and customer satisfaction. The findings should be interpreted in light of the following limitations. First, the review relied on the selected keywords and search strategy given in the methodology section to identify the required studies. As the topic is developing rapidly, new AI-related terms and concepts may emerge. Future reviews could update the search strategy as the field develops. Second, the analysis focused utilised bibliometric techniques to examine the current state of research on the topic. Methodological quality or practical effectiveness of each study was not examined. Future studies could combine bibliometric analysis with systematic reviews or empirical research to have a more comprehensive understanding of the topic. Finally, the 2026 publications were incomplete at the time of data collection, which may affect the observed

publication trends and emerging themes. Future studies can update the dataset when the 2026 publication year is complete.

Overall, this bibliometric review advances knowledge on AI in LMD by bringing together fragmented research and identifying three dominant areas: AI-based routing and optimisation, autonomous and drone delivery, and predictive and data-driven delivery planning. The review also highlights less-developed areas, including stochastic modeling, urban planning, customer satisfaction, policy, and research in developing countries. The findings show a clear shift from traditional optimisation and routing towards more advanced AI-enabled delivery systems. These findings provide a focused foundation for future research and support more balanced approaches to AI adoption in LMD. For instance, policymakers and delivery operators should consider not only routing efficiency and automation, but also urban conditions, customer needs, uncertainty, and the policy environment when implementing AI-enabled delivery solutions. The study's principal contribution is to specify the pathway through which this technological development may create business value. AI provides forecasting, learning and optimisation capabilities; firms embed these capabilities in routing, capacity planning, fleet monitoring and autonomous-delivery processes; the resulting operational changes affect delivery time, route distance, energy use, asset utilisation, service reliability and delivery cost; and these outcomes may subsequently influence customer satisfaction, profitability and competitiveness. The bibliometric evidence identifies the structure and emphasis of this pathway but does not demonstrate causality. Future empirical research should therefore test the full chain using paired technical, operational and business indicators rather than treating publication growth or algorithmic accuracy as evidence of business performance.

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