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Methodological advances in online food delivery: A systematic review, taxonomy, and research outlook

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ABSTRACT

Since the platformization of restaurant delivery, **Online Food Delivery (OFD)** has expanded rapidly, intensifying competition, compressing margins, and amplifying operational complexity. As in other transportation domains, **Operation Research (OR)** provides the methodological backbone for structuring and optimizing the **Food Delivery Service (FDS)**. The literature on **OFD** optimization is now flourishing, while emerging technologies create new challenges and modeling requirements. This article presents a **Systematic Literature Review (SLR)** of quantitative **OFD** research and offers a coherent reference for scholars and practitioners. We introduce a multidimensional classification that organizes the field by decision level, problem setting, and analytical approach, and we formalize a methodology that maps real-world **OFD** complexities into precise **OR** problem components, enabling consistent categorization and comparison. We also curate standardized tabular and visual summaries to support transparent description, benchmarking, and reproducibility. Finally, we articulate open research areas and corresponding directions to guide subsequent work.

1. Introduction

The rapid growth of Online Food Delivery (**OFD**) platforms has fundamentally transformed the Food Delivery System (**FDS**), meeting increasing consumer expectations for speed, convenience, and reliability (Meemken et al., 2022). Digital platforms connect customers, restaurants, and couriers, leveraging real-time tracking, dynamic routing, and crowd-sourcing to streamline delivery operations. However, this accelerated expansion has also intensified market competition, squeezing already thin margins and heightening pressure on both platforms and their partners (Oh et al., 2026). In such a fiercely contested environment, Operations Research (**OR**) techniques become indispensable for minimizing operating costs and sustaining competitive advantage. As **FDS** expands, it introduces complex operational challenges that require effective decision-making at multiple levels, from long-term strategic planning to real-time operational execution. These challenges are further compounded by uncertain factors, such as fluctuating demand patterns, unpredictable travel times, variable meal preparation times, and dynamic courier availability, which require the use of appropriate analytics methods.

FDS presents intricate decision-making problems spanning multiple decision levels. At the strategic level, long-term planning decisions must be made regarding the **Facility Location (FL)** such as depots and charging stations for drones (Pinto et al., 2020). At

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medium-level, *Fleet Sizing and Composition* (FS), *Shift Scheduling* (SS) (Xue et al., 2021), and *Pricing Scheme* (PS) (Das and Yadav, 2021) have been studied. In another aspect, operational-level decisions involve real-time *Order Dispatching* (OD) (Chen et al., 2024), *Order Grabbing* (OG) (Wang et al., 2023e), *Vehicle Routing* (VR) (Hu et al., 2023), *Service Coverage* (SC) (Ulmer et al., 2022), and dynamic PS (Bai et al., 2022).

Given the complexity of these decisions, mathematical models and analytical approaches have been widely applied to improve efficiency and service quality. Prior reviews of FDS research have only partially underlined OR questions. Alnaggar et al. (2021) analyzed OR studies on crowdsourced last-mile platforms, but their scope excluded dedicated studies on OFD, and any other paper published after 2018. Subsequent surveys did not bridge these gaps. Screening 59 studies from 2016 to 2020, Seghezzi et al. (2021) proposed an actor-activity taxonomy that connects platforms, restaurants, couriers, and customers to their value-creation tasks. Shroff et al. (2022) proposed a tri-method SLR to trace publication trends from 2015 to 2021. However, none of these studies focused on optimization models or organized findings by decision hierarchy. In crowdsourced delivery systems, Savelsbergh and Ulmer (2022) and Savelsbergh and Ulmer (2024) examined planning and operational challenges related to uncertain courier availability and capacity management. Their review presented an overview of research opportunities but did not systematically evaluate mathematical formulations or solution methodologies. Additionally, they focused primarily on capacity management.

Roy et al. (2022) reviewed restaurant operations such as queue and menu engineering while excluding delivery logistics. Most recently, Ashraf and Bardhan (2025) reviewed pre-delivery and delivery-stage problems. However, they closed their search window in January 2024 (capturing only a single 2024 paper) and excluded classification by decision level and problem setting. A comparative synopsis of these previous reviews is presented in Table 1. The cumulative result is a fragmented picture. To date, no review offers a unified framework that spans strategic, tactical, and operational tiers; cross-tabulates static versus dynamic, and deterministic versus stochastic problem settings; or links these contexts to predictive, prescriptive, and hybrid analytical approaches.

Building on this foundation, our review presents an updated and comprehensive analysis of OR problems faced by OFD platforms. We propose three classifications that distinguish problems across decision levels, which include *strategic*, *tactical*, and *operational*; problem settings, which consist of *static-deterministic*, *static-stochastic*, *dynamic-deterministic*, and *dynamic-stochastic*; and analytical approaches, which comprise *predictive*, *prescriptive*, and *data-driven hybrid*. This classification enables a more structured analysis of existing research by integrating factors related to decision-making complexity and uncertainty. It also reflects the growing importance of dynamic models, given the increasing use of real-time data, *Machine Learning* (ML), and *Reinforcement Learning* (RL) algorithms in FDS. To ensure a more up-to-date and comprehensive review, we extend the literature analysis to include studies published in 2024 and 2025. The detailed literature collection and screening methodology is provided in Appendix B. These studies include stochastic

Table 1
Characteristics of previous review papers.

Reference	Year	Area	Scope	Gaps and open issues	Period
Alnaggar et al. (2021)	2021	LMD	Reviews OR studies on crowdsourced last-mile platforms, focusing on order assignment and routing	Excludes dedicated OFD studies and literature published after 2018	Until 2018
Seghezzi et al. (2021)	2021	OFD	Develops an actor-activity taxonomy linking platforms, restaurants, couriers, and customers to value-creation tasks	Does not focus on optimization models or decision-level classification	2016–2020
Shroff et al. (2022)	2022	OFD	Tri-method review combining SLR, bibliometric mapping, and thematic analysis to identify research clusters	Lacks classification by decision hierarchy and problem setting	2015–2021
Savelsbergh and Ulmer (2022)	2022	LMD	Surveys crowdsourced delivery problems that acknowledge uncertainty in courier availability and capacity	Narrow focus on capacity uncertainty; lacks systematic analysis of mathematical formulations and solution methodologies	2016–2022
Roy et al. (2022)	2022	RO	Reviews analytical and data-driven studies on ROs, including queues and menu engineering	Excludes delivery logistics and platform-based fulfillment decisions	1990–2020
Savelsbergh and Ulmer (2024)	2024	LMD	Updated survey of crowdsourced delivery challenges focusing on problems with uncertain courier capacity	Narrow focus on capacity uncertainty; lacks systematic analysis of mathematical formulations and solution methodologies	2016–2024
Ashraf and Bardhan (2025)	2024	OFD	Reviews pre-delivery and delivery-stage OR problems in OFD platforms	Does not classify studies by decision tier or static/dynamic and deterministic/stochastic settings	2017–Jan 2024
This work	2025	OFD	Decision-oriented synthesis of OR models using a multidimensional taxonomy spanning decision levels, problem settings, and analytical approaches	–	Until 2025

LMD (Last-Mile Delivery); RO (Restaurant Operations); OFD (Online Food Delivery); OR (Operations Research); SLR (Systematic Literature Review)

Table 2
Key terminology in OFD.

Term	Description
Online Food Delivery Platform	Digital service connecting customers, restaurants, and couriers to facilitate food ordering and delivery.
Restaurant	Business entity or merchant that prepares and sells food through an online delivery platform.
Customer	End user who places an order via an OFD platform.
Courier	Delivery personnel are responsible for picking up and delivering orders.
Vehicle	Mode of transportation (bike, scooter, car, drone) used by couriers.
Depot / Hub	Place or location from which couriers start routes or recharge vehicles.
Transfer Station	Location where orders are temporarily stored or handed off between couriers for long-distance delivery.
Shift	Continuous, repetitive blocks of working hours that a courier commits to being available for deliveries.
Order	Request placed by a customer for meal delivery.
Order Fulfillment	Complete process from order placement through final delivery.
Strategic Decision Level	Long-term planning of network design, facility siting, and fleet composition.
Tactical Decision Level	Medium-term decisions such as pricing, capacity planning, and shift scheduling.
Operational Decision Level	Day-to-day execution decisions, including dispatching, routing, and real-time adjustments.
Order Grabbing	Couriers self-select available orders from a shared pool, rather than receiving a central dispatch.
Order Dispatching	Assigning a courier to pick up and deliver an order.
Bundling	Grouping multiple orders into a single delivery trip.
Splitting	Dividing a large or bundled order into separate deliveries.
Postponement	Delaying assignments or pickups to batch deliveries or optimizing routing.
Vehicle Routing	Optimizing the paths couriers follow to serve orders.
Service Coverage	Geographic area or set of customers served by a restaurant or courier network.
Shift Scheduling	Planning courier work shifts to meet demand patterns.
Fleet Sizing	Determining the number and type of vehicles needed for operations.
Pricing Scheme	Setting delivery fees and courier incentives.
Cross-Regional Delivery	Deliveries between distinct geographic regions, leveraging transfer stations or multi-modal transport.
Facility Location	Selecting hub or transfer-station sites to minimize cost and response time.
Homogeneous Fleet	Fleet consisting of identical vehicle types and contract terms.
Heterogeneous Fleet	Mixed fleet with different vehicle types or employment models.
Delay	Time difference between the promised delivery time and the actual delivery completion time.
Click-to-door Time	Time from the customer's click (order placement) until the meal is delivered at the door.
Pickup-to-door Time	Time from courier pickup at the restaurant until delivery completion at the customer's door.
Ready-to-pickup Time	Time from when the meal is marked "ready" by the restaurant until the courier arrives at the restaurant.
Ready-to-door Time	Time from when the meal is marked "ready" by the restaurant until it arrives at the customer's door.
Courier Utilization	Ratio of the time couriers spend actively delivering orders (traveling and servicing) to their total available or logged-in time.
Throughput	Number of orders completed on time within the promised window, i.e., picked up and delivered.
Courier Compensation	Payment structure and total earnings received by couriers, including base wages, per-order fees, and incentives.
Demand	Number and timing of customer orders, influenced by promotions, weather, or changing preferences.
Preparation Time	Time required for a restaurant to prepare a meal before it is ready for pickup.
Travel Time	Time duration for a courier to transport food from the restaurant to the customer's location.
Service Time	Time spent at pickup or drop-off points, including order-ready processing, parking, and customer handover.
Courier Availability	Availability and location of couriers, influenced by shifts, breaks, cancellations, or no-shows.
Idle Time	Period when a courier is logged in but not carrying an order.
First / Last Mile	First mile: courier travels to the restaurant; last mile: restaurant to customer.
Peak Time	Periods of elevated order volumes during meal peaks or promotions that strain system capacity.
Order Rejection	Rate at which couriers decline or cancel assigned orders, affecting delivery reliability.
Time Windows (Pickup/Delivery)	Allowable interval between the earliest and latest times for order pickup or delivery.

decision-making models that address uncertainties such as fluctuating demand (Lu et al., 2024), variable traffic conditions (Xue et al., 2024), and stochastic preparation times (Kancharla et al., 2024).

Recent advances also highlight the integration of RL models for OD (Zhou et al., 2025) and PS (Wang et al., 2025), the growing focus on sustainability through green logistics and eco-friendly delivery methods (Liu et al., 2024), and the exploration of demand-supply relation and multi-modal transportation systems (Huq et al., 2025).

In summary, this review contributes to the literature by:

- We introduce a rigorous, multidimensional classification framework that systematically organizes the operations research literature in OFD, capturing the interplay between decision levels, problem settings, and analytical approaches.
- We formalize a methodology that translates real-world OFD complexities, such as demand uncertainty, dynamic environments, and courier management, into precise OR problem components, enabling consistent categorization and comparison across studies.
- We provide comprehensive tables and visual syntheses that distill the essential characteristics, modeling approaches, and analytical paradigms of the reviewed literature, thereby equipping researchers and practitioners with an organized reference for navigating the field.
- Finally, we outline directions for future research and identify promising advanced analytical approaches to tackle future complexities arising in OFD.

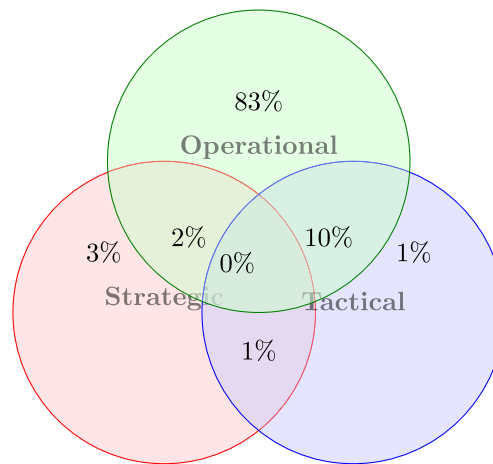


Fig. 1. Percentage of studies in OFD.

The rest of the paper is organized as follows: [Section 2](#) provides an overview of the problem description, terminology, and the foundational context of FDS. [Section 3](#) classifies problems into predictive categories and into strategic, tactical, and operational levels. [Section 4](#) examines dynamic and uncertain factors, explaining how they influence decision making and underscoring the need to address these complexities. [Section 5](#) reviews the models and solution approaches. [Section 6](#) presents key outcomes from case studies and datasets. [Section 7](#) discusses the gaps identified in the existing literature and, based on these, outlines potential future research directions. [Section 8](#) concludes with a synthesis of findings and recommendations for the field. In this section, we also discuss limitations and future directions for this scope review.

2. Problem description and terminology

OFD platforms facilitate the movement of prepared meals from restaurants to customers. FDS relies on a complex network of stakeholders, including customers, restaurants, couriers, and platform providers, each playing a crucial role in ensuring timely and efficient service. Each stakeholder faces distinct decision-making responsibilities. Customers demand quick, reliable, and affordable service while expecting high-quality food. They influence order preferences, delivery expectations, and tipping behavior, which in turn impact platform dynamics. Restaurants are responsible for meal preparation, order acceptance, and coordination with couriers, but face challenges due to unpredictable order volumes and preparation times. Couriers handle meal transportation, requiring efficient routing, optimal dispatching, and fair compensation to ensure workforce retention and service reliability. Platform providers serve as intermediaries, managing order fulfillment, pricing strategies, delivery time predictions, and fleet allocation to optimize operational performance. However, the nature of FDS introduces multiple challenges, as decision-making involves balancing customer satisfaction, cost efficiency, and dynamic logistical constraints.

The interactions among these stakeholders introduce multiple decision-making challenges at different operational levels. At a strategic level, long-term decisions include FL (Pinto et al., 2020) to enhance platform competitiveness and PS models (Bahrami et al., 2023) to support platform-level pricing and market equilibrium decisions. At a tactical level, mid-term decisions focus on FS (Yildiz and Savelsbergh, 2019b) and SS (Das and Yadav, 2021) to ensure cost-effective and scalable service operations. At an operational level, real-time decisions such as OD (Chen et al., 2024), OG (Wang et al., 2022), VR (Hu et al., 2023), and SC (Ulmer et al., 2022) must be made considering some operational restrictions. Additionally, evolving service models, such as hybrid fleet operations that integrate ground vehicles and Unmanned Aerial Vehicles (UAVs) (Gu et al., 2020), as well as sustainability-driven logistics (Liao et al., 2020), further complicate decision-making. Table 2 presents key terminology relevant to FDS problems, covering fundamental concepts related to stakeholders, logistics processes, and optimization challenges. These definitions serve as a basis for the subsequent analysis.

3. Decision problems in OFD

The decision problems in OFD can be categorized into three levels: strategic, tactical, and operational, corresponding to long-term, medium-term, and short-term planning horizons. Each level addresses different aspects of the delivery process, from high-level planning and resource allocation to day-to-day operations and real-time execution. In the following subsections, we review the decision problems at each level, along with the predictive studies, objective functions, constraints, and Key Performance Indicators (KPIs) discussed in the literature. As shown in Fig. 1, the reviewed studies are distributed across strategic, tactical, and operational decision levels, with their intersections indicating joint consideration of multiple horizons.

As evident in Fig. 1, the majority of studies have worked on the operational decision level. As an example of an operational process, Fig. 2 shows the full typical journey of a meal order. A customer places an order through the app. The restaurant then accepts the

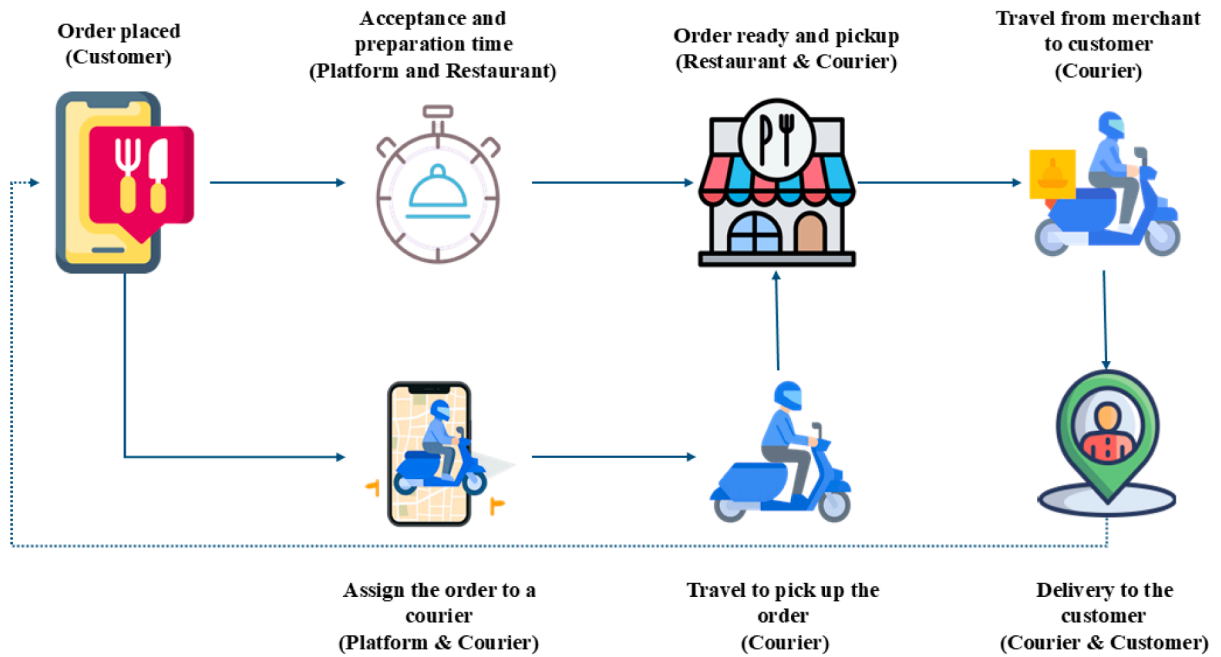


Fig. 2. Steps from order placement to delivery.

order and starts cooking. While the meal is being prepared, the platform selects a nearby courier. The courier rides to the restaurant, collects the ready meal, and drives to the customer. The arrows in the figure mark these steps and show that kitchen work, courier assignment, and travel all overlap. Keeping these three tasks in sync is key to fast and reliable delivery. Upon order completion, a service loop forms as the courier becomes available for the next assignment, and the system continuously processes incoming orders, creating a cyclical operational pattern that characterizes the dynamic nature of OFD platforms.

3.1. Strategic and tactical levels

Long- and mid-term decisions faced by OFD platforms concentrate on four decision areas: Facility Location (FL), Fleet Sizing and Composition (FS), Pricing Scheme (PS), and Shift Scheduling (SS).

3.1.1. Facility location

FL decisions have been studied within the scope of OFD systems, albeit in a limited context. In particular, explicit FL modeling arises in OFD platforms that employ drones as part of the delivery workforce. At the strategic network design, two facility archetypes shape such systems. Vehicle stops are temporary parking points where a truck stops and its onboard UAV are launched; their placement fixes the service radius, partitions customers among drones, and drives fleet size and total travel time (Gu et al., 2020). By contrast, drone-charging stations are permanent depots from which UAVs depart, fly to the restaurant pickup, proceed directly to the customer, and afterward return for battery replacement or recharging; locating these depots balances cost against the proportion of demand that can be served within a promised time window (Pinto et al., 2020). These studies show that locating UAVs launch and recharge hubs, whether ad-hoc vehicle stops or purpose-built charging depots, is the key strategic lever for achieving broad coverage and reliable lead times in drone-enabled FDS.

3.1.2. Fleet sizing and shift scheduling

OFD platforms must balance operational costs and service quality by making coordinated decisions about the number and type of couriers to employ and how to allocate them over time (Ulmer and Savelsbergh, 2020). Fleet sizing involves determining the composition and quantity of delivery personnel over extended periods, typically distinguishing between permanent salaried (in-house) drivers and flexible crowdsourced couriers (Zhang et al., 2026; Yildiz and Savelsbergh, 2019b). Luy et al. (2024) studied long-term staffing decisions that involve adjusting the number of salaried couriers over time, considering fluctuating demand and the uncertain supply of crowdsourced couriers. Dai and Liu (2020) considered a similar context, involving a diversified workforce composed of in-house drivers, full-time crowdsourced couriers, and part-time gig workers, managed over multiple time periods. Auad et al. (2024) examined FS in conjunction with platform-level strategies aimed at managing demand and capacity alignment over the long term. Zhang et al. (2025a) focused on external uncertainty factors, such as travel time, and introduced planning mechanisms that leverage flexible contracts and additional driver types to handle unanticipated demand surges. Complementary to FS, the SS

Table 3
Different OD strategies in OFD.

Strategy	Definition	Advantages	Disadvantages	References
Bundling	Combining multiple orders into one courier route, optimizing travel paths.	i) Fewer trips, lower time/cost. ii) Higher courier productivity.	i) Early orders may wait; possible food cooling. ii) More complex routing.	Ulmer et al. (2021), Simoni and Winkenbach (2023), Huq et al. (2025)
Splitting	Dividing a large or multi-item order among different couriers.	i) Faster partial deliveries. ii) Balances workload.	i) Higher total distance/cost. ii) Coordination overhead, hand-off errors.	
Postponement	Delaying the assignment until better batching or routing conditions arise.	i) Exploits batching to cut platform-wide delay. ii) Reduces rejected orders.	i) Uncertain delivery times can hurt satisfaction. ii) Risk of missing promised windows.	Reyes et al. (2018), Fotouhi et al. (2021)

problem focuses on assigning these couriers to daily or weekly shifts that ensure sufficient coverage during both peak and off-peak hours, while meeting legal and organizational constraints (Reyes et al., 2018; Das and Yadav, 2021; Xue et al., 2021).

3.1.3. Pricing scheme

Strategic delivery pricing models establish long-term fee and incentive structures to drive customer demand, courier participation, and platform profitability over extended planning horizons (Ashraf and Bardhan, 2025). Researchers have explored how platforms decide what to charge customers, how much to pay drivers, and what fees to collect from suppliers. Bahrami et al. (2023) studied this as a three-sided market of customers, suppliers, and drivers, treating the order assignment factor as an exogenous factor and examining both profit-maximizing and welfare-maximizing policies. Building on this, Ke et al. (2024) treated the assignment factor as a platform decision alongside price and wage, and analyzed the trade-off between profit and social welfare within an equilibrium framework linking demand, supply, and waiting times. Zhang et al. (2025a) built a two-stage optimization problem whose first stage selects discrete time-slot prices; the second stage runs order dispatching and routing, which will be discussed in the next sections. Optimal prices balance higher margins against the risk that extra orders overload capacity and violate time windows. Li and Liang (2022) developed a model that illustrates the interaction between demand and supply. In the model, the platform simultaneously sets both customer delivery fees and courier wages to maximize its own profit. Customer demand responds to price and follows a demand-price elasticity function. Courier participation changes in response to wage, according to a driver-wage elasticity function. The model identifies a balance where demand matches supply, so the chosen fee and wage sustain the system.

3.2. Operational level

This section presents the literature on operational-level decisions in FDS, highlighting how real-time, short-term decisions are critical to efficiently managing daily operations. This review covers six key areas: Order Dispatching (OD), Vehicle Routing (VR), Order Grabbing (OG), Service Coverage (SC), and dynamic Pricing Scheme (PS). Studies provide a base for understanding how platforms optimize daily operations to ensure timely deliveries, enhance customer satisfaction, and balance courier workloads, offering valuable insights for advancing research and practice in FDS.

3.2.1. Order dispatching

OD problem assigns each incoming order to an available courier in real time while respecting meal-preparation progress, promised delivery windows, and vehicle capacity. Platforms adjust three levers to meet these constraints: (i) bundling, grouping several orders on one trip; (ii) splitting, allowing different couriers to deliver parts of the same order; and (iii) postponement, deferring assignment until more information is known. The goal is to reduce customer waiting time without sacrificing fleet utilization or incurring excess travel cost (Reyes et al., 2018). Table 3 gives an overview of these strategies to assign orders in OFD, including what they mean, their pros and cons, and some example references. Ulmer et al. (2021) investigated a dynamic Pickup-and-Delivery Problem (PDP) for Meal Delivery Service (MDS), employing order bundling and postponement to manage a limited fleet while adhering to strict delivery deadlines, aiming to minimize delays. Steever et al. (2019) proposed a flexible framework that supports splitting, allowing a single customer order to be fulfilled by multiple couriers to maximize service earliness and minimize Ready-to-Door (RtD) and Pickup-to-Door (PtD) times. Liu (2019) addressed operational-level routing for drone-based OFD, incorporating capacity-constrained multi-order loading and endogenous dispatch postponement to enable drones to handle multiple meals within a single trip. Li et al. (2022) focused on integrated meal delivery routing for long-distance demands, while explicitly incorporating order bundling to improve flexibility and minimize travel time costs and overtime penalties. Kohar and Jakhar (2025) tackled the capacitated multi PDP with time windows, incorporating order bundling to efficiently fulfill customer requests within specified time constraints. Simoni and Winkenbach (2023) addressed OD problem in crowdsourced OFD, integrating order batching to minimize delivery costs and enhance fleet utilization within a short decision window. These studies highlight the critical role of bundling, splitting, and postponement in optimizing order dispatching, ensuring efficient resource allocation, and timely deliveries in dynamic operational environments. Fotouhi et al. (2021) explored real-time OD under curbside pickup capacity constraints, integrating postponement strategies to enhance order pairing opportunities and minimize Click-to-Door (CtD) time, thereby improving customer satisfaction.

3.2.2. Vehicle routing

Routing decisions in **FDS** encompass both standalone vehicle-routing challenges and integrated dispatching-routing decision problems, each addressing operational-level objectives. The optimization problems in this context are rooted in the extensive literature on vehicle routing problems, where several advances have been published in recent years, particularly in the design of exact methods for vehicle routing problems with pickup, deliveries, and time windows (see, e.g., Baldacci et al., 2011, 2012; Costa et al., 2019; Zhang et al., 2024). In standalone routing, Wang et al. (2021) formulated the route planning problem to minimize total delivery delay and travel distance for a single courier, subject to driver capacity and delivery time-window constraints. Liu et al. (2020) developed a learning-based framework to recommend courier routes by modeling rider preferences. Thipparthy et al. (2024) addressed simultaneous **PDP** with time windows, splitting infeasible orders into sub-routes to contain total fulfillment cost as a proxy for fuel use and emissions. Hu et al. (2023) focused on disruption recovery, dynamically reassigning orders and revising schedules after unexpected delays, while Bhuiyan et al. (2024) tackled one-hour drone routing with fleet-sizing and battery-swap constraints to fulfill urgent deliveries. Moreover, Xue et al. (2024) studied restaurant-delivery routing under uncertain food preparation and travel times. Besides, integrated dispatching and routing frameworks combine assignment with path generation to boost real-time efficiency. Steever et al. (2019) introduced a split-and-non-split delivery model that bundles and splits orders across multiple couriers to maximize earliness and minimize **PtD** times under capacity and time-window constraints. Liu (2019) integrated drone dispatch and dynamic routing, balancing safety, delay minimization, and efficiency within battery and charging constraints. Liao et al. (2020) expanded this scope in the green meal delivery routing problem by adding **FS**, optimizing customer satisfaction, carbon emissions, and workload balance. Wang and Jiang (2022) grouped orders spatially and optimized bundle routes to enhance time-sensitive satisfaction. Finally, Joshi et al. (2022) constructed efficient delivery batches via bipartite matching and heuristic refinements to minimize extra delivery time in a fast-evolving environment.

After reviewing studies on **OD** and **VR**, we examine how bundling, splitting, and postponement are represented within dispatching operations. These strategies shape whether orders are grouped, divided, or delayed, but their modeling depth varies from rule-based assumptions and implicit capacity or routing effects to explicit endogenous decisions. Therefore, Table 4 classifies their modeling treatments into three broad categories: exogenous rule-based, implicit by-product, and endogenous decision-based. Taking bundling as an illustrative case, three modeling treatments can be identified. In the first, bundles are formed before the main optimization procedure through fixed rules, preprocessing steps, platform policies, clustering methods, or zone- and time-based aggregation; the resulting bundles are then treated as inputs to the model (Bahrami et al., 2023; Dai and Liu, 2020). In the second, multi-order service is not modeled as a separate bundling decision, but emerges from capacity, assignment, multi-stop routing, or pickup-and-delivery constraints (Liu et al., 2018; Zhen et al., 2023). In the third, bundle composition is determined within the model or solution procedure, either through an integrated formulation or through a sequential procedure linked to assignment and routing decisions (Yildiz and Savelsbergh, 2019a; Simoni and Winkenbach, 2023).

A similar distinction applies to postponement. In exogenous rule-based treatments, deferral is imposed by a fixed rule, a waiting condition, a decision-point rule, or a feasibility condition, without optimizing when or whether to postpone an order (Tu et al., 2019; Zhang et al., 2025b). In endogenous decision-based treatments, deferral is determined within the model or solution procedure, where the model or algorithm decides when and for how long an order should wait before assignment, release, or dispatch (Ulmer et al., 2021; Chen et al., 2025). Splitting is less common, but it also appears in two forms. In exogenous rule-based treatments, a customer request is divided into sub-orders before assignment or routing decisions are optimized (Thipparthy et al., 2024; Liu et al., 2025a). In endogenous decision-based treatments, the model or solution procedure determines how an order is split across couriers, vehicles, drones, trips, transfer stations, or sub-orders (Steever et al., 2019; Li et al., 2025).

3.2.3. Order grabbing or recommendation

OG mechanisms shift the dispatch paradigm from platform-centered allocation to rider-centered choice. Instead of receiving a fixed assignment, each courier is presented with a personalized list of orders ranked by expected utility. The courier then selects one or more orders to accept. Wang et al. (2023d) addressed rider-centered order dispatching, where riders choose orders from personalized recommendation lists generated at each interaction step with the platform, optimizing assignment efficiency and rider satisfaction. Similarly, Wang et al. (2022) focused on real-time order allocation through a crowdsourced recommending-and-grabbing system, making dynamic decisions about which riders are exposed to which orders and how order lists are sequenced to ensure efficiency in a highly dynamic environment. Wang et al. (2023e) tackled the dynamic **OG** problem, generating order lists for multiple available riders at each decision point to maximize the number of successfully grabbed orders, minimize order-grabbing conflicts between riders, and reduce route length and delivery delays. These studies emphasize the importance of advanced recommendation systems for optimizing real-time order allocation, thereby enhancing operational efficiency and the rider experience in crowdsourced delivery settings.

3.2.4. Service coverage

Adjusting the **SC** radius and area enables the platform to screen incoming orders, control demand when capacity is tight, and redistribute work across couriers without altering routing policies. By expanding the radius, the system attracts more orders during slack periods; by shrinking it, the platform keeps promised lead times feasible when kitchens or riders approach saturation. The decision, therefore, links customer acceptance, workload balance, and on-time performance. Ulmer et al. (2022) addressed the problem by dynamically setting the service area radius every 15 minutes to determine whether a customer's location qualifies for service. This approach controls order acceptance, balances vehicle workload, and meets promised delivery times. Auad et al. (2023) studied incorporating real-time decisions on courier management and dynamic region reshaping through a **OR**-based

Table 4
Modeling treatments of OD strategies across studies.

Treatment	Definition	Studies
Bundling		
Exogenous Rule-Based	Orders are grouped before or outside the main optimization procedure through a fixed rule, a preprocessing step, a platform policy, a clustering method, or zone/time-based aggregation; the resulting bundles are treated as given inputs.	Wang and Jiang (2022), Bahrami et al. (2023), Yang et al. (2024b), Dai and Liu (2020)
Implicit By-product	Multi-order service is not modeled as a separate bundling decision, but emerges from the structure of capacity, assignment, multi-stop routing, or pickup-and-delivery constraints.	Wang (2018), Liu et al. (2018), Liu (2019), Aziez et al. (2020), Tu et al. (2019), Ulmer and Savelsbergh (2020), Chu et al. (2023), Zheng et al. (2021), Xue et al. (2021), Chen et al. (2022b), Zheng et al. (2022), Zhen et al. (2023), Zheng et al. (2023), Chen et al. (2023), Wang et al. (2023a), Hamid et al. (2023), Hu et al. (2023), Guo et al. (2024), Auad et al. (2024), Xue et al. (2024), Liu et al. (2024), Sun et al. (2024), Hou et al. (2024), Kancharla et al. (2024), Kong et al. (2025), Zhao et al. (2025), Liu et al. (2025a), Lu et al. (2025), Zhang et al. (2025b), Chen et al. (2025)
Endogenous Decision-Based	Bundle composition is explicitly determined within the model or solution process, either in an integrated formulation or in a sequential/decomposition-based procedure linked to assignment and/or routing decisions.	Reyes et al. (2018), Yildiz and Savelsbergh (2019a), Ulmer et al. (2021), Liao et al. (2020), Liu et al. (2021), Kohar and Jakhar (2025), Fotouhi et al. (2021), Huang et al. (2021), Chen et al. (2022a), Huq et al. (2022), Joshi et al. (2022), Li et al. (2022), Jahanshahi et al. (2022), Wang et al. (2023b), Tao et al. (2023), Agnetis et al. (2023), Simoni and Winkenbach (2023), Ke et al. (2024), Mehra et al. (2024), Kim and Do Chung (2024), Lu et al. (2024), Zhang et al. (2025a), Huq et al. (2025), Xue and Zou (2025)
Postponement		
Exogenous Rule-Based	Deferral is imposed by a fixed rule, waiting condition, decision-point rule, or feasibility condition outside the optimization logic; the model does not optimize whether or when an order should be postponed.	Tu et al. (2019), Joshi et al. (2022), Zhang et al. (2025b)
Endogenous Decision-Based	Deferral is determined within the model or solution process, where the model or algorithm decides whether, when, and how long an order should wait before being assigned, released, or dispatched.	Reyes et al. (2018), Steever et al. (2019), Liu (2019), Ulmer et al. (2021), Fotouhi et al. (2021), Jahanshahi et al. (2022), Auad et al. (2023), Lu et al. (2024), Li et al. (2025), Chen et al. (2025)
Splitting		
Exogenous Rule-Based	A customer request is divided into multiple sub-orders by a preprocessing step rule, service rule, or feasibility condition before assignment/routing decisions are optimized.	Thipparthi et al. (2024), Liu et al. (2025a)
Endogenous Decision-Based	Splitting is explicitly determined within the model or solution process, including splitting across couriers, vehicles, drones, trips, transfer stations, or sub-orders.	Steever et al. (2019), Li et al. (2022), Mehra et al. (2024), Li et al. (2025)

Rolling Horizon (RH) framework. Their work balanced customer service quality with courier satisfaction by adjusting the service area in response to real-time demand and supply conditions. These studies underscore the importance of dynamic **SC** adjustments to maintain operational efficiency and meet stringent delivery time requirements in fast-paced delivery environments. There is another type of **SC** decision: cross-regional coordination. It is an operational decision that determines how orders are transferred between distinct delivery zones. Li et al. (2022) introduced fixed transfer stations to consolidate and relay orders across regions, ensuring continuity in long-distance deliveries. Huq et al. (2025) extended this by partitioning the service area along boundaries and selecting meeting points with adequate parking and rider access for inter-regional delivery.

3.2.5. Dynamic pricing scheme

Transitioning to the operational level, problems shift to real-time adjustments that respond to instantaneous fluctuations in demand and supply. Bai et al. (2022) proposed an operational pricing mechanism balancing order fulfillment rates against fee reductions under computation limits, pricing protection rules, and service quality thresholds such as rejection and timeout rates. Wang et al. (2025) examined dynamic pricing and wage regulation, focusing on how platforms adjust payment policies to balance driver incentives with system efficiency. Horner et al. (2025) addressed an incentive scheme problem by designing personalized driver request menus and compensation packages to maximize expected net utility platform revenues, considering compensation costs and penalties for unserved drivers while enforcing menu-size limits, one-to-one assignment, compensation bounds, and stochastic acceptance models.

Tong et al. (2020) studied the problem of static versus dynamic delivery pricing, where static pricing relied solely on distance. In contrast, dynamic pricing determined customer fees based on distance and temporal and contextual factors, such as weekends, holidays, peak periods, and weather.

A substantial portion of the literature addresses joint decision problems. To highlight decision interdependencies, Table 5 lists studies that consider at least two decision problems. The “Approach” column distinguishes integrated solution approaches, in which multiple decisions are optimized within a single unified model or policy, from decomposition-based approaches, in which decisions are coordinated through hierarchical, sequential, modular, or temporal formulations and are often adopted to handle the complexity of large-scale instances. Specific solution approaches are detailed in Appendix C.

3.3. Objective functions

Objective functions in optimization models represent the goals the system seeks to achieve, such as maximizing profit, minimizing cost, or enhancing customer satisfaction. These objectives can be formulated, including a performance criterion such as delivery time, number of assigned orders, distance traveled, and courier utilization rate. Some studies have also employed various combinations or weights of these criteria within a single objective function, or have optimized multiple criteria simultaneously in a multi-objective framework. The objective functions discussed in this section are summarized in Table 6, which describes the main objectives used in OFD and categorizes them into customer-focused, platform-focused, or courier-focused goals.

3.3.1. Platform-focused

Platform-focused objectives aim to improve operational efficiency and financial performance. A fundamental goal is maximizing profit or revenue while managing costs (Zhang et al., 2025a; Deng et al., 2024; Horner et al., 2025). Another key objective is minimizing operational costs, including delivery costs, courier wages, and penalties (Dai and Liu, 2020; Thipparthi et al., 2024). Also, maximizing throughput, or the volume of orders processed efficiently, was considered by Reyes et al. (2018) and Cosmi et al. (2019). Reducing fleet size to optimize resource allocation was addressed by Gu et al. (2020) and Auad et al. (2024). Additionally, maximizing order assignments to improve successful match rates was considered in Yang et al. (2024b) and Ausseil et al. (2024).

3.3.2. Customer-focused

Customer-focused models in the literature emphasize three temporal metrics that jointly drive perceived service quality. Most studies minimize CtD time, the interval from order confirmation to delivery (Steever et al., 2019; Ulmer et al., 2021; Wang et al., 2021; Yildiz and Savelsbergh, 2019a; Kim and Do Chung, 2024). Others target the Dispatched-to-Door time to reduce the courier leg through tailored routing algorithms (Huq et al., 2022; Wang et al., 2023a). A complementary criterion, lateness, penalizes delay minutes beyond promised windows to secure punctuality (Reyes et al., 2018; Wang, 2018; Liu, 2019; Fotouhi et al., 2021; Zheng et al., 2022; Cosmi et al., 2025; Hou et al., 2024).

3.3.3. Courier-focused

Courier-focused objectives concentrate on enhancing the efficiency and well-being of delivery personnel. Balancing workload to ensure equitable task distribution was emphasized by Liao et al. (2020) and Martinez-Sykora et al. (2024). Maximizing courier utilization while avoiding overburdening was targeted by Jahanshahi et al. (2022). Ensuring fair compensation by supporting reasonable earnings and minimizing idle time is also critical for satisfaction and retention (Yildiz and Savelsbergh, 2019a; Wang et al., 2022).

3.3.4. Multi-objective studies

In OFD systems, multiple stakeholders pursue different objectives that may be in contradiction. For example, customers want to minimize delivery time, which may require using more couriers or longer shifts. Platforms aim to reduce travel costs, sometimes by batching deliveries or optimizing routes, which can delay individual orders. Riders, on the other hand, seek to maximize their revenue, while platforms simultaneously strive to minimize travel distance (Liu et al., 2025a). These goals can conflict directly, such as when reducing delivery time increases travel costs. Addressing such conflicting objectives requires multi-objective optimization, which explicitly balances these competing priorities according to the decision-maker's preferences and makes clear trade-offs between them.

Several studies have addressed multiple criteria simultaneously. Liao et al. (2020) focused on maximizing customer satisfaction, minimizing carbon emissions, and balancing courier utilization. Martinez-Sykora et al. (2024) aimed to reduce the variation in the number of orders handled by couriers, total travel time, total waiting time between orders, and differences in the proportion of waiting time relative to shift duration among couriers. Zheng et al. (2022) simultaneously minimized delays and distance-related costs. Huq et al. (2022) jointly maximized courier profit and minimized delivery time to enhance customer satisfaction. Gu et al. (2020) adopted a multi-level optimization approach, minimizing vehicle stops in the first level, followed by reducing the total number of vehicles dispatched and the total travel time simultaneously in the second level. Liu et al. (2024) balanced operational efficiency and environmental metrics by minimizing the cost of delivery distance, meal delays, and greenhouse gas emissions. Finally, Mehra et al. (2024) employed Pareto-based optimization to reduce the total travel distance, the number of vehicles required, and the additional delivery time resulting from detours and synchronization delays.

Table 5
Studies with at least two decision problems in OFD.

Reference	OG	OD	VR	SC	SS	FS	PS	FL	Approach
Zhang et al. (2022)	✓		✓						D
Wang et al. (2022)	✓		✓						D
Reyes et al. (2018)		✓	✓		✓				D
Liu et al. (2018)		✓	✓			✓			D
Wang (2018)		✓	✓						I
Steever et al. (2019)		✓	✓						D
Yildiz and Savelsbergh (2019a)		✓	✓		✓				I
Liu (2019)		✓	✓						D
Tu et al. (2019)		✓	✓						D
Ulmer and Savelsbergh (2020)		✓	✓		✓	✓			D
Dai and Liu (2020)		✓	✓		✓	✓			I
Liao et al. (2020)		✓	✓			✓			D
Gu et al. (2020)		✓	✓	✓		✓		✓	D
Ulmer et al. (2021)		✓	✓						I
Fotouhi et al. (2021)		✓	✓						D
Huang et al. (2021)		✓	✓						D
Xue et al. (2021)		✓	✓		✓	✓			D
Joshi et al. (2022)		✓	✓						D
Wang and Jiang (2022)		✓	✓						D
Li et al. (2022)		✓	✓						D
Jahanshahi et al. (2022)		✓	✓						I
Bozanta et al. (2022)		✓	✓						I
Chen et al. (2022a)		✓	✓						D
Zheng et al. (2022)		✓	✓	✓					D
Tao et al. (2023)		✓	✓						D
Hamid et al. (2023)		✓	✓						D
Zhen et al. (2023)		✓	✓						D
Wang et al. (2023c)		✓	✓						D
Chen et al. (2023)		✓	✓						D
Simoni and Winkenbach (2023)		✓	✓						D
Chu et al. (2023)		✓	✓						D
Zheng et al. (2023)		✓	✓						D
Wang et al. (2023b)		✓	✓	✓					D
Auad et al. (2023)		✓	✓	✓					D
Ke et al. (2024)		✓	✓				✓		I
Auad et al. (2024)		✓	✓			✓			I
Martinez-Sykora et al. (2024)		✓	✓		✓				I
Yang et al. (2024a)		✓	✓	✓					I
Hou et al. (2024)		✓	✓						I
Chen et al. (2024)		✓	✓						D
Liu et al. (2024)		✓	✓						D
Thipparthy et al. (2024)		✓	✓						I
Kim and Do Chung (2024)		✓	✓						I
Kancharla et al. (2024)		✓	✓						D
Bhuiyan et al. (2024)		✓	✓			✓			D
Xue et al. (2024)		✓	✓						D
Deng et al. (2024)		✓	✓				✓		D
Mehra et al. (2024)		✓	✓	✓		✓			D
Guo et al. (2024)		✓	✓						D
Yang et al. (2024b)		✓	✓						D
Luy et al. (2024)		✓	✓			✓			D
Sun et al. (2024)		✓	✓			✓			D
Zhang et al. (2025a)		✓	✓				✓		D
Kohar and Jakhar (2025)		✓	✓						I
Huq et al. (2025)		✓	✓	✓		✓	✓		D
Kong et al. (2025)		✓	✓						I
Horner et al. (2025)		✓	✓				✓		D
Zhao et al. (2025)		✓	✓			✓			D
Liu et al. (2025a)		✓	✓						D
Lu et al. (2025)		✓	✓						I
Li et al. (2025)		✓	✓						D
Du et al. (2025)		✓	✓			✓			D
Xue and Zou (2025)		✓	✓						D
Zhang et al. (2025b)		✓	✓						D
Chen et al. (2025)		✓	✓						D
Zhang et al. (2026)		✓				✓			D
Yildiz and Savelsbergh (2019b)				✓		✓	✓		I
Pinto et al. (2020)				✓				✓	I
Das and Yadav (2021)					✓	✓			I

OG (Order Grabbing); OD (Order Dispatching); VR (Vehicle Routing); SC (Service Coverage); SS (Shift Scheduling); FS (Fleet Sizing); PS (Pricing Scheme); FL (Facility Location); D (Decomposition-fashion); I (Integrated).

Table 6
Objective functions considered in OFD.

Objective Function	Level	Decision Problem	Description	References
Platform-focused				
Profit or Revenue	T, O	OG, OD, SC, FS, PS	Increase the platform's net revenue or profit.	Yildiz and Savelsbergh (2019b), Bahrami et al. (2023), Kancharla et al. (2024), Zhang et al. (2025a), Horner et al. (2025)
Operational Costs	S, T, O	OD, VR, SC, SS, FS, PS	Minimize courier wages, vehicle, fuel, overhead, and wage costs.	Dai and Liu (2020), Thipparthy et al. (2024), Wang (2018), Chu et al. (2023), Hamid et al. (2023), Das and Yadav (2021), Luy et al. (2024), Bhuiyan et al. (2024), Sun et al. (2024), Zhao et al. (2025), Zhang et al. (2026)
Travel Distance	O	OG, OD, VR, SC, SS, FS, PS, FL	Minimize total route length or time.	Liu (2019), Wang et al. (2021), Thipparthy et al. (2024), Lu et al. (2024), Liu et al. (2018), Zheng et al. (2021, 2022), Bozanta et al. (2022), Chen et al. (2023), Liu et al. (2024), Chen et al. (2024), Hou et al. (2024), Mehra et al. (2024)
Throughput	O	OD, VR, SC, SS, FS, PS	Maximize on-time fulfilled orders.	Reyes et al. (2018), Cosmi et al. (2019), Ulmer et al. (2022), Liao et al. (2020), Wang and Jiang (2022)
Fleet Size	S, T, O	OD, VR, SC, SS, FS, FL	Minimize the number of couriers or vehicles.	Liu et al. (2018), Gu et al. (2020), Xue et al. (2021), Auad et al. (2024), Mehra et al. (2024)
Matching	S, T, O	OG, OD, VR, SC, FS	Maximize assigned orders / minimize unfulfilled orders.	Wang et al. (2023e), Ausseil et al. (2024), Auad et al. (2024), Simoni and Winkenbach (2023), Dai and Liu (2020), Zhang et al. (2026)
Emission Costs	O	OD, VR, FS	Minimize greenhouse gas emission costs.	Liu et al. (2024), Liao et al. (2020)
Customer-focused				
Click-to-Door Time	O	OD, VR, SC	Minimize total customer wait time.	Yildiz and Savelsbergh (2019a), Kim and Do Chung (2024), Huq et al. (2022), Wang et al. (2023a)
Delay (Lateness)	O	OD, VR, SC, SS, FS, PS	Minimize late deliveries or delay minutes.	Reyes et al. (2018), Wang (2018), Steever et al. (2019), Liu (2019), Yildiz and Savelsbergh (2019a), Ulmer et al. (2021), Liu et al. (2021), Fotouhi et al. (2021), Zheng et al. (2022), Cosmi et al. (2025), Hou et al. (2024)
Courier-focused				
Balance Workload	O	OD, VR, SS, FS	Evenly distribute orders across couriers.	Liao et al. (2020), Martinez-Sykora et al. (2024), Wang et al. (2023a)
Courier Utilization	O	OD, VR, SC, SS	Increase active-delivery ratio; reduce idle time.	Wang et al. (2023b), Martinez-Sykora et al. (2024)
Fair Compensation	T, O	PS	Align earnings with delivered workload.	Bai et al. (2022), Wang et al. (2025)
Courier Profit	O	OD, PS	Maximize courier profit.	Huq et al. (2022), Zhou et al. (2025), Zhang et al. (2025b)

S (Strategic); T (Tactical); O (Operational); OG (Order Grabbing); OD (Order Dispatching); VR (Vehicle Routing); SC (Service Coverage); SS (Shift Scheduling); FS (Fleet Sizing); PS (Pricing Scheme); FL (Facility Location);

3.4. Constraints

Constraints in FDS are critical for ensuring operational feasibility, efficiency, and customer satisfaction. These limitations define the boundaries within which optimization occurs, reflecting real-world challenges such as time, capacity, and resource availability. A summary of the most common operational constraints identified in the literature is provided in Table 7.

3.4.1. Time-related constraints

Ensuring timeliness is a core requirement in FDS. Meals must be picked up and delivered within strict timeframes to maintain service quality. These constraints include pickup and delivery time windows. Orders must be collected after preparation and delivered by set deadlines (Reyes et al., 2018; Yildiz and Savelsbergh, 2019a). Preparation and service times at restaurants and customer locations are also considered. This practice aligns with realistic scheduling demands (Liu, 2019). Delay-related restrictions, whether

Table 7
Operational constraints in OFD.

Constraint	Description	Level	Decision problems	References
Time-Related Restrictions				
Pickup time window	Cannot pick up before the meal is ready	O	OD, VR	Reyes et al. (2018)
Delivery deadline	Must complete delivery by the promised latest time	O	OD, VR	Yildiz and Savelsbergh (2019a), Steever et al. (2019)
Delay cap	Bound on delay or minimum on-time rate	T, O	OD, VR	Ulmer et al. (2021), Huq et al. (2025)
Capacity & Assignment Constraints				
Load capacity	Order load must not exceed vehicle capacity	T, O	VR, FS	Liao et al. (2020), Thipparthi et al. (2024)
Resource budget cap	Courier and depot costs constrained by budget	S, T	FS, SS, FL	Dai and Liu (2020), Pinto et al. (2020)
Assignment cardinality	Each courier/order can appear at most once	O	OD	Chen et al. (2022b)
Demand conservation	All accepted orders must be served or dropped	O	OD, SS	Dai and Liu (2020)
Routing & Sequencing Limitations				
Pickup-before-delivery	Pickup must precede delivery	O	OD, VR	Zhen et al. (2023), Liu (2019)
Bundling radius	Spatial-temporal grouping of orders	O	OD, VR	Wang (2018)
Transfer synchronisation	Split orders must arrive simultaneously	O	S, SC	Li et al. (2022), Huq et al. (2025)
Workforce & Platform Policy Constraints				
Shift length	Shift must not exceed allowed time	T	SS, FS, OD	Reyes et al. (2018), Martinez-Sykora et al. (2024)
Sign-in/out window	Couriers must be logged in to be assigned	O	OD, OG	Yang et al. (2024b)
Exposure limit	Dispatch menus and exposures are bounded	O	OG	Wang et al. (2022)
Minimum guaranteed orders	Full-time couriers must get a minimum number of orders	T	SS, OD	Dai and Liu (2020)
Minimum courier wage	Pay must exceed the legal minimum	O	OD, PS	Kancharla et al. (2024), Horner et al. (2025)
Infrastructure & Spatial Constraints				
Drone battery endurance	UAV trips must respect battery endurance	O	VR	Gu et al. (2020), Bhuiyan et al. (2024)
Region eligibility	Couriers limited to service regions	O	SC, SS	Auad et al. (2023), Das and Yadav (2021)
Coverage radius	Customers must be within serviceable area	S, O	FL, SC	Gu et al. (2020), Pinto et al. (2020)

S (Strategic); T (Tactical); O (Operational); OG (Order Grabbing); OD (Order Dispatching); VR (Vehicle Routing); SC (Service Coverage); SS (Shift Scheduling); FS (Fleet Sizing); PS (Pricing Scheme); FL (Facility Location).

enforced as strict deadlines or through penalty functions, reinforce operational reliability (Ulmer et al., 2021). These time-based rules are especially critical for coordinating multi-trip operations. In such cases, precise timing across routes is essential (Wang, 2018; Zheng et al., 2021).

3.4.2. Capacity and resource constraints

The allocation of couriers, vehicles, and orders is controlled by capacity and resource limits to prevent inefficiencies or overloading. Vehicle and courier load capacities limit the number or weight of orders handled per trip (Liao et al., 2020; Zhen et al., 2023). Assignment rules often stipulate that each order is served by exactly one courier or vehicle, while some models allow reassignment, bundling, or partial fulfillment under controlled conditions (Chen et al., 2022b; Auad et al., 2023). Fleet availability and resource budget caps restrict the number of active couriers, depots, or vehicles, ensuring resource use remains feasible within operational or financial limits (Dai and Liu, 2020; Pinto et al., 2020). Together, these rules balance efficiency with the system's physical limits or engender a trade-off between them.

3.4.3. Routing and sequencing rules

Designing feasible and efficient delivery paths requires adherence to a set of routing and sequencing rules. Precedence rules requiring pickup before delivery are fundamental to PDP models (Zhen et al., 2023). Flow conservation and sub-tour elimination

Table 8

Key performance indicators in OFD.

Indicator	Description	Level	Problems	References
Delivery Timeliness				
Click-to-Door Time	Time from order placement to delivery	O	OD, VR	Reyes et al. (2018), Yildiz and Savelsbergh (2019a), Fotouhi et al. (2021), Kim and Do Chung (2024)
Ready-to-Pickup Time	Waiting time from order readiness until pickup	O	OD, VR	Yildiz and Savelsbergh (2019a), Auad et al. (2023)
Ready-to-Door Time	Time from meal readiness to drop-off in customer location	O	OD, VR	Steever et al. (2019), Fotouhi et al. (2021)
Pickup-to-Door Time	Time between pickup and customer handoff	O	OD, VR	Steever et al. (2019)
Delay (Tardiness)	Average or max delay and number of late deliveries	O	OD, PS, VR	Liu (2019), Ulmer et al. (2022), Chen et al. (2022a), Zheng et al. (2022)
Service Reliability & Satisfaction				
On-time delivery ratio	Share of orders delivered within promised time windows	O	OD, VR	Huq et al. (2022), Yang et al. (2024a), Huq et al. (2025)
Order fulfillment rate	Proportion of accepted orders successfully delivered	O	OD, SS	Bai et al. (2022), Lu et al. (2024), Huang et al. (2021)
Order rejection rate	Frequency of declined orders	O	OD, SS	Joshi et al. (2022), Zhao et al. (2025)
Efficiency, Environmental & Resource Utilization				
Courier utilization	Share of courier shift spent on active deliveries	T,O	SS, OD	Reyes et al. (2018), Dai and Liu (2020), Luy et al. (2024)
Traveled distance	Average distance per order	O	VR, OD	Steever et al. (2019), Wang et al. (2021), Yang et al. (2024a)
Fleet size	Number of couriers or vehicles deployed	T	FS, SS	Bhuiyan et al. (2024), Auad et al. (2024)
Idle time	Time spent waiting or repositioning without orders	O	SS, OD	Martinez-Sykora et al. (2024), Wang et al. (2023b)
Energy consumption	Battery swaps or energy per distance or order	O	VR	Liu (2019)
Orders per bundle size	Average number of orders grouped into a delivery trip	O	OD, VR	Reyes et al. (2018), Auad et al. (2024)
Cost per order	Cost per order, operating cost, penalties	T,O	PS, OD	Li et al. (2022), Zhao et al. (2025)
Carbon emissions	Greenhouse gas footprint per order or distance	O	VR, FS	Liao et al. (2020), Liu et al. (2024)

S (Strategic); T (Tactical); O (Operational); OD (Order Dispatching); VR (Vehicle Routing); SS (Shift Scheduling); FS (Fleet Sizing); PS (Pricing Scheme).

constraints maintain route connectivity and prevent infeasible loops (Kohar and Jakhar, 2025). In bundled or split-delivery services, additional rules, such as spatiotemporal limits for order grouping (Wang, 2018) or synchronization requirements for split orders (Li et al., 2022; Huq et al., 2025), enforce coherence in multi-order or multi-modal operations.

3.4.4. Workforce and platform policy constraints

Platform and workforce regulations impose restrictions shaping courier participation and assignments. Courier availability is controlled by shift length limits and sign-in/out periods (Yildiz and Savelsbergh, 2019a; Yang et al., 2024b). In OG problems, exposure caps limit the number of offers visible to couriers and the duration of their availability, influencing assignment dynamics (Wang et al., 2022). Platforms also set guarantees to ensure compliance with courier standards and maintain incentive structures. Minimum wage policies or guaranteed pay rates ensure equitable treatment of couriers and incentivize participation (Kancharla et al., 2024; Horner et al., 2025). On the system side, budget or cost caps limit expenditures on couriers, vehicles, depots, or infrastructure, keeping operations economically sustainable (Pinto et al., 2020; Das and Yadav, 2021).

3.4.5. Infrastructure and spatial constraints

Geographic boundaries and technological limits form another layer of restrictions in FDS. Coverage constraints define the maximum serviceable radius or eligibility zones for couriers and customers (Gu et al., 2020; Pinto et al., 2020). Regional assignment rules restrict couriers to designated service zones (Auad et al., 2023; Das and Yadav, 2021). For technology-enabled delivery, drone endurance and battery capacity constraints limit range and energy consumption (Bhuiyan et al., 2024). These restrictions align delivery operations with environmental and infrastructural realities.

Objectives and constraints are used to define the decision problem before it is solved. In the evaluation stage, KPIs are used to assess the quality of the solution. Table 8 summarizes the measures found in the literature. These metrics are used for performance analysis, benchmarking, business dashboards, and post-optimization assessment.

3.5. Predictive problems

The decision problems described in previous sections inherently depend on estimates of uncertain operational parameters. Objective functions that minimize Ctd time, delay penalties, or operational costs, as well as constraints governing time windows, routing feasibility, and capacity limits, all require reliable forecasts of demand arrival patterns, meal preparation durations, courier travel times, and Estimated Time of Arrival (ETA) realizations. Predictive problems address this requirement by generating short-horizon forecasts that parameterize the prescriptive framework, enabling the objectives and constraints to reflect real-time system states and support robust decision-making under uncertainty. The following sections examine the principal forecasting tasks, including demand forecasting, ETA estimation, and preparation and travel time prediction, that supply the inputs to operational optimization in OFD platforms.

3.5.1. Demand forecasting

Demand forecasting is a pivotal predictive task that informs operational decisions such as dynamic pricing, order bundling, and courier relocation in FDS (Hess et al., 2021). Accurate demand forecasting enables platforms to adapt to fluctuating customer needs and optimize resource allocation. Crivellari et al. (2022) studied the operational challenge of matching courier supply to dynamic spatial demand in OFD platforms. Their work focused on predicting the short-term spatial distribution of customer orders, enabling platforms to prevent driver shortages in some zones and oversupply in others. Liang et al. (2023) explored demand forecasting, highlighting sharp fluctuations caused by lunch and dinner peaks, uneven order distributions, and weather conditions. They argued that forecasting demand as a range with upper and lower bounds enables platforms to implement more resilient strategies in decision-making problems such as PS and proactive OD. Nie et al. (2025) addressed the challenge of forecasting delivery demand across metropolitan networks while ensuring the forecasting approach can be transferred to cities with little or no historical data. Their study framed demand prediction as a prerequisite for balancing courier capacity, routing resources, and service quality citywide, highlighting the need to account for spatial interdependence among neighborhoods and to generalize insights from data-rich to data-scarce urban contexts. Although this task indirectly supports decisions such as FS, its primary application is operational, focusing on immediate responses to demand fluctuations.

3.5.2. Estimated time of arrival

Accurately ETA is essential to managing customer expectations and optimizing delivery planning. This task involves forecasting the time from order placement to delivery under uncertain conditions, such as variable traffic or order preparation times, to minimize the deviation between predicted and actual arrival times. Hildebrandt and Ulmer (2022) addressed this challenge by employing ML models designed to reduce prediction errors. Their approach incorporated service-level constraints, such as a 15-minute delay cap for bundled deliveries, ensuring that predictions align with operational goals, including timely delivery and customer satisfaction. Fu et al. (2025) investigated the estimation of arrival times on an OFD platform, where courier data is limited, heterogeneous, and constrained by privacy. They identified accurate ETA prediction as essential for optimizing driver allocation and fulfilling promised delivery windows, but challenging due to fragmented driver records and the implicit, experience-based nature of much courier routing knowledge.

3.5.3. Estimation of preparation and travel time

Another important predictive task is estimating preparation time, which directly impacts total fulfillment time and downstream operational decisions such as OD. Accurate forecasts enable platforms to align courier assignments with actual preparation timelines, thereby reducing delays and enhancing service reliability. Dai et al. (2023) developed a framework that infers order preparation time from couriers' reported arrival timestamps using self-supervised and semi-supervised learning. By providing more precise preparation time estimates, their framework supported fulfillment time estimation, OD, and pickup route recommendations, highlighting the importance of accurate preparation time inference for operational efficiency in OFD platforms. Predicting origin-destination travel times is also vital for efficient routing and scheduling in FDS, as it informs decisions about courier assignments and delivery timelines. This task involves estimating travel times between points when routes are not predetermined, accounting for factors such as traffic conditions and environmental conditions. Liu et al. (2025b) proposed a model that inferred driver route preferences and predicted travel times by integrating historical trajectory data with real-time inputs, including temperature, precipitation, visibility, humidity, wind speed, and traffic conditions. Their approach enhanced prediction accuracy by capturing the complex interplay of these factors, providing reliable travel time estimates that support operational efficiency.

4. Static and dynamic problem settings

This section introduces a novel categorization of problem settings in FDS literature, which constitutes a significant contribution of this review. The proposed framework classifies studies into four distinct categories: *static-deterministic*, *dynamic-deterministic*, *static-stochastic*, and *dynamic-stochastic*. This categorization not only provides a structured overview of the existing research but also highlights the varying approaches to addressing the inherent uncertainties in OFD operations. The following subsections delve into each category, examining their characteristics and implications for real-world applications.

4.1. Static-deterministic

In this setting, all relevant parameters, such as order requests, restaurant and customer locations, travel times, service times, preparation times, courier availability, and delivery time windows, are assumed to be known in advance and remain fixed throughout the planning horizon. This setting provides a controlled environment that eliminates real-time uncertainties and dynamic changes, allowing researchers to focus on the core challenges of FDS under idealized conditions. Wang (2018) formulated OD and VR with restaurants as fixed meal-production sites and all parameters predetermined, thereby establishing a foundational framework in this context. Cosmi et al. (2019), Zhen et al. (2023), and Li et al. (2022) also operated under this setting, assuming full prior knowledge of orders, courier availability, and operational times to focus on pre-planned scheduling and delivery operations.

In the static-deterministic setting, researchers often impose specific constraints to reflect operational realities while maintaining the environment's static and deterministic nature. For example, Kohar and Jakhar (2025) examined a multi-period PDP where the fixed capacity constraints and strict time windows are known in advance. Xue et al. (2021) explored FDS with predetermined orders over a fixed planning horizon, while Gu et al. (2020) integrated ground vehicles and UAVs under these static conditions. Additional works, such as Liu et al. (2020) and Wang et al. (2021), used deterministic parameters derived from historical data and predefined inputs, ensuring that the system's behavior remained predictable and analyzable in this setting. The static-deterministic setting is valuable for establishing benchmarks and understanding fundamental system dynamics. Yildiz and Savelsbergh (2019a) adopted a clairvoyant assumption, implying perfect foresight of all parameters to set optimal performance standards within this controlled framework. Thippaarthi et al. (2024) and Kim and Do Chung (2024) similarly analyzed their systems under deterministic conditions. Wang et al. (2023c) used this setting as a baseline for comparison with more complex scenarios in which orders arrive dynamically, highlighting its role in validating operational strategies. Specialized applications further demonstrate the versatility of the static-deterministic setting. Hamid et al. (2023) modeled homemade meal delivery with stringent, predefined time windows, ensuring that all parameters remain fixed. Bhuiyan et al. (2024) optimized drone-based systems with known energy consumption and fleet composition, and Pinto et al. (2020) addressed infrastructure planning by optimizing charging station locations under static conditions.

Despite its widespread use, the static-deterministic setting has inherent limitations. By design, it overlooks real-world complexities such as real-time order arrival, traffic variability, order cancellations, and dynamic courier behavior, which are critical in actual OFD operations. However, this simplification allows researchers to isolate and analyze the core logistical challenges, providing a crucial starting point for understanding the system and developing initial strategies that can later be adapted to more realistic, dynamic contexts.

4.2. Dynamic-deterministic

The dynamic-deterministic setting provides a structured framework for managing short-term or real-time decision-making in OFD, where operational conditions, such as order arrivals, courier availability, and travel times, evolve continuously over time. Unlike stochastic approaches that account for uncertainty, this setting assumes that all parameters are known and fixed at each decision point, simplifying the modeling process while still addressing the need for adaptability. This balance makes it particularly valuable for applications that require rapid and scalable solutions. In the context of FDS, the approach ensures that platforms can efficiently handle fluctuating demands and logistical constraints, maintaining responsiveness without the computational overhead of probabilistic methods.

One key strategy in this setting is periodic decision-making, in which the system reassesses and optimizes operations at fixed intervals using the most recent available data. This method enables platforms to systematically incorporate updates, striking a balance between foresight and computational efficiency. Huq et al. (2025) implemented an RH approach that used forecasts of order patterns and travel times to adjust delivery schedules proactively. Similarly, Chen et al. (2024) updated decisions every minute, leveraging snapshots of order arrivals and courier positions to refine assignments. Cosmi et al. (2025) applied this technique to prescheduled orders, resetting plans as new requests arrive. These examples demonstrate how periodic updates enable platforms to adapt to dynamic conditions while keeping computation manageable. Alternatively, event-driven decision-making triggers actions in response to specific occurrences, such as new order placements, offering a more immediate and flexible response mechanism. This approach prioritizes dynamic adaptability, using deterministic inputs to make swift, incremental decisions. Jorge et al. (2024) tackled a dynamic landscape of orders and traffic, treating each decision point as a deterministic scenario to ensure timely responses. Sun et al. (2024) dispatched orders instantly as they arrive, updating parameters with each cycle. These cases highlight how event-driven methods excel in fast-paced environments, leveraging deterministic clarity to enhance operational agility. By employing either periodic or event-driven strategies, the dynamic-deterministic setting provides a versatile foundation for optimizing OFD.

4.3. Static-stochastic

The static-stochastic setting provides a structured approach to examining OFD. In this context, the planning decisions are made once at the beginning of the horizon. However, specific operational parameters, such as order arrivals, courier arrivals, meal preparation, and travel times, are uncertain and exhibit inherent variability in real-world conditions. To address these uncertainties, researchers have employed stochastic modeling techniques, which enable a nuanced understanding of how unpredictable factors influence delivery operations. Yildiz and Savelsbergh (2019b) illustrated this approach by combining deterministic and stochastic components. Their formulation assumed a stable planning interval with stochastic order arrivals and courier availability, while deterministic structural parameters such as service-area radius, vehicle speed, unit revenue, and courier compensation were specified

for the analysis. Similarly, Xue et al. (2024) conducted their analysis in a static setting in which order demands were known. They accounted for uncertainties in preparation time and travel time, representing these through probability distributions. They investigated a range of potential outcomes through scenario-based simulations, which provided insights into the effects of factors on delivery performance. Along the same lines, Zhang et al. (2026) examined a static but stochastic setting at the tactical and operational levels, where demand and ad hoc driver availability remain uncertain, modeled using a two-stage Stochastic Programming (SP) and Distributionally Robust Optimization (DRO) framework. Liu et al. (2021) treated service time at each customer location as an uncertain random variable, and integrated it into their two-stage SP formulation and a DRO model. The static-stochastic setting provides a more detailed examination of the challenges in OFD, but it also complicates the problem and reduces the efficiency of potential solutions.

4.4. Dynamic-stochastic

In the dynamic-stochastic setting, OFD must contend with both temporal evolution and inherent uncertainty across operational parameters. Unlike static frameworks, this setting captures the real-time adaptability required to handle fluctuating demand, variable travel conditions, and uncertain resource availability. Researchers have modeled these complexities by integrating stochastic and dynamic elements into their frameworks, addressing uncertainties that impact system efficiency and customer satisfaction. This subsection reviews key studies, categorizing them by the primary sources of uncertainty they address: order requests and arrivals; courier behavior; availability and location; service time; travel time and speed; and preparation time. By categorizing these factors, the review offers valuable insights into enhancing system efficiency, adaptability, and customer satisfaction, thereby paving the way for more resilient delivery platforms. The key uncertain factors in OFD operations and their associated research are summarized in Table 9.

4.4.1. Demand and order arrivals

Uncertainty in demand and order arrivals drives the need for real-time system adaptability. Ulmer et al. (2022) modeled order arrivals as a nonhomogeneous Poisson process calibrated to peak and off-peak rates, capturing temporal and spatial demand variability. Jahanshahi et al. (2022) used an exponential distribution for inter-arrival times, varying by time of day to reflect peak periods. Lu et al. (2024) employed Poisson processes for continuous order arrivals, enabling dynamic bundling and dispatching. These studies illustrate how demand uncertainty shapes resource allocation and operational strategies. Fotouhi et al. (2021) employed a Poisson-based arrival process to capture spatial and temporal demand variability, integrating these stochastic order events into their simulation to guide assignment and routing decisions. Deng et al. (2024) modeled order arrivals as a stochastic process within a fixed 480-minute window. They generated arrival times either uniformly to represent stable, non-peak demand periods or via a Poisson process to simulate surge conditions, with peaks around noon and 6 pm. Zhang et al. (2025a) generated demand scenarios by sampling historical order volumes and customer preferences to create discrete order batches revealed in RL dispatch waves, rather than modeling a continuous arrival process. Luy et al. (2024) modeled request and courier arrivals in each region as Poisson processes with time-varying rates, capturing dynamic and stochastic demand fluctuations linked to platform supply patterns. These studies illustrate how demand uncertainty shapes resource allocation and operational strategies.

4.4.2. Preparation time

Preparation time uncertainty, tied to food readiness, affects synchronization between couriers and restaurants. Kancharla et al. (2024) modeled preparation times with a gamma distribution in a dynamic-stochastic setting, reflecting operational realism. Yang et al. (2024a) used the gamma distribution for preparation times and integrated it into a dynamic optimization framework. Fotouhi et al. (2021) also considered stochastic preparation times, sampled during simulation, highlighting their impact on order readiness. Liu (2019) tested each order's preparation time from a uniform distribution [2–7 min] during simulation, embedding stochastic readiness delays into the dispatch model. These models emphasize the need to account for preparation time variability to optimize pickup schedules.

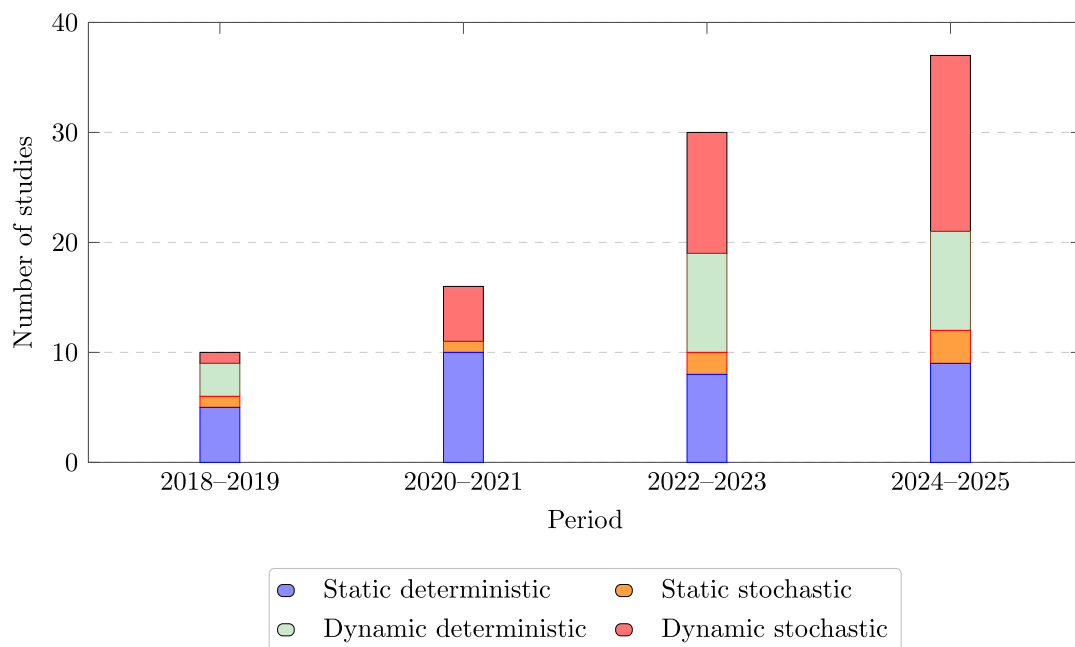
4.4.3. Speed, travel and service time

Travel time and speed uncertainties, driven by traffic dynamics and route variability, are critical in urban delivery contexts. Chu et al. (2023) employed ML to address stochastic travel times. Mehra et al. (2024) simulated stochastic travel times by updating road segment durations every two minutes from a uniform distribution, varying them randomly to mimic traffic fluctuations. Hu et al. (2023) considered stochastic travel times due to disruptions like traffic jams, necessitating adaptive strategies. These studies demonstrate the value of modeling travel time uncertainties to improve delivery reliability. Xue et al. (2024) captured travel time uncertainty via scenario-based sampling and embedded the resulting distributions directly into a chance-constrained routing model to ensure robustness against varying conditions. Fotouhi et al. (2021) derived baseline travel times from historical distance data, and capture uncertainty by simulating realized travel durations uniformly, thereby reflecting variability due to traffic and operational conditions. Service time uncertainty refers to the variability inherent in on-site operations at both restaurants and customer locations. This factor encompasses the time required for couriers or delivery vehicles to complete essential tasks, such as parking, loading and unloading orders, and interacting with customers. Fotouhi et al. (2021) also modeled pickup and drop-off handling times as random variables following uniform distributions.

Table 9

Uncertain factors and related research papers.

Uncertain Factor	References
Demand and Order Arrivals	Ulmer and Savelsbergh (2020), Zhang et al. (2025a), Yang et al. (2024a), Ulmer et al. (2021), Fotouhi et al. (2021), Simoni and Winkenbach (2023), Lu et al. (2024), Huang et al. (2021), Kancharla et al. (2024), Jahanshahi et al. (2022), Bozanta et al. (2022), Deng et al. (2024), Ausseil et al. (2024), Zheng et al. (2022), Wang et al. (2023b), Wang et al. (2023a), Auad et al. (2023), Luy et al. (2024), Zhao et al. (2025), Yildiz and Savelsbergh (2019b), Ulmer et al. (2022), Mehra et al. (2024), Zhou et al. (2025), Du et al. (2025), Zhang et al. (2026), Liu et al. (2025a), Li et al. (2025), Zhang et al. (2025b), Wang et al. (2025).
Preparation Time	Zhang et al. (2022), Yang et al. (2024a), Ulmer et al. (2021), Fotouhi et al. (2021), Kancharla et al. (2024), Xue et al. (2024), Jahanshahi et al. (2022), Zheng et al. (2021), Zhou et al. (2025).
Travel Time	Liu et al. (2021), Fotouhi et al. (2021), Chu et al. (2023), Xue et al. (2024), Mehra et al. (2024).
Service Time	Liu et al. (2021), Fotouhi et al. (2021)
Courier Behavior	Wang et al. (2022), Wang et al. (2023d), Wang et al. (2023e), Fotouhi et al. (2021), Chu et al. (2023), Ausseil et al. (2024), Horner et al. (2025), Yang et al. (2024b), Zheng et al. (2022), Yildiz and Savelsbergh (2019b).
Courier Availability and Location	Ulmer and Savelsbergh (2020), Fotouhi et al. (2021), Simoni and Winkenbach (2023), Ausseil et al. (2024), Wang et al. (2023b), Luy et al. (2024), Zhao et al. (2025), Yildiz and Savelsbergh (2019b), Wang et al. (2025), Zhang et al. (2026), Zhang et al. (2025b).

**Fig. 3.** Evolution of problem settings in OFD optimization studies from 2018 to 2025.

4.4.4. Courier behavior and availability

Uncertainty in courier behavior and availability poses significant challenges to delivery optimization, as it affects resource allocation and dispatching decisions. Fotouhi et al. (2021) developed a stochastic simulation to capture the uncertainty in courier availability. Their model considered random courier check-ins and check-outs, varying start locations that changed after each delivery, and probabilistic acceptance of new orders. Simoni and Winkenbach (2023) modeled a dynamic and stochastic environment where couriers log in and out unpredictably, employing RH optimization to adapt to fluctuating availability. Wang et al. (2023d) incorporated stochastic rider behavior and variable order acceptance rates, emphasizing real-time responsiveness. Ausseil et al. (2024) treated courier acceptance as a stochastic process, dependent on factors like travel distance and incentives. Zhao et al. (2025) further addressed the unpredictable availability of crowdsourced drivers, necessitating adaptive scheduling. These studies underscore the importance of modeling courier-related uncertainties to enhance operational robustness.

Fig. 3 indicates the evolution of problem settings across the OFD studies from 2018 to 2025. Early contributions were mainly static, deterministic, or simplified dynamic deterministic models. Over time, the literature increasingly shifted toward dynamic and stochastic settings, especially during 2022–2025. This trend suggests a gradual maturation of OFD optimization research, moving from stylized formulations with fixed input information toward models that better reflect real-time order arrivals, uncertain demand, courier availability, and operational variability. The complete study-level classification, including the setting of each study, is reported in Appendix C, Table C.14.

5. Predictive and prescriptive approaches

As described in previous sections, OFD platforms operate in highly dynamic and uncertain environments, requiring advanced models and solution approaches to optimize operations. This section reviews a broad spectrum of techniques from recent research, categorized into predictive analytics, prescriptive optimization (split into deterministic and stochastic models), and hybrid data-driven systems. It also examines the role of Artificial Intelligence, ML, and digital platforms in improving efficiency and scalability. These approaches are analyzed based on their mathematical foundations and solution methodologies, providing a thorough overview of their applications in modern food delivery systems.

5.1. Predictive analytical approaches

Predictive analytics focuses on forecasting key variables such as demand, preparation times, and travel durations to support operational decisions (see, e.g. Zohdi et al., 2022). These methods primarily employ statistical and ML algorithms. Hess et al. (2021) modeled demand forecasting using the Seasonal and Trend decomposition method to address intermittent demand and double seasonality. The study benchmarked classical time series methods, such as exponential smoothing, AutoRegressive Integrated Moving Average, and Error-Trend-Seasonal, against ML models, including Random Forest and Support Vector Regression. Crivellari et al. (2022) formulated short-term demand as a multi-target regression problem to predict order volumes across city areas. The authors proposed a Convolutional Neural Network (CNN)-Long Short-Term Memory (LSTM) architecture. In this approach, convolutional layers extracted features from spatiotemporal sequences, while LSTM layers captured sequential dependencies. A dense output layer then provided area-specific forecasts. Nie et al. (2025) approached city-wide delivery demand forecasting as a joint estimation and prediction problem. The authors introduced a spatiotemporal Graph Neural Network (GNN) enhanced with a large language model. Message-passing layers capture spatial interactions, while temporal encoders model sequential demand patterns. The dense output layer produces multi-step forecasts. Their framework supported accurate predictions for existing regions and enabled demand estimation for new areas or cities. Liang et al. (2023) introduced a Poisson-based distribution-prediction framework to model demand as probability distributions, enabling more reliable range forecasts across regions and time periods. The framework was implemented with neural networks, multi-layer perceptrons, temporal convolutional networks, and LSTM, as feature extractors for temporal and weather inputs. Dai et al. (2023) proposed a semi-supervised Cat-Boost regressor for preparation time prediction, incorporating a self-supervised classifier to improve accuracy with limited annotated data. Liu et al. (2025b) combined active adversarial inverse RL with an AdaBoost multi-fusion graph convolutional transformer to infer personalized route preferences and predict travel times with high precision. Additional studies from recent research further enrich this category. Hildebrandt and Ulmer (2022) proposed supervised learning approaches for arrival time estimation. They developed an offline method based on Gradient boosted Decision Tree (GBDT) and an online-offline hybrid method using Deep Neural Network (DNN) to approximate routing policies.

5.2. Prescriptive optimization models

Prescriptive optimization models aim to deliver actionable decisions by optimizing system states under specific constraints. These models address the problems stated in Section 3 and are categorized into deterministic and stochastic models based on their approach to handling uncertainty, with solution methods ranging from exact algorithms to heuristics and learning-based methods.

5.2.1. Deterministic models

Deterministic models assume fixed, known parameters within the decision horizon and can be implemented in either static or dynamic settings. Steever et al. (2019) developed a Mixed-Integer Programming (MIP) for dispatching, enhanced by an auction-based heuristic to improve scalability and task allocation. Cosmi et al. (2019) studied a deterministic single-courier single-restaurant MDS problem without routing and reduced it to a throughput-maximization single-machine scheduling problem with release times and bounded slacks, solved through a dynamic programming algorithm. Dai and Liu (2020) proposed an MIP solved via Branch-and-Bound (B&B) to minimize delivery costs. Li et al. (2022) developed a three-stage framework integrating clustering, transfer-station location analysis, and Adaptive Large Neighborhood Search (ALNS) for routing and resource allocation optimization. Kohar and Jakhar (2025) extended MIP formulations with branch-and-cut techniques and valid inequalities for larger instances. Reyes et al. (2018) utilized MIP within an RH heuristic, incorporating repeated bipartite matching and bundling strategies. O'Neil and Hoffman (2019) introduced a decision diagram-based optimization model solved with a B&B heuristic, offering a novel approach to deterministic optimization. These models utilize exact solvers, such as Gurobi and CPLEX, and heuristic techniques to support computational tractability and, when exact methods are used, provide optimality guarantees.

5.2.2. Stochastic models

Stochastic models account for uncertainty in demand, order arrivals, preparation times, travel or service times, courier behavior, and courier availability, providing adaptive solutions for dynamic environments. Ulmer et al. (2021) formulated an Markov Decision Process (MDP) with an approximate cost-function-based assignment policy to manage uncertainties in dispatching. Jahanshahi et al. (2022) employed an MDP solved via Deep RL, testing variants such as a double deep Q-network for real-time routing optimization. Xue et al. (2025) addressed uncertain demand through stochastic order cancellations by customers, formulating a two-stage SP model with sample average approximation to optimize routing under probabilistic cancellation scenarios. Kancharla et al. (2024) developed a two-stage SP model within an RH framework to address stochastic meal preparation times, future order numbers, and future customer

locations. Additional contributions include Liu et al. (2021), which integrated SP with DRO, solving the problem using branch-and-price and multi-period heuristics to handle service time uncertainty. Zhang et al. (2026) introduced a two-stage SP and DRO model for FS, incorporating uncertainty in demand and ad-hoc driver availability through contextual features such as weather, promotion, weekday, and congestion degree. They solved the problem via the Benders decomposition algorithm. Deng et al. (2024) modeled the problem as an MDP, applying RL with a proximal policy optimization algorithm and heuristics for dynamic adaptation. Ulmer et al. (2022) designed an MDP model with a hybrid solution combining continuous approximation heuristics, value function approximation from RL, and real-time correction mechanisms. Wang et al. (2023e) also employed an MDP with an actor-critic network featuring LSTM units and an encoder-decoder architecture for sequential rider decisions.

5.3. Hybrid data-driven decision systems

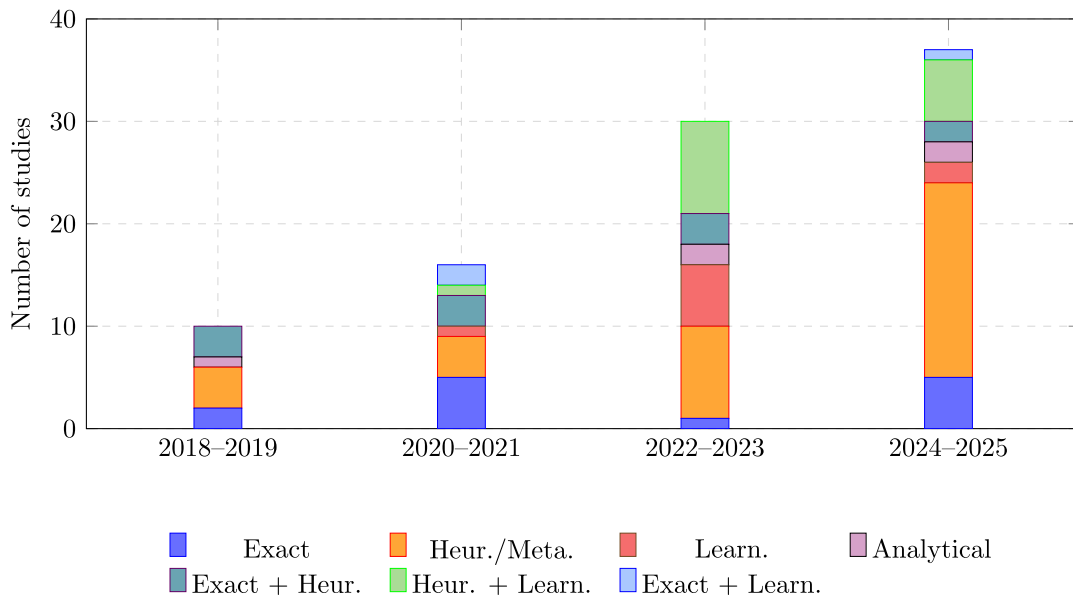
Hybrid data-driven systems integrate predictive analytics with prescriptive optimization, embedding ML-driven forecasts into optimization frameworks to address dynamic and uncertain environments. Wang et al. (2021) formulated the route planning problem as an MIP model and proposed an XGBoost-enhanced constructive heuristic, where predictive insights guide the selection of sequencing rules to accelerate route optimization. Liu et al. (2021), who developed SP, also considered ML-based travel time predictions to enhance routing efficiency. Huq et al. (2025) integrated XGBoost and LSTM forecasts into an MIP and ALNS for order assignment, improving allocation accuracy. Wang et al. (2022) developed a framework that operated in two stages: first, an XGBoost model predicts each rider's likelihood of grabbing an order; the resulting probabilities are then fed into an allocating-and-sequencing heuristic that balances travel cost and exposure fairness to generate personalized order recommendations. Further examples include Chen et al. (2022a), which proposed an MIP model with an imitation-learning-enhanced iterated matching algorithm that uses XGBoost to refine dispatching decisions. Chu et al. (2023) employed a hybrid approach where ML predicts travel times, feeding into a MIP model optimized via Simulated Annealing (SA) and local search. Luy et al. (2024) developed a two-tier framework that integrates a MDP for strategic workforce planning with a closed queueing network and optimization model for operational dispatching, solved via approximate dynamic programming. Chen et al. (2024) proposed a two-phase dispatching system in which a GNN evaluates the evolving rider-order graph to identify a small set of high-affinity rider candidates for each new order. Subsequently, those candidate sets are fed into a greedy heuristic that assigns orders one by one, choosing matches that minimize future regret and satisfy real-time constraints. Tao et al. (2023) developed a hybrid personalized dispatch framework that incorporates ML-based forecasts into a prescriptive optimization model. The framework included two predictive components. A personalized delivery speed model that utilized Boruta feature selection and random forest algorithms, and a customized delivery capacity model that leveraged clustering of historical trip data. These predictive models were integrated into an MIP formulation for OD and VR. The resulting optimization problem is solved using a Tabu Search (TS) metaheuristic within an RH framework.

5.4. Evolution of solution approaches

Fig. 4 summarizes the evolution of solution approaches in OFD optimization studies from 2018 to 2025. Heuristic and metaheuristic approaches form the largest standalone category. This is consistent with the structure of many OFD problems, in which dispatching and routing decisions must be repeatedly solved within short decision intervals. Hybrid approaches also represent an important part of the literature, especially in recent years. In this review, a study is classified as hybrid only when different solution components are combined within the proposed solution framework. Therefore, studies that use exact optimization only as a benchmark, or apply different methods to separate problem variants, are not classified as hybrid.

The reviewed studies show three main forms of hybridization. The first combines exact optimization with heuristic or metaheuristic procedures. For example, exact optimization components have been used within RH or reoptimization frameworks for dynamic dispatching (Liu, 2019), while MIP subproblems have been embedded within auction-based or simulation-based heuristic procedures (Steever et al., 2019; Fotouhi et al., 2021). Exact solver components have also been combined with metaheuristic search in large-scale operational models (Xue et al., 2021). The second form combines heuristic or algorithmic procedures with learning components. Examples include RL-assisted greedy matching procedures (Chen et al., 2023), task buffering based on a Deep Q-Network combined with agent-based simulation and matching algorithms (Lu et al., 2024), and heuristic procedures combined with RL in sequential decision settings (Chen et al., 2025). The third form integrates prediction models with exact mathematical optimization, such as travel-time or delivery-time prediction models embedded in mathematical programming formulations (Liu et al., 2020; Yang et al., 2024a).

Standalone heuristic and metaheuristic approaches remain important throughout the review period. ALNS has been used for large-scale routing decisions (Wang, 2018; Liu et al., 2018), TS has been applied to joint OD and VR settings (Tu et al., 2019), Genetic Algorithm has been used for routing and assignment decisions (Thipparthy et al., 2024), and RH heuristics have been adopted for real-time dispatching and routing (Reyes et al., 2018). Learning-based approaches also appear as standalone solution paradigms, particularly in studies of dynamic and sequential decisions. Deep RL has been used for dynamic dispatching and routing decisions (Jahanshahi et al., 2022), RL has been applied to online OD or matching decisions (Wang et al., 2023d), and multi-agent RL has been used for dynamic order matching and courier coordination (Wang et al., 2023b). The evolution indicates a gradual shift from standalone exact and heuristic methods toward more diverse computational frameworks, especially hybrid and learning-assisted approaches, as OFD models increasingly address real-time, large-scale, and uncertain operational environments.



Note: Heur./Meta. denotes heuristic/metaheuristic; Learn. denotes learning-based.

Fig. 4. Evolution of solution approaches in OFD optimization studies from 2018 to 2025. Note: Heur./Meta. denotes heuristic/metaheuristic; Learn. denotes learning-based.

6. Datasets, resources and results

In this section, we will report the outcomes of studies in the literature. To do this, we need to understand their experimental settings and the types of datasets they used to test and validate their solutions.

6.1. Resources: case study, datasets

Empirical, experimental, and theoretical validations are essential for evaluating optimization models in FDS, ensuring that theoretical solutions translate effectively into real-world scenarios. This subsection details the diverse datasets and case studies used in the reviewed studies, encompassing real-world operational data, simulation results, and standardized benchmarks. These resources enable researchers to evaluate models across a spectrum of conditions, ranging from small-scale simulations to large-scale urban operations. Additionally, several studies have made their datasets publicly available, fostering reproducibility and further exploration in this domain.

Real-world datasets from OFD platforms such as Meituan (China), Grubhub (USA), Ele.me (China), and Swiggy (India) provide critical insights into practical model performance. For instance, Liu et al. (2021) and Zheng et al. (2021) leveraged Meituan's historical delivery data, spanning millions of orders across urban China over multiple months. This dataset includes time-stamped order details, spatial coordinates, and delivery routes, enabling route prediction enhancements and achieving millisecond-level efficiency gains. Similarly, Wang et al. (2023d) analyzed 2.93 million rider-platform interactions from Meituan, optimizing OG and reducing interaction times. Grubhub Meal Delivery Routing Problem library offers 240 test instances derived from ten real days of urban operations. It features historical and optimized courier shifts, supporting up to 505 orders and 117 couriers, as well as larger scenarios that reach 1746 orders with 432 couriers (Reyes et al., 2018). Key studies leveraging this dataset include Yildiz and Savelsbergh (2019a), Fotouhi et al. (2021), and Kancharla et al. (2024). Xue et al. (2021) employed data from a Dalian-based platform (China), covering over 5000 daily orders across 23 sub-regions, achieving an 8% reduction in rider numbers. Additionally, Joshi et al. (2022) integrated Swiggy and Grubhub data, incorporating order volumes and courier movements to reduce delivery times by 30% in large urban settings. Kong et al. (2025) applied a dataset using real-world order data from Ele.me in Dalian (China), including twelve instances with varying node counts and 1682 actual orders for dynamic simulation.

Synthetic datasets provide a controlled environment for testing specific scenarios and refining optimization models. Bozanta et al. (2022) employed grid-based simulations ranging from 3×3 to 8×8 grids, with synthetically generated orders based on realistic probability distributions for origins and destinations. With varying courier numbers, these simulations outperformed rule-based benchmarks in terms of delivered orders using RL policies. Yang et al. (2024b) and Mehra et al. (2024) simulated urban environments inspired by Manhattan and Chicago, respectively. Hu et al. (2023) tested scenarios with up to 500 requests using a Barcelona-based dataset, focusing on response time reductions. Auad et al. (2024) evaluated medium-demand scenarios (100–500 orders), optimizing fleet size reductions under controlled conditions. Thipparthy et al. (2024) evaluated their method using instances from the

Table 10

Summary of datasets used in reviewed OFD studies.

Dataset Name	Case \Platform	Data Scale	Data Features	Public	Access Link	References
Grubhub MDRP Library	Grubhub	505–1746 orders; 117–432 couriers	Anonymized delivery data; courier schedules; travel/preparation times	Yes	GitHub	Reyes et al. (2018) , Yildiz and Savelsbergh (2019a) , Fotouhi et al. (2021) , Kancharla et al. (2024)
Solomon VRPTW Benchmark Set	–	100 customers and one depot	Synthetic VRPTW; clustered/random/mixed patterns; vehicle capacities; time windows	Yes	–	Solomon (1987) , Li and Lim (2001) , Aziez et al. (2020) , Kohar and Jakhar (2025)
Zomato Bangalore Restaurants	Zomato	12000 restaurants	Restaurant locations, cuisines, pricing, ratings, reviews, online ordering, Bengaluru neighborhood coverage	Yes	Kaggle	Huq et al. (2025)
Swiggy Multi-City	Swiggy	3 cities; 23000–159000 orders	Road networks, GPS trajectories, preparation times	No	Code	Joshi et al. (2022)
DR-PDPTW Instances (Barcelona, Harbin)	Barcelona taxi; Harbin OFD	21–501 nodes	GPS coordinates; time windows (60–180 min); capacity (100–300); cluster-random/real distributions	Yes	GitHub	Hu et al. (2023)
Rome Meal Delivery Dataset	Case study (Rome)	169–239 orders; 23–32 couriers	Order timestamps; pickup/delivery locations; time windows; courier release times	Yes	GitHub	Cosmi et al. (2025)
Ele.me O2O Food Delivery Dataset (Dalian)	Ele.me	1682 orders, 40 couriers	Merchant/customer/depot nodes; travel times; time window	Yes	OneDrive	Kong et al. (2025)

UCI “Vehicle Routing and Scheduling Problems” repository. Standardized benchmark datasets facilitate consistent performance comparisons across studies. [Kohar and Jakhar \(2025\)](#) utilized benchmarks from [Aziez et al. \(2020\)](#), featuring instances with 25–100 nodes, varying request sizes (short: max 4 pickup/delivery nodes, long: max 8), and time window constraints (without, normal, and large). These benchmarks enabled the authors to solve 66 of the 120 instances within an hour, improving prior results by approximately 10% in terms of the number of benchmark instances solved to optimality. Additionally, [Xue et al. \(2024\)](#) modified the benchmarks in [Ropke et al. \(2007\)](#) to incorporate uncertainty in cooking and travel times, testing the robustness of their algorithm under stochastic conditions. [Cosmi et al. \(2025\)](#) provided a [Rome-based dataset](#) covering January to March 2019, including order timestamps, courier movements, and delivery details, accessible for replication of their scheduling optimization work. These diverse resources have enabled significant performance improvements, as explored in the next subsection. [Table 10](#) provides a structured summary of the datasets used in the reviewed studies, including their sources, scale, key features, and accessibility.

6.2. Spatial representations

Across the reviewed studies, five distinct classes of spatial representation can be identified. The most abstract class relies on a pure graph structure with no coordinate geometry ([Aziez et al., 2020](#)). A second class employs stylized geometric structures, such as one-dimensional line segments, star topologies for multi-depot settings ([Aued et al., 2024](#)), and abstract scalar distance parameters ([Cosmi et al., 2019](#)), chosen to enable tractable analytical results. One of the most widely adopted class places entities as coordinate points in a Euclidean plane, with travel costs computed as straight-line distances scaled by vehicle speed; this class appears across both ground-based courier models ([Reyes et al., 2018](#); [Yildiz and Savelsbergh, 2019b](#)) and drone delivery systems ([Gu et al., 2020](#); [Pinto et al., 2020](#)), owing to its analytical tractability. A fourth class uses the Manhattan distance as a simplified approximation of urban travel costs based on rectilinear distance ([Liu et al., 2018](#)). Several studies also use real road networks and travel times sourced from routing APIs ([Steever et al., 2019](#)) or operational platform data, reflecting actual traffic conditions in the delivery environment ([Wang, 2018](#); [O’Neil and Hoffman, 2019](#); [Yildiz and Savelsbergh, 2019a](#)).

Table 11 provides a structured summary of spatial representation classes.

6.3. Results

This subsection synthesizes the quantitative performance metrics reported in the reviewed studies, highlighting improvements in cost efficiency, delivery timeliness, customer satisfaction, and environmental outcomes in [FDS](#). To reflect decision scope and analytics type, the results of studies are organized into three parts: (i) Operational-level results, (ii) Tactical and strategic level results, and (iii) Predictive studies that quantify gains from forecasting models.

Table 11
Classification of spatial representations in OFD studies.

Class	Spatial Representation	Travel Metric	References
Abstract Graph	Nodes and arcs with abstract cost parameters; no explicit coordinates or maps.	Abstract arc costs, benchmark costs, or shortest-path costs on non-geographic arcs.	Aziez et al. (2020), Kohar and Jakhar (2025), Guo et al. (2024)
Euclidean Plane	Restaurants, customers, and couriers are represented as points in continuous space.	Euclidean distance, straight-line distance, or coordinate-based distance scaled by speed.	Reyes et al. (2018), Yildiz and Savelsbergh (2019b), Gu et al. (2020), Tu et al. (2019), Pinto et al. (2020), Liao et al. (2020), Ulmer et al. (2021), Chu et al. (2023), Fotouhi et al. (2021), Huang et al. (2021), Wang et al. (2023c), Wang and Jiang (2022), Ulmer et al. (2022), Auad et al. (2023), Xue et al. (2024), Sun et al. (2024), Thipparthy et al. (2024), Luy et al. (2024), Lu et al. (2025), Li et al. (2025)
Manhattan Distance	Coordinate or grid-based locations with rectilinear movement assumptions.	Manhattan distance, rectilinear distance, or grid-based movement cost.	Liu et al. (2018), Bozanta et al. (2022), Li et al. (2022), Jahanshahi et al. (2022), Wang et al. (2023b), Simoni and Winkenbach (2023), Ausseil et al. (2024), Sun et al. (2024), Lu et al. (2024), Zhang et al. (2026), Zhou et al. (2025), Huq et al. (2025), Dai and Liu (2020), Liu et al. (2025a), Wang et al. (2025)
Real Road Network	Locations embedded in real maps or operational delivery networks.	Road-network distance, map-based shortest path, API-based travel time, or empirical travel time.	Wang (2018), Steever et al. (2019), O'Neil and Hoffman (2019), Yildiz and Savelsbergh (2019a), Liu et al. (2021), Ulmer and Savelsbergh (2020), Zheng et al. (2021), Xue et al. (2021), Chen et al. (2022a), Huq et al. (2022), Chen et al. (2022b), Joshi et al. (2022), Zhang et al. (2022), Zheng et al. (2022), Tao et al. (2023), Zheng et al. (2023), Wang et al. (2023d), Chen et al. (2023), Wang et al. (2022, 2023a,e), Zhen et al. (2023), Liu et al. (2024), Mehra et al. (2024), Yang et al. (2024b), Lu et al. (2024), Martinez-Sykora et al. (2024), Kong et al. (2025), Zhang et al. (2025a), Xue and Zou (2025)
Stylized Geometry	Purpose-built analytical structures, such as lines, zones, service regions, or idealized markets.	Analytical distance, aggregate distance, or zone-based distance.	Auad et al. (2024), Cosmi et al. (2019), Bahrami et al. (2023), Ke et al. (2024)

6.3.1. Operational level

On routing and bundling, Wang (2018) proposed exclusive delivery with two sharing schemes: switching restaurants after completing deliveries reduced average total costs by more than 16%, while allowing mid-route restaurant visits reduced costs by more than 24%. These schemes cut the number of vehicles by up to 33%, increased trips per vehicle from 2.91 to 4.14, and reduced average delivery-time deviation from 21.74 minutes to 7.62 minutes; however, the most flexible variant increased fixed driver costs due to multi-restaurant operational complexity. Under stochastic cooking and travel times, Xue et al. (2024) showed that accounting for uncertainty increased initial routing cost but lowered delay penalties and controlled extreme delays; feasibility increased from 2 feasible instances at an on-time requirement of 0.8 to 12 at 0.5, implying a small resource increase to protect reliability. In time-window routing with time-sensitive satisfaction, Wang and Jiang (2022) completed all orders within 60 minutes (average delivery time 7.96 minutes per order), achieved average satisfaction scores of 0.876 (low-sensitivity) and 0.835 (medium-sensitivity), and obtained a perfect satisfaction score of 1.0 in five of eight scenarios (most deliveries within 30 minutes); for a 41-order instance with eight riders, total completion time was bounded at 294.5 minutes with no route exceeding 60 minutes. Liao et al. (2020) reported stable outcomes across instance sizes: average delivery time per order was no more than 4 minutes, all deliveries were completed within 45 minutes, customer satisfaction (fuzzy membership) ranged from 0.73 to 0.95, and total carbon emissions increased with scale from about 1.61 kg (30 customers) to 6.05 kg (100 customers), while rider workload balance remained 0.76 to 1.

Regarding dynamic dispatching, Joshi et al. (2022) found that dynamic batching and matching reduced delivery time by 30% versus greedy baselines, increased orders delivered per kilometer by 20%, and reduced restaurant waiting time by roughly 40% (about 2000 man-hours saved per day in large cities); reducing the fleet to 20% of its original size caused a 30% order rejection rate under a 45-minute delivery window, whereas moderate reductions preserved customer outcomes. Using time-driven simulation-optimization, Jorge et al. (2024) reduced CtD time by 4.5% to 4.8% versus historical rules, with at least two-thirds of orders within 45 minutes and over 95% within 90 minutes (all orders fulfilled across scenarios); average delivery times were 31–35 minutes and courier productivity was 3.1 to 5.3 orders, and bicycles were fastest because they were unaffected by congestion penalties. A reinforcement-learning dispatching framework in Wang et al. (2023a) increased total revenue by 22% and reduced the overdue rate by 21.6% (overdue rate reached 1.45% in a high-volume Shanghai region); midday peaks saw a 16.6% revenue increase over greedy dispatching, couriers handled a median of 2 orders per trip and about 23 per day, only 29.5% of sequences remained unchanged, and decision latency stayed below 40 milliseconds. An adaptive agent-based approach in Lu et al. (2024) increased customer satisfaction by up to 275.42% while reducing total delivery distance by 11.38% on average; completion rates stayed above 80% under high demand with limited fleets (baselines dropped to 31.10%), and the system used 16.28% fewer couriers per hour on average than non-batching models. Using real-world Chicago data, Mehra et al. (2024) reduced total travel distance by 16% and fleet size by

15%, increased fleet utilization by 50% relative to point-to-point delivery, maintained a success ratio above 0.95 within a 15-minute delivery window, and improved peak-period delivery time by 13%–15%; under high demand, distance reductions reached 7.5% versus advanced bundling and up to 16% versus direct delivery. In a dynamic simulation with real-world orders, Kong et al. (2025) achieved an average CtD time of 1350.1 seconds and a maximum CtD time of 1895 seconds, while reducing timeout orders to two (versus up to 214 obtained from SA). Considering real-data of Rome, Cosmi et al. (2025) studied one-order-per-trip policies and compared offline (perfect information) and online sequential planning (orders revealed every five minutes): at order-to-courier ratios 6.47 to 7.62, it produced zero delays and zero order rejections (delays exceeding 60 minutes) in 32 of 33 instances; online matched the offline optimal cost in 17 of 33 instances, and as intensity increased, the cost gap decreased from 6.86 at a ratio of 8 to 1.5 at a ratio of 10.

Sustainability-focused operations in Liu et al. (2024) preserved service while cutting emissions via the integration of electric vehicles: 75% of orders were on time, the maximum CtD stayed below 50 minutes, and the eco-friendly policy delivered at least 30% greenhouse gas reduction and up to 96.80% at 80% fleet electrification. This policy slightly increased the financial cost (largely due to bundling-induced delay costs). At the same time, the electric-vehicle miles-traveled share ranged from 65% to 78%, and the average CtD deviation remained below 1 minute relative to cost-focused policies. Pricing and incentives improved reliability in several settings. Bai et al. (2022) showed that in premium regions, a 10% delivery-fee reduction preserved completion rates above 99.5%, while in inferior locations, targeted subsidies raised completion rates by 3%, linking rejection and dispatch times to courier earning rates. For cancellations, Deng et al. (2024) reallocated canceled orders to alternative customers and achieved the highest revenue across scenarios, remaining robust as cancellation rates increased from 10% to 50%; aggressive pricing improved reassignment success but could increase delivery costs, requiring a balance between profitability and sustainability. For the freelance-driver choice, Yang et al. (2024b) increased the average matching rate from 65.8% (standard baselines) to 75.7% and 80.8% with bundling, and reduced the mean matching time from 47.8 seconds to 21.7–28.3 seconds; offering multiple choices increased pickup times relative to distance minimization, but by less than 5 minutes. Service area control and coverage expansion yielded measurable improvements in throughput and scale. Ulmer et al. (2022) found that dynamic resizing served 22.4% more customers while keeping the average delay per customer below 1 minute, maintaining 90th-percentile delays between 0 and 3 minutes, and limiting the average maximum delay per day to 19.78 minutes. Extending coverage via cross-regional delivery, Huq et al. (2025) maintained an average service delay of 38.82 minutes while improving latency and on-time delivery relative to benchmarks; as cross-regional order volume increased, average delivery cost declined, customer satisfaction was nearly 70%, and average rider incentives rose with volume.

6.3.2. Strategic and tactical level

At the strategic level, Pinto et al. (2020) studied a FL problem in which drones served as the delivery fleet and charging stations were supporting facilities. They showed that station placement and the number of active stations determine the maximum achievable demand coverage: in a case with 100 customers and 40 restaurants, activating more than 15 stations did not improve the objective. The experiments also revealed a coverage–variety trade-off: requiring at least 10 reachable restaurants reduced maximum coverage to 2%, and increasing the activation budget from 4 to 8 stations produced no coverage gain under this high-variety requirement. Finally, increasing the allowable delivery time from 20 to 35 minutes increased achievable coverage for a fixed number of stations.

Luy et al. (2024) quantified the value of forward-looking workforce planning for hybrid fleets. Anticipating future growth in crowdsourced drivers reduced total costs by up to 19% (and by up to 10% relative to a full-lookahead benchmark). They also found that salaried drivers remained a major cost driver, accounting for up to 50% of total costs, and that their share increased to about 82% in high-demand-density settings when crowdsourced supply did not scale proportionally. Dedicated gig drivers reduced costs more than opportunistic gig drivers, although opportunistic drivers had higher value when their availability aligned with demand. Their results further highlighted a strategic hedge: hiring fewer salaried drivers early reduced the risk of later overstaffing when firing was costly.

Bahrami et al. (2023) analyzed equilibrium outcomes in a three-sided on-demand delivery market and showed how market size and operational parameters affected participation and platform profit. Profit was most sensitive to the potential supplier pool: a 10% increase raised profit from 37.50 to 64.48 (a 71.95% gain). A 10% increase in potential customers increased the realized driver population from 9 to 14. In contrast, a 10% increase in restaurant preparation time reduced profit to 24.80 and reduced the realized customer and driver populations by about 22% and 44%, respectively. They also found that product price changes did not affect player populations or platform profit because the platform adjusted commission rates, while larger service areas reduced driver participation due to longer delivery routes.

At the tactical level, Reyes et al. (2018) compared historical and optimized shift schedules and found that optimization reduced undelivered orders by 60% and shortened mean Ready-to-Pickup (RtP) time by 40%; when historical schedules were used, the system increased orders per bundle, indicating bundling as a recourse for insufficient planned capacity. Under an explicit service-level target, Ulmer and Savelsbergh (2020) showed that, with their method, achieving a 90% service level requires 56 scheduled driver-hours on average, whereas a fixed staffing policy requires 42.9% more driver-hours to reach the same target. Beyond shift scheduling, Dai and Liu (2020) evaluated fleet-structure policies for mixed in-house and crowdsourced workforces. A single-service mode tailored to full-time crowdsourced shifts to cover a single demand peak reduced unfulfilled orders by 71.4% and total cost by 20.5%. They also showed that conservative guaranteed minimum order thresholds could motivate full-time crowdsourced couriers without harming efficiency, while overly high guarantees induced substitution toward more expensive in-house drivers and increased expenses. Adding flexibility (detour tolerance and multi-depot crowdsourcing) improved part-time matching and delivered an additional 15.45% reduction in total system cost.

Regarding FS, Auad et al. (2024) showed that keeping a 45-minute target time while relaxing the hard deadline from 45 to 60 minutes reduced required fleet size by 33%, with only 5% of orders delivered after the target time. The same study found that limited resource pooling can be beneficial: sharing couriers between two depots reduced required fleet size by 21% relative to a dedicated-fleet design, provided depots were within a 60-minute travel distance. Using a heterogeneous fleet, Zhang et al. (2026) provided zone-level staffing prescriptions; for a three-zone network, recommended in-house staffing levels were 5.6, 4.6, and 5.8 couriers on average, minimizing combined hiring, variable delivery, and service-penalty costs. Their sensitivity results indicated substitution effects: higher fixed costs reduced in-house recruitment, whereas higher expected ad-hoc availability shifted capacity away from permanent staffing. On the scheduling side, Das and Yadav (2021) reported that replacing static peak-hour estimation with demand-driven planning and three overlapping shifts reduced cost by 21.4% without eroding service levels. Regarding dynamic PS, Zhang et al. (2025a) studied differentiated time-slot pricing as a demand-shaping mechanism. Compared with fixed pricing, their approach reduced total matching costs by 90.21% on average, driven primarily by a 98.14% reduction in delay-penalty cost, consistent with 93%–96% of customers selecting time slots aligned with available capacity. The induced smoothing also improved consolidation opportunities, yielding an 18.99% reduction in routing costs.

6.3.3. Predictive results

In an urban MDS setting, Hess et al. (2021) reported that the accuracy of demand forecasting was largely driven by average daily demand and training horizon. In low-demand areas, zero-demand and moving-average baselines dominated; with sufficient history, seasonal exponential smoothing performed best. In high-demand areas with limited data, short-horizon autocorrelation models performed better, and the Random Forest forecaster was mainly competitive for intermediate short horizons. Longer training horizons could reduce accuracy in sparse areas, and external data (e.g., weather or neighborhood features) did not improve performance beyond historical demand.

Focusing on next-hour OFD demand distribution prediction (updated every 15 minutes), Crivellari et al. (2022) found that a multi-target CNN-LSTM outperformed cyclical recurrence baselines, achieving Mean Squared Error (MSE) 115.8 versus 161.2 for the best baseline. Weighted evaluations amplified gains in high-demand areas and high-volume periods, and the model reduced the spatial spread of large errors. Autoregressive Integrated Moving Average (ARIMA) and FBprophet (tested in selected high-demand areas) were less effective at capturing rapid fluctuations and required separate fits for each area. Liang et al. (2023) showed that Historical Average and ARIMA performed worst, whereas learning-based models reduced point errors (e.g., Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE)) by capturing long-tailed demand with occasional peak spikes. For demand ranges, predicting a demand distribution achieved higher coverage probability than quantile regression, produced slightly wider intervals, and yielded a lower interval score while representing peak-hour demand more effectively. Weather features improved performance, and removing them degraded accuracy, especially during peak periods. Nie et al. (2025) indicated that defining demand as total pickup and drop-off orders per region improved accuracy across multiple cities, with improvements of up to 27.4% in MAE and 28.7% in RMSE over baselines. The study also demonstrated zero-shot transfer to new cities and data-scarce regions, relied on Large Language Model (LLM)-derived functional similarity rather than proximity alone, and reported that joint estimation and prediction outperformed treating the tasks separately as unseen regions increased.

Turning to time estimation, Hildebrandt and Ulmer (2022) reported that GBDT and simulation with DNN achieved lower MSE than a myopic baseline and accuracy close to near-optimal online simulations at much lower computational cost. The offline GBDT reduced delays over 15 minutes from 6.3% to 1.6% and lowered average delivery and food freshness times; spatial features improved prediction quality, higher variability in restaurant preparation times worsened accuracy and reduced orders for unreliable restaurants (with only a small effect on total platform orders), and results remained robust under higher demand, larger fleets, and misspecified customer choice behavior. For travel time estimation when the exact route is unknown, Liu et al. (2025b) reported improvements in route inference (F1-score) of up to 3.35% and reductions in travel-time MAE of up to 11.66% relative to benchmarks.

6.3.4. Cross-study performance patterns

The performance improvements should be interpreted with caution because the reviewed studies differ in assumptions, datasets, case-study settings, instance sizes, objective functions, and baseline policies. Therefore, the results cannot be directly compared based only on the magnitude of percentage improvements. Accordingly, this subsection adds a synthesis layer by identifying recurring performance patterns across the reviewed studies.

Seven recurring patterns are identified. First, *P1 – Dynamic service improvement* indicates that dynamic operational studies commonly report improvements in time-based service outcomes, such as delivery time, restaurant waiting time, overdue rate, timeout orders, and completion rate. Second, *P2 – Conditional consolidation value* shows that bundling and related consolidation strategies can improve resource utilization, but their value depends on spatial and temporal compatibility among orders and may involve delay or coordination trade-offs. Third, *P3 – Delay-control modeling* reflects the role of service limits, uncertainty modeling, and penalty costs in controlling lateness, infeasibility, and service-quality deterioration. Fourth, *P4 – Capacity-demand alignment* captures the tactical value of aligning courier supply with demand through FS and SS. Fifth, *P5 – Conditional flexibility benefits* indicates that additional resources or operational flexibility do not always improve performance; their benefits depend on demand intensity, spatial structure, travel distance, and workforce availability. Sixth, *P6 – Sustainability trade-offs* shows that environmental improvements may conflict with cost, service, energy-use, or fairness objectives. Finally, *P7 – Context-dependent prediction gains* indicates that predictive improvements depend on demand density, temporal variation, spatial heterogeneity, peak-period effects, and route-related variability. These patterns are summarized in Table 12.

Table 12
Recurring performance patterns across OFD studies.

Pattern	Decision Problems	Main KPIs	Interpretation	Related studies
P1 – Dynamic service improvement	OD, OG, VR, SC	Delivery time, restaurant waiting time, overdue rate, timeout orders, peak-period delivery time, success ratio, and completion rate.	Real-time control is associated with better service-time performance, but reported gains are not directly comparable across studies.	Joshi et al. (2022); Jorge et al. (2024); Wang et al. (2023a); Lu et al. (2024); Mehra et al. (2024); Kong et al. (2025); Cosmi et al. (2025)
P2 – Conditional bundling value	OD, VR	Cost, fleet size, orders per kilometer, matching rate, fleet utilization, pickup time, and fixed driver cost.	Consolidation improves resource use when orders are spatially and temporally compatible, but may increase delay or coordination costs.	Wang (2018); Joshi et al. (2022); Simoni and Winkenbach (2023); Yang et al. (2024b); Mehra et al. (2024)
P3 – Delay-control modeling	OD, VR, SS, PS	Feasibility rate; delay penalty; delivery-time bound; customer satisfaction; service-level attainment; penalty cost.	Explicit service control can reduce lateness or infeasibility, sometimes at the cost of higher routing or planning effort.	Xue et al. (2024); Wang and Jiang (2022); Liao et al. (2020); Ulmer and Savelsbergh (2020); Zhang et al. (2025a)
P4 – Capacity-demand alignment	SS, FS	Undelivered or unfulfilled orders; ready-to-pickup time; required driver-hours; total cost; service level.	Better alignment between planned courier capacity and demand improves cost and service outcomes.	Reyes et al. (2018); Ulmer and Savelsbergh (2020); Dai and Liu (2020); Das and Yadav (2021); Zhang et al. (2026)
P5 – Conditional flexibility benefits	FL, FS, SC, OD	Coverage, fleet size, driver participation, service-area size, and resource-sharing benefit.	More resources or flexibility are beneficial only under suitable demand, spatial, and workforce conditions.	Pinto et al. (2020); Auad et al. (2024); Jahanshahi et al. (2022); Wang et al. (2023b)
P6 – Sustainability trade-offs	OD, VR, FS	Greenhouse gas emissions; energy savings; delivery cost; travel distance; fairness; service performance.	Environmental gains may conflict with cost, service, energy-use, or fairness objectives.	Liu et al. (2024); Xue and Zou (2025); Sun et al. (2024); Lu et al. (2025)
P7 – Context-dependent prediction gains	Predictive problems supporting OD, VR, and FS	MSE; MAE; RMSE; interval score; route-inference F1-score; travel-time MAE.	Prediction gains are context-dependent and are strongest when temporal, spatial, peak-period, or route variation is meaningful.	Hess et al. (2021); Crivellari et al. (2022); Liang et al. (2023); Nie et al. (2025); Hildebrandt and Ulmer (2022); Liu et al. (2025b)

OD (Order Dispatching); OG (Order Grabbing); VR (Vehicle Routing); SC (Service Coverage); SS (Shift Scheduling); FS (Fleet Sizing); FL (Facility Location); KPI (Key Performance Indicator); MSE (Mean Squared Error); MAE (Mean Absolute Error); RMSE (Root Mean Squared Error).

7. Discussion and future research directions

We summarize the existing prescriptive studies on OFD problems in Table C.14 (see Appendix C), with respect to the problem level, setting and decision, the objective functions employed, the uncertain factors characterizing the models, the solution approaches, and the ML techniques they used, which provides a concise reference framework for the discussion that follows.

7.1. Decision levels and operational strategies in OFD

Our analysis shows that OD is the most frequently studied decision in the reviewed literature, and that most studies investigating OD also incorporate VR, indicating that these two operational problems are often considered jointly. In contrast, strategic and tactical decisions receive less attention, with SC, SS, FS, and PS appearing in smaller subsets of the literature. This imbalance suggests opportunities for future research to broaden the scope of OFD models beyond dispatching and routing, and to further develop less-explored decision areas. Within SC, courier positioning constitutes an emerging stream. Tavasoli et al. (2026) introduced a dynamic waiting point location problem in which temporary waiting point activation, restaurant allocation, courier assignment, and courier relocation decisions are jointly optimized to improve demand coverage. Future research may extend this stream by integrating courier positioning with real-time dispatching and routing. More broadly, these developments point to the need for stronger integration across decision levels. Although isolated strategic (Luy et al., 2024) or tactical (Zhao et al., 2025) studies exist, no current research examines the interconnection of all decision levels.

Integrating these levels is critical; Pinto et al. (2020) suggests that combining strategic considerations like FL with operational OD and VR improves overall service quality. However, such joint modeling introduces significant challenges. It intensifies conflicting objectives (e.g., Niu et al., 2024) and results in high-dimensional, computationally demanding formulations, for example, when linking workforce capacity with dispatching and routing (Auad et al., 2024; Luy et al., 2024). To navigate this complexity, recent frameworks have adopted hierarchical optimization (e.g., Zhao et al., 2025) or problem simplification (e.g., Auad et al., 2024). A common approach is decomposition, where a long-term phase first establishes resource boundaries that constrain subsequent operational routing and dispatching subproblems (e.g., Zhang et al., 2026; Luy et al., 2024). Building on the initial body of joint studies and expanding it to

cover SC, SS, FS, and PS in a unified architecture is essential for delivering reliable, scalable service quality in practice and can then be considered in future research.

Building on the discussion of decision types, another operational characteristic concerns the incorporation of bundling, splitting, and postponement in optimization models. Following the modeling treatment classification in Table 4, bundling, splitting, and postponement are compared only when they are treated as endogenous decisions in the model or solution procedure. Under this criterion, bundling is incorporated in a larger subset of studies (e.g., Ulmer et al., 2021), whereas splitting (e.g., Steever et al., 2019) and postponement (e.g., Lu et al., 2024) are addressed in smaller subsets of the literature. The predominance of bundling reflects its strong alignment with the operational characteristics of OFD, as consolidating multiple orders into a single trip reduces travel costs and improves courier utilization. Order splitting, which involves dividing a single customer order among multiple couriers, has received comparatively limited attention in the OFD literature. This may reflect the fact that splitting is less commonly aligned with prevailing operational practices, as it introduces additional coordination requirements and service-level considerations. At the same time, the small number of existing studies suggests a potential research gap. In particular, future work may explore conditions under which splitting strategies could be beneficial, such as in systems with heterogeneous fleets, capacity-constrained couriers, or cross-regional delivery, where orders need to be transferred at meeting points between couriers. Postponement, the practice of delaying orders to improve matching, can enhance overall system performance. An interesting avenue of research is the adaptation of performance measures to account for the risk associated with late deliveries. (Zhang et al., 2019, 2024). Also, further research may extend this stream by integrating customer-specific tolerance, stochastic preparation times, or reliability-based service metrics.

7.2. Fleet, courier models, and uncertainty

In addition to order management strategies, fleet composition is another area where modeling assumptions diverge from industry realities (Baldacci et al., 2008). A large subset of studies assumes homogeneous fleets (e.g., Yang et al., 2024a) with identical capacity and speed, which provides modeling simplicity but only partially reflects industry practice. Companies typically deploy heterogeneous fleets (e.g., Hamid et al., 2023), including bicycles, vans, cars, and drones. For example, bicycles may offer cost advantages due to lower maintenance and no fuel expenses, making them suitable for short-distance deliveries in congested urban areas. Cars, on the other hand, while more expensive to maintain, could provide better service for longer distances or bulkier orders. This economic difference highlights the importance of fleet heterogeneity in improving service efficiency and reducing costs. Additionally, many studies focus on in-house couriers or riders with fixed salaries (e.g., Kim and Do Chung, 2024), whereas companies frequently employ both in-house and crowdsourced couriers (e.g., Luy et al., 2024) to provide services. The integration of in-house and crowdsourced couriers and the investigation of mitigation strategies to hedge against the absenteeism of occasional drivers (see, e.g., Zhou et al., 2026; Mancini et al., 2025) into the solution planning process, therefore, represents interesting avenues of research. Additionally, modeling rider-to-rider interactions through information diffusion, which enables more profitable and efficient order allocation, is also an interesting area of research (see, e.g., Badiie et al., 2023).

While the reviewed studies often emphasize operational feasibility constraints such as time windows, routing, and capacity, economic and strategic factors are rarely modeled. Although some research addresses courier payment guarantees (Yildiz and Savelsbergh, 2019a), minimum compensation and customer payment limits (Kancharla et al., 2024), participation equilibrium of stakeholders (Bahrami et al., 2023), and integrated pricing and dispatching mechanisms (Zhang et al., 2025a; Bai et al., 2022), significant gaps remain. In particular, areas like inter-platform competition, courier retention strategies, and overtime compensation are largely unexplored in the context of FDS. These topics thus offer valuable directions for future research.

Regarding the problem setting, deterministic formulations are used in a substantial share of the reviewed studies. These formulations support computational tractability but may not fully capture real-world variability, such as sudden demand spikes or unpredictable delivery times. This reliance risks missing volatility in factors such as fluctuating demand, preparation time, travel time, service time, courier behavior, and availability. Among studies addressing uncertainty, order arrival time and order request information receive the most attention (e.g., Bozanta et al., 2022), whereas preparation time (Xue et al., 2024), travel time (Chu et al., 2023), service time (Fotouhi et al., 2021), courier behavior (Bozanta et al., 2022), and courier availability (Ausseil et al., 2024) are considered in smaller subsets of the literature. Research on uncertainty in areas such as preparation time, service time, travel time, courier behavior, and availability in crowdsourced fleets aligns closely with operational realities and is recommended for future work. Additionally, integrating uncertainty factors with sustainability-driven objectives (see, e.g., Liu et al., 2025c) in FDS also represents an interesting avenue for future research.

7.3. Objectives, optimization approaches, and machine learning integration

Another important observation of the literature is the prioritization of a few objectives in optimization models. A significant part of studies prioritize minimizing delays (Agnetis et al., 2023) to enhance service quality and reducing travel time (Chen et al., 2024) to increase operational efficiency. These objectives are central to decision-making in OFD and are expected to remain prominent in future research. However, limited attention has been afforded to objectives relevant to couriers, such as equitable compensation (Bai et al., 2022). Addressing these topics in the future may increase participation by crowdsourced couriers in delivery operations.

It is also important to note the optimization approach. Although some studies include criteria such as delay and travel time within a weighted single-objective function (Wang et al., 2023c; Chen et al., 2023; Zheng et al., 2023), multi-objective optimization frameworks are addressed in a smaller subset of studies (Liao et al., 2020; Martinez-Sykora et al., 2024; Zheng et al., 2022). Due to the involvement of various stakeholders, some objectives conflict with one another. For example, minimizing travel costs may increase

delivery times and compromise service levels. In such circumstances, a research direction can consider multi-objective optimization, which will be crucial for making trade-offs between the criteria and producing non-dominated solutions. In addition to operational and service-related objectives, environmental considerations are still rare in the research landscape. Among the reviewed studies, only a small number include greenhouse gas emission costs as objectives alongside operational and service-related goals (Liao et al., 2020; Liu et al., 2024). Expanding research to consider environmental concerns represents a promising direction for future work.

Some researchers have developed exact, approximation, and heuristic algorithms for optimization challenges in OFD decision problems. However, exact approaches usually scale only to small instances (Luy et al., 2024) (as shown in Fig. 4). To meet real-world requirements, there is a clear need for more scalable techniques, such as decomposition algorithms, as suggested by Kohar and Jakhar (2025). These methods can handle large-scale OFD scenarios within practical time limits. Notably, time limitation is most critical for OD. Accordingly, many OD studies employ heuristic, metaheuristic, and hybrid methods to generate solutions efficiently, prioritizing computational efficiency over guaranteed optimality (Xue et al., 2021). It is expected that researchers will continue to advance these algorithms. In contrast, when moving from short-term OD to mid-term and long-term decisions such as FL, FS, SS, and PS, it is recommended to develop exact solutions to achieve optimality as a future direction.

Building on these methodological choices, MIP models are widely used for optimization, with both exact and heuristic methods applied on an RH basis. In response to dynamic and uncertain factors, recent research has increasingly shifted toward MDP models and RL techniques. This transition underscores the need for real-time optimization approaches that address the evolving characteristics of operational environments. However, while RL-based dispatch policies often operate as opaque black boxes, this underscores the ongoing need for research on their interpretability and fairness, as suggested by Auad et al. (2023). Advancements in these areas will help ensure that both managers and couriers can trust algorithmic decisions, making this a likely area for continued progress.

The integration of ML techniques for parameter prediction with downstream optimization models remains limited in the surveyed literature. Existing studies focus on predicting specific factors, such as demand volumes (Huq et al., 2025), meal preparation times (Zheng et al., 2021), travel times (Chu et al., 2023), and courier acceptance behavior (Wang et al., 2022), which are then embedded into the optimization framework. This approach will help address uncertainty by predicting parameter values from historical data and incorporating them into an optimization model. Extending this line of research could identify new integration strategies that address current limitations in handling real-world uncertainties, potentially leading to improved service quality and increased system efficiency within the OFD context.

7.4. Data sources and performance evaluation

Empirical evidence in OFD literature relies on a limited number of public datasets and a predominance of proprietary data. Most studies utilize platform-specific transaction logs, such as the multi-city Meituan datasets (Zheng et al., 2021; Liu et al., 2020; Chen et al., 2023; Wang et al., 2021), which remain inaccessible to the broader research community. Publicly reusable datasets are limited. The Grubhub Meal-Delivery Routing Problem library of Reyes et al. (2018) used by Yildiz and Savelsbergh (2019a), Kancharla et al. (2024), Martinez-Sykora et al. (2024), Simoni and Winkenbach (2023) is the most frequently cited, as well as the PDP instances of Naccache et al. (2018) reused by Aziez et al. (2020) and Kohar and Jakhar (2025). In terms of KPIs for evaluating solution performance, economic metrics, such as cost per order, total profit, and revenue per hour, are commonly used alongside service quality metrics, such as CtD time, lateness, and on-time ratio. Operational metrics, such as courier utilization and bundle size, are considered in only a limited number of studies. Environmental metrics, such as greenhouse gas emissions or the share of electric vehicles, are rarely quantified to evaluate performance. This diversity in datasets and KPIs impedes direct comparison of solution approaches and complicates managerial insights. Advancing the field will require the establishment of an accessible benchmark suite that reflects diverse urban forms, demand profiles, and fleet configurations, combined with a standardized set of KPIs such as cost per order, on-time ratio, CtD time, courier utilization, and emissions, supplemented by problem-specific measures.

8. Conclusions

The evolution of Online Food Delivery (OFD) systems has fundamentally redefined urban logistics, catalyzing new forms of connectivity between consumers, restaurants, and couriers while introducing profound operational, tactical, and strategic challenges. In this landscape, the application of Operations Research (OR) is not a matter of incremental efficiency but a critical lever for reconciling real-time uncertainty, multi-actor coordination, and market competitiveness. However, despite the proliferation of quantitative studies and methodological advances, the literature has remained fragmented, lacking a unifying taxonomy that reveals the insights in OFD.

The analysis indicates that OR in OFD primarily focuses on Order Dispatching (OD) and Vehicle Routing (VR). Most studies assume homogeneous fleets, address deterministic or narrowly defined uncertainties related to order arrivals, and employ single-objective functions that minimize delay or travel cost. Strategic and tactical decisions, including Service Coverage area (SC), Fleet Sizing (FS), Shift Scheduling (SS), and Pricing Schemes (PS), are addressed infrequently and are rarely integrated with operational decision-making, which impedes the development of comprehensive end-to-end solutions. Within dispatching operations, bundling is the most frequently examined strategy, but its modeling depth varies substantially across studies, ranging from implicit treatments to explicit endogenous decisions about bundle formation. By contrast, splitting and postponement appear in smaller subsets of the literature, especially when attention is restricted to studies that model these strategies as endogenous decisions rather than imposing them through exogenous rules or feasibility conditions. Environmental objectives and considerations of courier fairness are seldom incorporated into existing models. Reinforcement Learning (RL) methods are emerging to reflect better the real-time nature of Food

Delivery Services (FDS); however, their interpretability should be transparent to stakeholders. Besides, Machine Learning (ML) algorithms are rarely integrated with optimization problems to predict factors such as preparation or travel time. Finally, empirical validation predominantly relies on proprietary datasets, with limited use of public benchmarks and inconsistent reporting standards, thereby restricting comparability and practical relevance.

The emphasis on quantitative, platform-enabled OFD models in this review excludes perspectives, including qualitative analyses and developments in related sectors such as grocery delivery and self-managed restaurant logistics. To maintain the relevance of this review, we recommend regularly updating the synthesis to address current limitations and reflect emerging trends, including platformization, the decarbonization of logistics, and the algorithmic management of couriers.

AI-assisted technologies

The current study uses ChatGPT, an AI tool, for passage checking and grammatical revision. We guarantee the validity of the passage, and human knowledge verifies its accuracy.

CRedit authorship contribution statement

Mohammadamin Tavasoli: Writing – review & editing, Writing – original draft; **Roberto Baldacci:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Conceptualization; **Vahid Kayvanfar:** Writing – review & editing, Writing – original draft; **Yu Zhang:** Writing – review & editing, Writing – original draft, Funding acquisition, Conceptualization; **Chefi Triki:** Writing – review & editing, Writing – original draft, Funding acquisition, Conceptualization; **Adel Elomri:** Writing – review & editing.

Data availability

No data was used for the research described in the article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. List of Acronyms

OFD	Online Food Delivery
OR	Operation Research
RL	Reinforcement Learning
LMD	Last-mile Delivery
FDS	Food Delivery Service
FL	Facility Location
FS	Fleet Sizing and Composition
SS	Shift Scheduling
PS	Pricing Scheme
OD	Order Dispatching
OG	Order Grabbing
VR	Vehicle Routing
SC	Service Coverage
CS	Compensation Scheme
SLR	Systematic Literature Review
RO	Restaurant Operation
ML	Machine Learning
MDS	Meal Delivery Service
IDS	Instant Delivery Service
UAV	Unmanned Aerial Vehicle
CtD	Click-to-Door
PtD	Pickup-to-Door
RtD	Ready-to-Door
RtP	Ready-to-Pickup
DtD	Dispatched-to-Door
PDP	Pickup-and-Delivery Problem
RH	Rolling Horizon
KPI	Key Performance Indicator
SP	Stochastic Programming
DRO	Distributionally Robust Optimization
AI	Artificial Intelligence
MIP	Mixed-Integer Programming
DNN	Deep Neural Network
GNN	Graph Neural Network
MDP	Markov Decision Process
ALNS	Adaptive Large Neighborhood Search
BB	Branch-and-Bound
BP	Branch-and-Price
BC	Branch-and-Cut
GA	Genetic Algorithm
TS	Tabu Search
LSTM	Long Short-Term Memory
CNN	Convolutional Neural Network
SA	Simulated Annealing
GBDT	Gradient boosted Decision Tree
ETA	Estimated Time of Arrival
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
ARIMA	Autoregressive Integrated Moving Average
LLM	Large Language Model

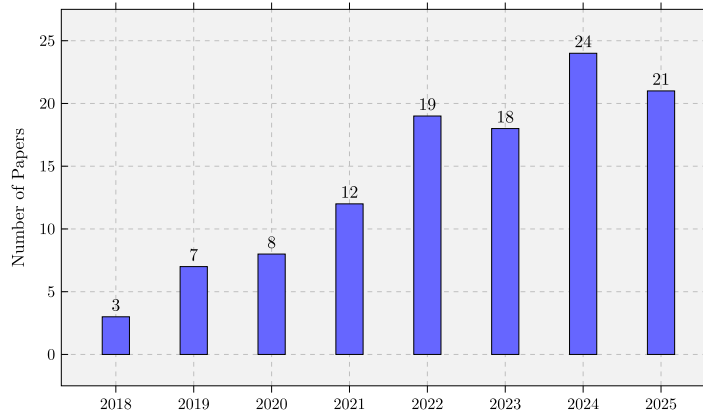
Appendix B. Literature collection

The methodology for this review aligns with its focus on decision-making problems in [OFD](#), emphasizing the role of uncertain factors. The article selection targets the intersection of three key dimensions: (1) studies that address [FDS](#), [MDS](#), or [Instant Delivery Service \(IDS\)](#) applicable to food delivery, ensuring relevance to their unique operational and logistical challenges; (2) optimization-based decision-making processes at strategic, tactical and operational levels, including [FL](#), [FS](#), [SS](#), [PS](#), [OD](#), [OG](#), [VR](#), [SC](#); and (3) Models

Table B.13

Three-tier keyword search structure.

Tier 1		("meal delivery" OR "food delivery" OR "restaurant delivery" OR "instant delivery" OR "o2o delivery" OR "online-to-offline delivery" OR "online to offline delivery" OR "on-demand delivery" OR "on demand delivery")
Tier 2	And	("vehicle routing" OR "route plan*" OR "resource plan*" OR "workforce plan*" OR "dispatch*" OR "assign*" OR "allocat*" OR "schedul*" OR "pickup and delivery" OR "decision-making" OR "optimization" OR "prescriptive analytic*" OR "business analytic*" OR "data analytic*" OR "predictive analytic*")
Tier 3	And	("machine learning" OR "deep learning" OR "reinforcement learning" OR "supervised learning" OR "unsupervised learning" OR "simulation" OR "Markov decision" OR "linear programming" OR "integer programming" OR "mixed integer" OR "exact algorithm*" OR "branch-and-cut" OR "heuristic*" OR "metaheuristic*" OR "adaptive large neighborhood search" OR "genetic algorithm*" OR "ant colony" OR "simulated annealing" OR "tabu search" OR "particle swarm" OR "stochastic" OR "dynamic*" OR "robust" OR "fuzzy")

**Fig. B.5.** Distribution of studies over years.

and solution approaches for addressing these challenges, such as exact methods, heuristics, metaheuristics, and **ML**-based techniques tailored to use in predictive settings.

Inclusion and exclusion criteria. This review exclusively examines studies on **FDS** facilitated by online platforms, focusing on decision-making complexities unique to these systems. It excludes research related to other **IDS**, such as grocery delivery or restaurant-managed delivery services that operate independently of digital platforms. This scope ensures an in-depth analysis of platform-enabled **FDS** in dynamic, uncertain environments. Articles were retrieved through a structured search of Scopus and Web of Science, utilizing a three-tier keyword structure applied to titles, abstracts, and keywords to ensure specificity and relevance, as detailed in [Table B.13](#).

Using a systematic approach across Scopus and Web of Science, we shortlisted 397 papers. Initially, we focused on reviewing journal articles, excluding books, book chapters, and conference papers, which reduced the total to 247 papers. After reviewing the abstracts, some articles were excluded from the dataset because they were not relevant to the scope of **FDS**. Some articles were primarily unrelated to the topic, focusing on digital security or cloud computing. Also, some addressed broader transportation and traffic management and **FL** problems without specific implications for **OFD** platforms. In addition to keyword searches, a snowballing approach was used to examine the reference lists of key articles to identify additional relevant studies. This step aimed to capture influential contributions that may not be retrieved solely through keyword searches, while remaining consistent with the defined inclusion criteria. Ultimately, 112 papers were reviewed and systematically categorized in the literature review study, establishing a solid foundation for analyzing the nuances of meal delivery services.

[Fig. B.5](#) shows a consistent rise in work on **OFD**. Annual publications remained below 12 studies from 2018 to 2020, increased to 12 in 2021, accelerated to 19 in 2022, and reached 24 in 2024. The tally for 2025 is 21 as of August. Taken together, these counts indicate a sustained expansion of the field in recent years.

Appendix C. Summary of existing **OFD** studies by key features

Table C.14
Reviewed prescriptive studies in OFD.

#	Reference	Decision Levels	Dynamic Setting	Uncertain Factor	Decision Problems										Fleet Type	Objective Function	Model	Solution	AI/ML Technique	Real Data
					OG	OD	B	SP	P	VR	SC	SS	FS	PS						
1	Zhang et al. (2022)	O		PT	✓						✓					MIP	Meta. (WWO, TS)	ANN	✓	
2	Wang et al. (2022)	O	✓	CB	✓						✓					MIP	Heur. + Learn.	XG-Boost	✓	
3	Wang et al. (2023d)	O	✓	CB	✓											MDP	Learn.	Deep RL	✓	
4	Wang et al. (2023e)	O	✓	CB	✓											MDP	Learn.	RL, SL	✓	
5	Reyes et al. (2018)	T, O	✓	-	✓	✓		✓			✓		✓			MIP	Heur. (RH)	-	✓	
6	Liu et al. (2018)	O		-	✓						✓			✓		MIP	Meta. (ALNS, SA)	-	✓	
7	Wang (2018)	O		-	✓						✓					MIP	Meta. (LS, ALNS)	-	✓	
8	Steever et al. (2019)	O	✓	-	✓	✓	✓	✓	✓	✓	✓					MIP	Exact + Heur. (MIP, auction)	-	✓	
9	Yildiz and Savelsbergh (2019a)	O		-	✓	✓					✓		✓			MIP	Exact (CRG)	-	✓	
10	Liu (2019)	O	✓	-	✓				✓	✓	✓					MIP	Exact + Heur. (RH)	-		
11	Tu et al. (2019)	O	✓	-	✓						✓					MIP	Meta. (ALNS, TS)	-		
12	Cosmi et al. (2019)	O		-	✓											AM	Exact (DP)	-		
13	Ulmer and Savelsbergh (2020)	T, O	✓	D, CA	✓						✓		✓			SO	Heur.	-	✓	

Table C.14
continued.

#	Refer- ence	Deci- sion Levels	Dy- namic Setting	Uncer- tain Factor	Decision Problems										Fleet Type	Objective Function	Model	Solution	AI/ML Tech- nique	Real Data	
					OG	OD	B	SP	P	VR	SC	SS	FS	PS							FL
14	Dai and Liu (2020)	T, O		-	✓						✓		✓			HET	MOC, MOM	MIP	Exact (BB)	-	✓
15	Liao et al. (2020)	O		-	✓		✓				✓			✓		HOM	MTH, BWL, MCE	MIP	Meta. (NSGA- II, ALNS)	-	✓
16	Gu et al. (2020)	O		-	✓		✓				✓	✓		✓		HET	MFS, MTT	MIP	Exact + Meta. (ACO)	-	✓
17	Liu et al. (2021)	O		TT, ST	✓		✓									HOM	MDL	SP, DRO	Exact + Learn. (BP, ML)	SVR, RF	✓
18	Ulmer et al. (2021)	O	✓	D, PT	✓		✓			✓						HOM	MDL	MDP	Heur. (ML)	-	✓
19	Fotouhi et al. (2021)	O	✓	CB, D, TT, ST, PT, CL, CA	✓		✓			✓						HET	MTT, MDL	MIP	Exact + Heur. (SIM, IP Solver)	-	✓
20	Huang et al. (2021)	O	✓	D	✓		✓				✓					HOM	MDL	SO	Heur. (K- means, SA)	-	✓
21	Xue et al. (2021)	T, O		-	✓							✓	✓			HOM	MTT, MOC, MFS	MIP	Exact + Meta. (LNS)	-	✓
22	Joshi et al. (2022)	O	✓	-	✓		✓				✓					HOM	MDL, MOM	GBM	Heur.	-	✓
23	Wang and Jiang (2022)	O		-	✓						✓					HOM	MTH, MDL	MIP	Heur. + Meta. (greedy, GA)	-	✓
24	Li et al. (2022)	O		-	✓		✓	✓			✓					HOM	MOC, MTT	MIP	Meta. (ALNS)	-	✓
25	Jahan- shahi et al. (2022)	O	✓	D, PT	✓		✓			✓						HOM	MDL, MCU	MDP	Learn. Deep RL	Deep RL	✓
26	Chen et al. (2022b)	O	✓	-	✓											HOM	MOC	MIP	Heur. + Learn. XG- Boost	XG- Boost	✓

Table C.14
continued.

#	Refer- ence	Deci- sion Levels	Dy- namic Setting	Uncer- tain Factor	Decision Problems										Fleet Type	Objective Function	Model	Solution	AI/ML Tech- nique	Real Data
					OG	OD	B	SP	P	VR	SC	SS	FS	PS						
27	Bozanta et al. (2022)	O	✓	D	✓						✓				HOM	MPR	MDP	Learn.	DQN	
28	Chen et al. (2022a)	O	✓	-	✓	✓					✓				HOM	MDL, MTT	MIP	Heur. + Learn.	XG- Boost	✓
29	Zheng et al. (2022)	O	✓	CB, D	✓	✓					✓	✓			HOM	MDL, MTT	FBM	Heur. + Learn.	XG- Boost	✓
30	Huq et al. (2022)	O	✓		✓	✓									HET	MCP, MCtD	MIP	Meta. (WWO)	-	✓
31	Tao et al. (2023)	O	✓	CB, TT	✓	✓					✓				HET	MDL, MOC	NLP	Meta. + Learn. (TS, ML)	RF	✓
32	Hamid et al. (2023)	O		-	✓						✓				HET	MOC, MDL, MTH	MIP	Heur.	-	✓
33	Zhen et al. (2023)	O		-	✓	✓					✓				HOM	MTT, MDL	MIP	Exact + Heur. (CG)	-	✓
34	Wang et al. (2023c)	O		-	✓	✓					✓				HOM, HET	MIC, MTT	MIP	Heur.	-	✓
35	Chen et al. (2023)	O	✓	-	✓	✓					✓				HET	MDL, MTT	GBM	Heur. + Learn. (greedy)	RL	✓
36	Simoni and Winken- bach (2023)	O	✓	D, CA	✓	✓					✓				HET	MTT, MOM	MIP	Heur.	-	✓
37	Chu et al. (2023)	O		CB, TT	✓						✓				HET	MOC, MTT	MIP	Heur. + Learn. (SA, ML)	LR	
38	Zheng et al. (2023)	O	✓	-	✓	✓					✓				HET	MCtT, MDL	HM	Heur. + Learn.	DL	✓
39	Wang et al. (2023b)	O	✓	D, CL, CA	✓	✓						✓			HOM	MOM, MCU	MDP	Learn.	Multi- Agent RL	✓

Table C.14
continued.

#	Reference	Decision Levels	Dynamic Setting	Uncertain Factor	Decision Problems										Fleet Type	Objective Function	Model	Solution	AI/ML Technique	Real Data	
					OG	OD	B	SP	P	VR	SC	SS	FS	PS							FL
40	Agnietis et al. (2023)	O	✓	-	✓	✓										HOM	MDL	MIP	Exact (BB)	-	✓
41	Auad et al. (2023)	O	✓	D	✓			✓		✓						HOM	MDL, MCtD	MDP, MIP	Heur. (RH)	-	✓
42	Wang et al. (2023a)	O	✓	D	✓											HOM	MPR, BWL	MDP	Learn.	RL	✓
43	Ke et al. (2024)	S, O		-	✓	✓							✓			HOM	MPR, MSW	AM	AEA	-	✓
44	Auad et al. (2024)	T, O		-	✓								✓			HOM	MOM, MFS, MDL	MIP	Exact	-	
45	Martinez-Sykora et al. (2024)	O		-	✓					✓						HET	BWL, MTT, MCU	MIP	Meta. (VNS)	-	✓
46	Yang et al. (2024a)	O	✓	D, PT	✓					✓		✓				HOM	MTH	MIP	Exact + Learn.(ML)	MLR, MTR	✓
47	Hou et al. (2024)	O		-	✓					✓						HOM	MTT, MDL	MIP	Meta. (ACO)	-	
48	Chen et al. (2024)	O	✓	-	✓					✓						HOM	MDL, MTT	MIP	Heur. + Learn. (greedy)	GNN	✓
49	Liu et al. (2024)	O	✓	-	✓					✓						HET	MOC, MDL, MCE	MIP	Meta. (RH, ALNS, LS)	-	✓
50	Thipparthy et al. (2024)	O		-	✓					✓						HOM	MTT, MOC	MIP	Meta. (GA)	-	✓
51	Kim and Do Chung (2024)	O		-	✓	✓				✓						HOM	MCtD, MDL	MIP	Exact + Meta. (TS)	-	
52	Lu et al. (2024)	O	✓	D	✓	✓		✓								HOM	MTH, MDL, MTT	ABM	Heur. + Learn. (KM match-ing)	DQN	✓

Table C.14
continued.

#	Reference	Decision Levels	Dynamic Setting	Uncertain Factor	Decision Problems										Fleet Type	Objective Function	Model	Solution	AI/ML Technique	Real Data
					OG	OD	B	SP	P	VR	SC	SS	FS	PS						
53	Kancharla et al. (2024)	O	✓	D, PT	✓						✓					SP	Meta. (SAA, ALNS, RH)	-	✓	
54	Bhuiyan et al. (2024)	O		-	✓						✓	✓				MIP	Heur. + Meta. (greedy, GA)	-	✓	
55	Xue et al. (2024)	O		TT, PT	✓						✓					MIP	Meta. (IHS)	-		
56	Jorge et al. (2024)	O	✓	-	✓											MIP	Exact	-	✓	
57	Deng et al. (2024)	O	✓	D	✓						✓		✓			MDP	Heur. + Learn.	RL	✓	
58	Ausseil et al. (2024)	O	✓	CB, D, CA	✓											SO, MIP	Exact + Heur.	-		
59	Mehra et al. (2024)	O	✓	D, TT, ST	✓	✓	✓	✓			✓	✓				MDP	Heur. + Learn.	RL	✓	
60	Guo et al. (2024)	O	✓	-	✓						✓					GBM	(greedy) Online Algorithm	-		
61	Yang et al. (2024b)	O	✓	CB	✓						✓					-	Heur. (greedy, LS)	-	✓	
62	Luy et al. (2024)	S, O	✓	D, CA	✓						✓	✓				HM	Approximate DP	-		
63	Sun et al. (2024)	O	✓	-	✓						✓		✓			MIP	Meta. (ALNS, RH)	-	✓	
64	Zhang et al. (2025a)	T, O	✓	D	✓	✓	✓				✓			✓		MIP	Meta. (ALNS)	-	✓	
65	Huq et al. (2025)	O	✓	-	✓	✓	✓	✓			✓	✓		✓		MIP	Meta. + Learn. (ALNS, SA)	LSTM, XG-Boost		

Table C.14
continued.

#	Reference	Decision Levels	Dynamic Setting	Uncertain Factor	Decision Problems										Fleet Type	Objective Function	Model	Solution	AI/ML Technique	Real Data	
					OG	OD	B	SP	P	VR	SC	SS	FS	PS							FL
66	Zhou et al. (2025)	O	✓	D, PT, CA	✓											HET	MCP	MDP	Learn.	DRL	✓
67	Cosmi et al. (2025)	O	✓	-	✓											HOM	MDL, MOM	MIP	Exact	-	✓
68	Kong et al. (2025)	O	✓	-	✓						✓					HOM	MCD	MIP	Meta. (memetic algo-rithm)	-	✓
69	Homer et al. (2025)	O	✓	CB	✓								✓			HET	MPR, MOC	MIP	Exact + Meta.	-	✓
70	Zhao et al. (2025)	T, O	✓	D, CL, CA	✓						✓					HET	MOC, MOM	MDP	Heur.	-	✓
71	Liu et al. (2025a)	O	✓	D	✓						✓					HOM	MTT, MCP	ABM	Heur.	-	
72	Lu et al. (2025)	O		-	✓						✓					HOM	MTT, MOC	MIP	Exact	-	
73	Li et al. (2025)	O	✓	D	✓		✓	✓			✓					HOM	MDL, MOC	MIP	Meta. (ALNS, RH)	-	✓
74	Du et al. (2025)	T, O		D	✓						✓					HOM	MTT, MDL, MOC	SP	Meta. (ALNS, SA)	-	✓
75	Xue and Zou (2025)	O		-	✓		✓				✓					HOM	MCE	MIP	Meta. (VNS)	-	✓
76	Zhang et al. (2025b)	O	✓	D, CL, CA	✓						✓					HET	MCP	MIP	Heur. (greedy, RH)	-	✓
77	Chen et al. (2025)	O	✓	-	✓					✓	✓					HOM	MTT, MDL	MDP	Heur. + Learn.	Double DQN	✓
78	Kohar and Jakhar (2025)	O		-	✓		✓				✓					HOM	MTT	MIP	Exact (BC)	-	
79	Zhang et al. (2026)	T, O		D, CA	✓								✓			HET	MOC, MOM	SP, DRO	Exact (BD)	-	✓
80	O'Neil and Hoffman (2019)	O		-							✓					HOM	MOC	GBM	Exact + Heur. (BB)	-	✓
81	Aziez et al. (2020)	O		-							✓					HOM	MOC	MIP	Exact (BC)	-	
82	Liu et al. (2020)	O		-							✓					HOM	MTT	MDP	Learn.	Inverse RL	✓
83	Wang et al. (2021)	O		-							✓					HOM	MDL, MTT	MIP	Heur. + XG-Boost		✓
84	Zheng et al. (2021)	O	✓	PT							✓					HOM	MTT, MDL	SP	Learn. (greedy)	LSTM, CNN	✓

Table C.14
continued.

#	Reference	Decision Levels	Dynamic Setting	Uncertain Factor	Decision Problems										Fleet Type	Objective Function	Model	Solution	AI/ML Technique	Real Data
					OG	OD	B	SP	P	VR	SC	SS	FS	PS	FL					
85	Yildiz and Savelsbergh (2019b)	S, T		CB, D, CA						✓	✓	✓	✓	✓		HET	MPR	AM	Analytical Derivation	-
86	Pinto et al. (2020)	S		-						✓				✓		HOM	MOM	MIP	Exact	-
87	Ulmer et al. (2022)	O	✓	D						✓						HOM	MTH	MDP	Heur. + Learn.	RL
88	Das and Yadav (2021)	T		-								✓	✓			HET	MOC	MIP	Exact	-
89	Bai et al. (2022)	O	✓	-									✓	✓		HET	MTH, EFC	GTM	Heur.	-
90	Li and Liang (2022)	S		-										✓		HOM	MPR	AM	Analytical	-
91	Bahrami et al. (2023)	S		-									✓	✓		HOM	MPR, MSW	AM	AEA	-
92	Wang et al. (2025)	O	✓	D, CL										✓		HET	MTH, EFC	MDP	Learn.	RL

S (Strategic); T (Tactical); O (Operational); SD (Static-Deterministic setting); DD (Dynamic-Deterministic setting); SS (Static-Stochastic setting); DS (Dynamic-Stochastic setting); OG (Order Grabbing); OD (Order Dispatching); B (Bundling); Sp (Splitting); P (Postponement); VR (Vehicle Routing); SC (Service Coverage); SS (Shift Scheduling decision); FS (Fleet Sizing); PS (Pricing Scheme); FL (Facility Location); MPR (Maximize Profit or Revenue); MOC (Minimize Operational Cost); MTT (Minimize Travel Time or Distance cost); MTH (Maximize Throughput); MFS (Minimize Fleet Size); MOM (Maximize Order Matching or Assignment); MCE (Minimize Carbon Emission Cost); MCTD (Minimize Click-to-Door Time); MPD (Minimize Pickup-to-Door Time); MRTD (Minimize Ready-to-Door Time); MDL (Minimize Delay or Lateness); BWL (Balance Workload); MCU (Maximize Courier Utilization); EFC (Ensure Fair Compensation); MCP (Maximize Courier Profit); MSW (Maximize Social Welfare); MDP (Markov Decision Process); MIP (Mixed-Integer Programming); NLP (Nonlinear Programming); SP (Stochastic Programming); SO (Stochastic Optimization); DRO (Distributionally Robust Optimization); ABM (Agent-based Model); GBM (Graph-based Model); FBM (Fuzzy-based Model); AM (Analytical Model); HM (Hybrid Model); GTM (Game-theoretical Model); SIM (Simulation); D (Demand); PT (Preparation Time); CB (Courier Behavior); TT (Travel Time); ST (Service Time); CL (Courier Location); CA (Courier Availability); AI (Artificial Intelligence); ML (Machine Learning); RF (Random Forest); GNN (Graph Neural Network); RL (Reinforcement Learning); DL (Deep Learning); GBDT (Gradient Boosted Decision Trees); DNN (Deep Neural Networks); DDQN (Double Deep Q-Network); HOM (Homogeneous Fleet); HET (Heterogeneous Fleet); ANN (Artificial Neural Network); XGBoost (eXtreme Gradient Boosting); SL (Supervised Learning); LR (Linear Regression); SVR (Support Vector Regression); MLR (Multinomial Logistic Regression); MTR (Model Tree Regression); LSTM (Long Short-Term Memory); CNN (Convolutional Neural Network); DQN (Deep Q-Network); Heur. (Heuristic); Meta. (Metaheuristic); Learn. (Learning-based); TS (Tabu Search); SA (Simulated Annealing); GA (Genetic Algorithm); ACO (Ant Colony Optimization); WWO (Water Wave Optimization); IHS (Island Harmony Search); VNS (Variable Neighborhood Search); ALNS (Adaptive Large Neighborhood Search); DP (Dynamic Programming); CG (Column Generation); CRG (Column and Row Generation); BB (Branch and Bound); BC (Branch and Cut); BP (Branch and Price); RH (Rolling Horizon); LNS (Large Neighborhood Search); LS (Local Search); BD (Benders Decomposition); AEA (Analytical Equilibrium Analysis).

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