Marco Gotelli*, Giovanni Maria Ferraris, Fabio Ferrero, Antonio Giovannetti and Agostino G. Bruzzone

Online food delivery and supply chain management by optimization of innovative models

https://doi.org/10.1515/ijfe-2025-0028
Received January 30, 2025; accepted November 9, 2025; published online December 5, 2025

Abstract: The study develops an empirically validated simulation framework to optimize urban food delivery through vehicle differentiation, multi-order management, and shortest-path routing. Using an empirical dataset from a medium-sized European city, three models are compared: single-order, greedy multi-order, and optimized multi-order delivery. Routing combines Dijkstra and *Traveling Salesman Problem* heuristics, with travel times predicted by a k-Nearest Neighbors model. The simulation closely reproduces observed operational patterns and shows that multiple-order delivery reduces average delivery time by 15 %–20 %, while the optimized model achieves an additional 8 % improvement. Outcomes indicate higher operational efficiency, better vehicle utilization, and reduced idle time. Overall, the approach supports both economic and environmental sustainability in last-mile logistics, offering a realistic benchmark for algorithmic coordination in heterogeneous delivery fleets offering better customer satisfaction.

Keywords: food delivery; modeling and simulation; machine learning

1 Introduction

In recent years, the evolution of digital technologies has radically transformed consumption patterns and business models across multiple economic sectors, including catering and food services. The rapid expansion of e-commerce and business-to-consumer (B2C) platforms has reshaped how customers interact with restaurants, creating new opportunities for convenience, personalization, and efficiency. Among these innovations, *food delivery* has emerged as one of the most dynamic and disruptive sectors, redefining the relationship between restaurants and consumers on a global scale.

The COVID-19 pandemic further accelerated this transformation by forcing both consumers and businesses to adopt online delivery solutions. According to McKinsey & Company [1], the global food delivery market more than doubled during the pandemic, exceeding $150 billion in the United States alone. Restrictions on mobility and the closure of dine-in facilities made home delivery an essential component of daily life, rather than a complementary service. As a result, platforms such as Deliveroo, Glovo, and Uber Eats have become key players in the digital economy, integrating advanced logistical and technological systems to manage real-time demand.

Within this framework, the phenomenon of *platformization* [2] has profoundly transformed the logistics of the food delivery sector. The platforms act as intermediaries that coordinate the interactions among customers, restaurants, and riders through dynamic assignment algorithms. Once an order is placed, the system automatically identifies and notifies available riders near the restaurant, optimizing delivery based on proximity and expected travel time. The quality and efficiency of these algorithms have become critical determinants of both customer satisfaction and platform competitiveness.

However, as food delivery systems become more complex, new challenges emerge in optimizing delivery operations. In particular, the need to (i) differentiate riders by vehicle type (bicycle or scooter), (ii) manage multiple simultaneous deliveries (multi-drop delivery), and (iii) ensure optimized routing through shortest-path algorithms has become central to the pursuit of operational efficiency. Traditional delivery models, which assign a single order to each rider, often fail to capture the logistical potential of multi-order optimization and heterogeneous vehicle fleets. This study builds upon a previous work [3–5], extending its

***Corresponding author: Marco Gotelli**, Simulation Team, Via Magliotto 2, 17100, Savona, Italy; and DIME, University of Genoa, Via Opera Pia 15a, 16145, Genova, Italy, E-mail: marco.gotelli@unige.it
Giovanni Maria Ferraris and Agostino G. Bruzzone, Simulation Team, Via Magliotto 2, 17100, Savona, Italy; and DIME, University of Genoa, Via Opera Pia 15a, 16145, Genova, Italy
Fabio Ferrero, DIEC, University of Genoa, Via Vivaldi 5, 16126, Genova, Italy
Antonio Giovannetti, Simulation Team, Via Magliotto 2, 17100, Savona, Italy; and DIEC, University of Genoa, Via Vivaldi 5, 16126, Genova, Italy

framework toward an operational and simulation-based perspective.

Specifically, the article proposes a three-level simulation model aimed at improving the efficiency of urban food delivery systems through:

(1) **Vehicle-based rider assignment**, selecting the most suitable means of transport (bicycle or scooter) according to distance and delivery context;
(2) **Multi-order delivery management**, grouping compatible orders in space and time; and
(3) **Optimized routing**, minimizing total travel distance and ensuring efficient sequencing of deliveries.

The proposed model is tested in three progressive configurations—single-order delivery, multi-order delivery, and optimized multi-order delivery—and compared through quantitative and qualitative performance metrics. The objective is to evaluate how integrated optimization strategies can enhance delivery efficiency while maintaining service reliability and customer satisfaction.

2 State of the art

2.1 Customer experience and key service dimensions

The quality of food delivery services has been widely analyzed in terms of customer experience, emphasizing the multidimensional nature of user satisfaction. Previous studies identify four main determinants: application quality, perceived price value, delivery time, and overall service quality. The quality of the application influences user satisfaction by shaping the accessibility and intuitiveness of the ordering process. Features such as simplified interfaces, customizable options, and real-time order tracking contribute to improved usability and customer retention [6–8]. Similarly, diversified payment systems and responsive communication tools—such as direct contact with riders or restaurants—enhance trust and perceived reliability [9].

The perceived price value extends beyond cost, encompassing intangible elements such as social reputation, sustainability, and ethical consumption [10, 11]. Promotions and membership programs can influence purchase frequency, but long-term loyalty ultimately depends on perceived consistency and transparency [12].

Among the four factors, delivery time has consistently emerged as the most influential determinant of customer satisfaction [13, 14]. The ability to ensure timely, accurate deliveries directly affects consumer trust, particularly in dense urban environments where expectations for punctuality are high. Therefore, optimizing delivery time not only improves operational performance but also represents a key driver of customer experience and platform reputation.

While these dimensions provide valuable insight into user perception, they do not directly address the operational and algorithmic mechanisms that produce such outcomes. The following section focuses on the technical foundations and optimization models that enable the achievement of these service objectives.

2.2 Optimization models and simulations approach in food delivery logistics

Recent advances in data analytics and machine learning have led to a new generation of delivery optimization models, aimed at improving both routing and order assignment efficiency. The problem of delivery time optimization is often conceptualized as a variant of the *estimated time of arrival* (ETA) problem [15, 16], which seeks to predict or minimize travel times between multiple locations under uncertain and dynamic conditions.

In the field of food delivery, ETA optimization is particularly challenging due to its dependence on real-time variables—such as traffic, restaurant preparation delays, and rider availability—that evolve continuously within the system. Studies by Liu et al. [17], Hildebrandt and Ulmer [18], and Gao et al. [19] integrate predictive analytics with order assignment logic, combining supervised learning and simulation to optimize dispatch decisions. Similarly, Salari et al. [20] propose a data-driven framework that determines optimal promised delivery times through decision tree-based models, bridging the gap between customer expectations and operational feasibility.

Beyond ETA prediction, researchers have also explored route optimization and vehicle routing problems (VRP) [21, 22]. Foundational algorithms such as Dijkstra's shortest-path method [23] remain crucial to these models [24], providing computational efficiency and theoretical rigor for distance minimization in complex urban networks.

A more recent research stream focuses on multi-order (or batch) delivery optimization, which aims to group temporally and spatially compatible orders to improve fleet utilization. Multi-drop models have been shown to significantly reduce total travel distance and idle time, especially during peak hours [25, 26]. Among these, priority-based optimization frameworks [27] offer an additional refinement by dynamically sequencing orders according to urgency and preparation readiness, further improving overall service efficiency. However, such systems also introduce challenges related to route complexity and fairness among customers with different delivery priorities.

Another emerging area involves heterogeneous fleet models, which consider differences in vehicle speed, accessibility, and environmental impact [28]. These models highlight the operational advantages of assigning riders with different vehicles – such as bicycles and scooters—based on travel distance, delivery density, and urban topology. Despite their potential, few studies have integrated this aspect into full-scale simulations of urban delivery systems.

2.3 Research gap and contribution

Although substantial progress has been made in ETA estimation, route optimization, and order assignment, the integration of these components into a unified, realistic simulation framework remains limited. Most existing approaches either focus on single-order scenarios or assume homogeneous rider fleets, overlooking the heterogeneity and real-time adaptability required in modern delivery ecosystems.

This study addresses this gap by developing a three-level simulation model that combines:
- vehicle-based rider assignment,
- multi-order (batch) delivery management, and
- shortest-path route optimization.

By merging these dimensions, the proposed framework bridges the gap between theoretical optimization models and practical logistics operations, offering a more comprehensive representation of urban food delivery dynamics. The next section details the methodological approach used to implement and compare the three proposed delivery models.

3 Methodology

3.1 Experimental setting and empirical dataset

The proposed simulation replicates an urban food delivery ecosystem during peak operating hours (18:00–20:00), using empirical data collected from a real delivery platform operating in a medium-sized European city. The dataset collected by survey includes historical records of completed deliveries, providing detailed information on order creation times, restaurant and customer coordinates, preparation durations, and actual delivery timestamps. Each observation $o_i$is defined by the tuple $\left(t_i^{\text{ord}}, t_i^{\text{ready}}, p_i, d_i, v_i, r_i\right)$, where t_i^{ord} and t_i^{ready} denote the order placement and ready times respectively, $p_i$and $d_i$represent pickup and drop-off coordinates, $v_i$is the vehicle type used (bicycle or scooter), and $r_i$the assigned rider. The empirical dataset covers a three-week period and contains approximately 3,000 deliveries, which are used both to parameterize and validate the simulation model. The follow figure depicts the conceptual architecture (Figure 1).

Descriptive statistics from the dataset inform the main parameters of the simulation:
- 65 % of deliveries were completed by bicycle, 35 % by scooter;
- Average restaurant-to-customer distance: 2.7 ± 1.2 km;
- Average preparation time: 11.8 ± 4.5 min;
- Mean delivery time: 21.3 ± 5.7 min.

Rider speeds and service areas are calibrated from GPS traces, yielding empirical velocity distributions: $v_{\text{bike}} \in [9.16]$ km/h and $v_{\text{scooter}} \in [18.32]$ km/h. These empirical profiles ensure that the model's variability reflects observed operational conditions.

Spatial routing occurs on a reconstructed street graph $G = (V, E)$, extracted from "OpenStreetMap" data (Figure 2). Edge weights $w_e$correspond to empirically estimated travel times derived from the dataset's historical routes, aggregated by road category and vehicle type. Route computation follows Dijkstra's algorithm for single-order deliveries and a simplified *traveling salesman problem* (TSP) heuristic (nearest-neighbor + 2-opt) for multi-stop scenarios.

The vehicle assignment follows an empirically validated rule (equation (1)):

$$\text{vehicle}\,(o) = \begin{cases} \text{bike}, & \text{if dist}\,(p, d) \le D_{\text{bike}} \text{ and } \widehat{T}_{\text{bike}}\,(o) \le \widehat{T}_{\text{scooter}}\,(o); \\ \text{scooter}, & \text{otherwise.} \end{cases} \tag{1}$$

where D_{bike}corresponds to the 80th percentile of bicycle trip distances observed in the empirical dataset (approximately 3.0 km).

3.2 Single-order delivery model (baseline)

In the first configuration (Model 1), each rider is assigned exactly one order per trip. The system simulates the

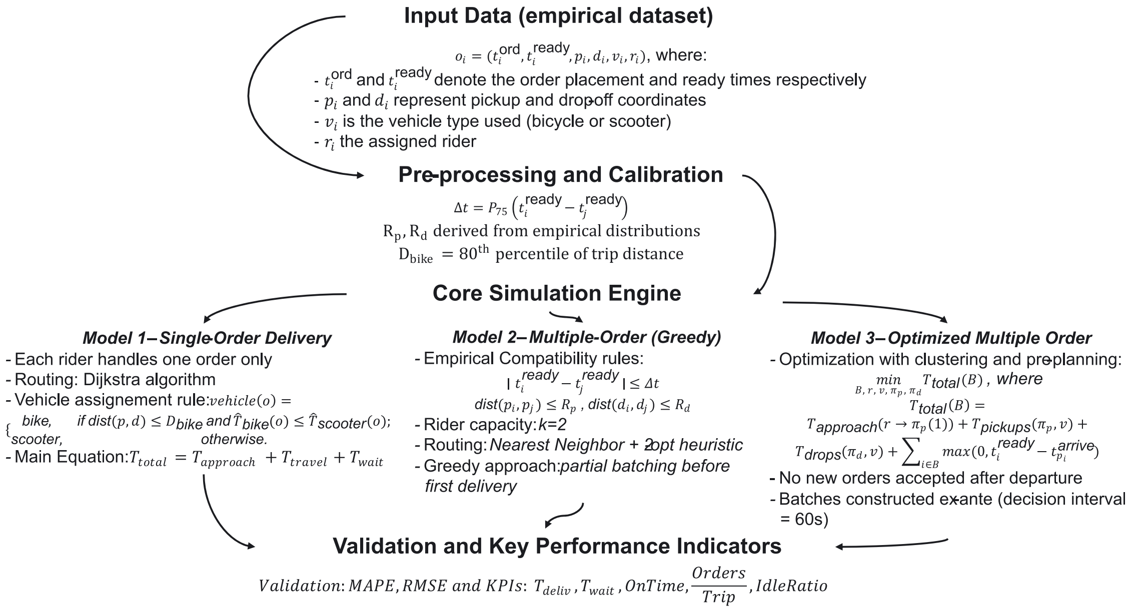

Figure 1: Simulation-based optimization framework.

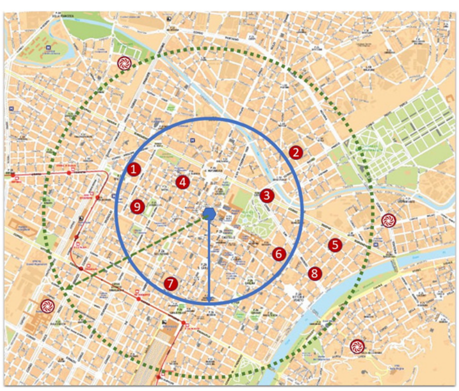

Figure 2: Customers' orders area.

operational paradigm of most existing delivery platforms, where batching is not permitted and routing is optimized only for the shortest path between the pickup and drop-off points. For every order that becomes available ($t \ge t_i^{ready}$), the model evaluates both vehicle types and selects the one with the lowest expected travel time, based on empirical averages from the dataset. The chosen order is assigned to the nearest idle rider of that type, determined by equation (2):

$$r^* = \arg\min_{r \in \mathscr{R}_v} \text{ETA}(r \to p_i) \tag{2}$$

The resulting route $r^* \to p_i \to d_i$ is computed using Dijkstra's algorithm. Riders remain unavailable until the order is completed, preventing new assignments mid-trip. This model forms the baseline scenario for efficiency comparisons.

3.3 Multiple-order delivery model (greedy batching)

The second configuration (Model 2) introduces the possibility of multi-order delivery through a greedy batching mechanism. Orders are grouped when their pickup and delivery coordinates, as well as preparation times, satisfy empirical compatibility thresholds derived from the observed data:

– Temporal proximity: $|t_i^{ready} - t_j^{ready}| \le \Delta t$, where Δt equals the 75th percentile of preparation-time differences (≈5 min);
– Pickup proximity: $\text{dist}(p_i, p_j) \le R_p$, with R_p = 400 m;
– Drop-off proximity: $\text{dist}(d_i, d_j) \le R_d$, with R_d = 700 m.

Batches are built greedily from the pool of available orders until the capacity k = 2 is reached. The route structure includes all pickups ordered by readiness time and all drop-offs sequenced by nearest neighbor. Riders may accept additional compatible orders before their first delivery, reflecting the partial dynamism observed in actual platforms.

This model approximates real-world practice, improving resource utilization while accepting limited inefficiency from non-optimal routing. It represents an intermediate configuration between operational realism and optimization.

3.4 Optimized multiple-order delivery model

The third configuration (Model 3) extends the previous one by introducing full pre-planning and routing optimization. All orders in a batch are pre-assigned before departure, and no additional tasks are accepted once the trip begins.

At discrete decision intervals (every 60 s), the system analyzes the active order pool and constructs candidate batches through spatial clustering, using empirical radii R_p and R_d as derived from paragraph 3.3. For each batch B, feasible pickup and drop-off sequences (π_p, π_d) are generated and their total travel time estimated by following equation (3):

$$T_{\text{total}}(B) = T_{\text{approach}}\left(r \to \pi_p(1)\right) + T_{\text{pickups}}(\pi_p, v) + T_{\text{drops}}(\pi_d, v) + \sum_{i \in B} \max\left(0, t_i^{\text{ready}} - t_{p_i}^{\text{arrive}}\right) \quad (3)$$

The optimal batch minimizes $T_{\text{total}}(B)$ jointly over rider, vehicle, and sequence configurations (equation (4)):

$$\min_{B, r, v, \pi_p, \pi_d} T_{\text{total}}(B) \quad (4)$$

This *optimized multiple-delivery model* aims to capture the performance of an algorithmically advanced platform capable of planning entire delivery rounds *ex ante*, balancing travel efficiency with service reliability.

3.5 Learning and routing components

Empirical records from historical deliveries are used to train a k-nearest neighbors (k-NN) regressor that predicts travel times for each segment e and vehicle v (equation (5)):

$$\hat{t}_e(v) = \frac{1}{K} \sum_{k \in \mathcal{N}_K(e,v)} t_e^{(k)} \quad (5)$$

where $\mathcal{N}_K(e, v)$ represents the Kmost similar past observations by distance, traffic condition, and time of day.

For route computation, Dijkstra's algorithm is applied to single-order paths, while a TSP heuristic combining nearest-neighbor initialization and 2-opt refinement is used for multi-stop optimization. These techniques ensure computational tractability while maintaining alignment with real routing data.

3.6 Evaluation metrics and validation protocol

Model performance is evaluated using both empirical validation and simulation-based comparison.

Customer-oriented metrics include:
- Mean delivery time T_{deliv};
- Mean waiting time after preparation T_{wait};
- On-time delivery rate for thresholds $\tau \in \{25, 35\}$ min.

Operational metrics include:
- Orders per trip (OPT);
- Distance per order (km/order);
- Idle time ratio (waiting/active time);
- Vehicle utilization rate (bikes vs scooters);
- Batch share (% of orders delivered in batches).

All results from the simulated models are compared against the empirical benchmarks extracted from the dataset, enabling quantitative validation of each configuration.

The multiple-order model is expected to outperform the single-order baseline, while the optimized multiple-order model should further reduce delivery times and distances, demonstrating its validity and practical potential when aligned with real-world delivery data.

To ensure the reliability and external validity of the proposed simulation framework, a two-step validation process is adopted. The first phase consists of parameter calibration using empirical data, while the second focuses on model validation through quantitative comparison between simulated outcomes and observed real-world performance.

Empirical data described in paragraph 3.1 (dataset description) are used to calibrate the model's key parameters:
- Mean and variance of restaurant preparation times;
- Average rider speeds and their distribution by vehicle type;
- Typical pickup–delivery distances and time-window thresholds (Δt, R_p, R_d);
- Historical order density over time (orders/hour).

Calibration minimizes the mean absolute percentage error (MAPE) between simulated and observed trip durations for the single-order baseline, depicted in equation (6).

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{T_i^{\text{sim}} - T_i^{\text{obs}}}{T_i^{\text{obs}}} \right| \times 100 \quad (6)$$

The model is considered sufficiently calibrated when MAPE ≤10 %, indicating that simulated delivery times approximate the empirical distributions within acceptable bounds.

The second phase evaluates the predictive consistency of the simulation by comparing model outputs with held-out empirical data. Three key aspects are assessed:

(1) **Temporal validation:** comparison of average delivery time trends (15 min intervals) between empirical and simulated datasets using Pearson [29] correlation r and Root Mean Square Error (RMSE), visible in equation (7).
(2) **Spatial validation:** comparison of mean delivery distances across city zones to verify consistency of routing patterns.
(3) **Operational validation:** evaluation of vehicle usage and batching rates against observed values, using chi-square goodness-of-fit tests.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(T_i^{\mathrm{sim}} - T_i^{\mathrm{obs}}\right)^2} \tag{7}$$

Model reliability is confirmed when correlation $r > 0.85$ and RMSE ≤3 min for delivery times. The validation process is repeated independently for bicycles and scooters to ensure that both fleet components are realistically reproduced.

Finally, the simulated performance of the three models —single-order, multiple-order, and optimized multiple-order—is benchmarked against the empirical baseline extracted from the dataset. Statistical tests—Wilcoxon signed-rank for paired measures, analysis of variance (ANOVA) for aggregated metrics)—determine whether observed improvements are significant at a 95 % confidence level [28, 30].

This validation setup provides a robust methodological link between empirical observations and simulated optimization results, ensuring that the model's conclusions are grounded in real operational data.

4 Results and discussion

The simulation outputs were validated against the empirical dataset described in paragraph 3.1 to assess predictive reliability. Across all configurations, simulated delivery times and distances were strongly correlated with observed data, confirming the robustness of the calibration and validation phases (paragraph 3.6). The overall correlation coefficient between simulated and empirical delivery times was $r = 0.88$ (RMSE = 2.7 min), indicating that the model reproduces real operational dynamics with high fidelity. Correlation was slightly higher for scooters ($r = 0.91$) than for bicycles ($r = 0.86$), consistent with the lower variance observed in scooter speeds. Average simulated trip distances matched empirical observations closely (mean difference = 0.14 km), and the spatial distribution of deliveries per zone followed the empirical pattern (χ^2 test, $p > 0.05$). Overall, the model accurately represents the real delivery network and the heterogeneity of the fleet.

Table 1 summarizes the main quantitative results obtained from the three simulation models and the empirical benchmark.

The multiple-order configuration (Model 2) reduced the mean delivery time by 15.4 % compared to the single-order baseline, while the optimized version (Model 3) achieved an additional 8 % reduction. The average number of orders per trip rose from 1.0 to 1.8, confirming a substantial improvement in operational efficiency without a proportional increase in travel distance. Differences between models were statistically significant ($p < 0.01$, ANOVA), confirming that improvements were not due to random variation.

Temporal aggregation shows that the optimized model consistently outperformed the others throughout the simulation window, with the greatest time savings during peak demand (18:45–19:30), when higher order density enabled efficient batching. Spatially, gains were concentrated in central areas with dense restaurant clusters, whereas peripheral zones benefited less because of longer average travel distances and fewer batching opportunities. This confirms that the advantages of optimization depend on the spatial concentration of demand, consistent with findings by Li et al. [26] and Yildiz and Kara [28].

Further insight can be gained by disaggregating results by vehicle type (Table 2).

Scooters consistently exhibited shorter mean delivery times due to higher cruising speeds, while bicycles achieved greater operational density in central areas. The optimized model (Model 3) balanced fleet utilization more effectively, reducing idle time for both categories. Average idle ratios declined from 0.29 to 0.21 for bicycles and from 0.25 to 0.20

Table 1: Overall model comparison.

Metric	Empirical	Model 1 (single)	Model 2 (multiple)	Model 3 (optimized)
Mean delivery time (min)	21.3	22.1	18.7	17.2
Mean waiting time (min)	9.4	9.8	7.1	6.3
Order per trip	1.00	1.00	1.72	1.80
Distance per order (km)	2.7	2.8	2.1	1.9
On-time rate (<35 min)	91.2	89.8	94.1	96.3
% bicycle trips	65	62	64	66
% scooter trips	35	38	36	34

Table 2: Model performance by vehicle type.

Vehicle type	Mean delivery time (min)	Order per trip	Idle time ratio	Mean distance per order
Bike - Model 1	23.5	1.0	0.29	2.1
Bike - Model 2	19.3	1.6	0.23	1.9
Bike - Model 3	17.6	1.8	0.21	1.8
Scooter - Model 1	20.8	1.0	0.25	3.4
Scooter - Model 2	18.2	1.7	0.21	2.9
Scooter - Model 3	16.8	1.9	0.20	2.7

for scooters, showing that optimization improved resource coordination across vehicle types. These findings confirm that vehicle differentiation enhances fleet efficiency when integrated with multi-order routing, especially by assigning bicycles to short intra-cluster routes and scooters to longer or peripheral ones.

Statistical validation reinforced these outcomes. The Wilcoxon signed-rank test [30] indicated significant differences in delivery-time distributions among models ($Z = -4.72$, $p < 0.001$), while Levene's test [31] showed no significant rise in variance ($p > 0.05$), suggesting that optimization reduces mean times without increasing volatility. Pairwise comparisons revealed that the optimized model achieved an average travel-time saving of 14.5 % per order relative to Model 2 and 21.8 % relative to Model 1, with a 95 % confidence interval of ± 2.3 %.

Overall, the empirical evidence demonstrates that the integration of vehicle differentiation, multi-order delivery, and shortest-path optimization yields consistent operational gains under realistic conditions. Improvements are moderate in magnitude but statistically robust and obtained without compromising reliability, an aspect particularly relevant for platforms seeking stability rather than aggressive performance increases. In practical terms, multi-order delivery can raise throughput by roughly 60 %–80 % with only minor growth in travel distance, while vehicle-aware assignment prevents inefficiencies from mismatched routes. Optimization of batch sequencing in Model 3 provides an incremental yet stable reduction in delivery time and idle intervals, effectively refining the greedy batching logic of Model 2 into a globally optimized planning process. Thus, Model 3 can be regarded as the fully optimized evolution of Model 2, preserving its operational structure while eliminating local inefficiencies (Figure 3).

4.1 Model assumptions and limitations

The proposed simulation relies on several simplifying assumptions that enable analytical tractability but may limit generalization. First, the model assumes that all restaurants and customers are static points on a fixed street network, neglecting short-term variations in accessibility or temporary closures. Rider behavior is modeled deterministically within each delivery phase—pickup, travel, and drop-off—without accounting for micro-level variability such as waiting at traffic lights or searching for parking.

The fleet is considered fully available during the simulation window, and rider cancellations or off-platform activities are not simulated. Similarly, restaurant preparation times are treated as exogenous and independent across orders, although in practice they may depend on kitchen

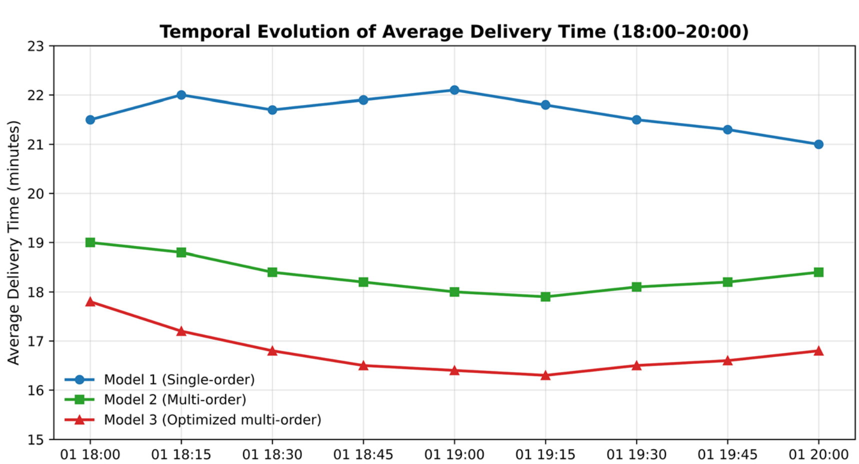

Figure 3: Average delivery time temporal evolution.

workload and staffing levels. The model does not incorporate stochastic traffic congestion or weather disruptions, which could affect real-world travel speeds.

Another limitation concerns the optimization scope. The optimized multiple-order model assumes perfect information about order readiness and travel conditions at the time of assignment, which may not always be achievable in operational settings. While empirical calibration mitigates some of these biases, real-time uncertainty remains a challenge for future extensions.

Despite these simplifications, the model reproduces aggregate performance patterns observed in empirical data with high fidelity. Therefore, the assumptions primarily affect the precision of individual predictions rather than the validity of the overall comparative results. Future research could address these limitations by integrating stochastic travel models, real-time rider behavior, and adaptive reallocation mechanisms after batch completion.

5 Conclusions

In a context initially characterized by a Blue Ocean but now evolved into a Red Ocean due to emerging competition, capturing and retaining customers becomes essential for business survival [32].

This study developed and validated a simulation framework for optimizing urban food delivery operations through the joint consideration of vehicle differentiation, multiple-order management, and route optimization. Building on previous research in ETA prediction and on-demand logistics, the model introduced a structured comparison between three delivery configurations: the single-order baseline, a greedy multiple-order system, and an optimized multiple-order model integrating global batch planning and shortest-path routing.

Empirical validation against real delivery data confirmed that the simulation accurately reproduces operational patterns across both bicycles and scooters, with strong correlation coefficients ($r > 0.85$) and low RMSE values. Comparative analysis demonstrated that the multiple-order strategy improves average delivery efficiency by 15–20 % relative to single-order operations, while the optimized configuration achieves a further 8 % reduction in delivery times. These improvements are statistically significant yet moderate in scale, supporting the feasibility of gradual implementation without compromising service reliability.

Beyond operational efficiency, the findings highlight broader economic and sustainability implications. Shorter and better-coordinated delivery routes reduce total vehicle kilometers and idle time, leading to lower fuel consumption and carbon emissions. The optimization of vehicle assignment also enhances fleet productivity, enabling more deliveries per rider and improving platform-level profitability. From the customer perspective, reduced waiting times and more consistent delivery performance contribute directly to higher satisfaction, perceived reliability, and potential retention-key drivers of long-term competitive advantage for on-demand platforms. Consequently, the proposed approach supports both economic sustainability (through cost efficiency and productivity gains) and environmental sustainability (through smarter allocation of low-impact vehicles and reduced travel redundancy).

The analysis also highlighted several simplifying assumptions that constrain generalization, namely fixed network topology, full rider availability, and deterministic travel times. Nonetheless, these simplifications affect only the granularity of predictions, not the consistency of comparative findings. Future work should extend the framework by incorporating stochastic traffic conditions, dynamic reallocation after batch completion, and adaptive dispatch algorithms capable of learning from real-time performance feedback. Such developments could further improve utilization efficiency and reduce idle travel, bringing simulation outcomes even closer to real operational performance.

It should therefore be noted that this work, while contributing to the development of existing models, at the same time needs further study with future applications and implementations due to the limitations of components integration such as ETA estimation, route optimization and order assignment, in unified and realistic simulation framework that currently remains limited and improvable.

In conclusion, the proposed approach demonstrates that algorithmic coordination—combining multi-order delivery, vehicle-aware assignment, and optimized routing—can deliver tangible efficiency improvements under realistic conditions. While the model simplifies certain behavioral and environmental aspects, it provides a transparent, empirically grounded basis for advancing both the economic viability and environmental sustainability of urban food delivery systems.

Abbreviations

ANOVA	Analysis of variance
B2C	Business-to-consumer
ETA	Estimated time of arrival
k-NN	k-nearest neighbors
MAPE	Mean absolute percentage error
RMSE	Root mean square error

TSP	Traveling salesman problem
VRP	Vehicle routing problems

Research ethics: Not applicable.
Informed consent: Not applicable.
Author contributions: All authors have accepted responsibility for the entire content of this manuscript and approved its submission.
Use of Large Language Models, AI and Machine Learning Tools: None declared.
Conflict of interest: No conflict of interest.
Research funding: None declared.
Data availability: None declared.

References

1. Ahuja K, Chandra V, Lord V, Peens C. Ordering in: the rapid evolution of food delivery. New York: Technology, Media & Telecommunications Practice, McKinsey Global Publishing, McKinsey and Company; 2021.
2. Bivona E. Determinants of performance drivers in online food delivery platforms: a dynamic performance management perspective. Int J Prod Perform Manag 2023;72:2497–517.
3. Bruzzone AG, Massei M, Bocca E. Fresh-food supply chain. In: Simulation-based case studies in logistics: education and applied Research. London: Springer; 2009:127–46 pp.
4. Bruzzone AG, Massei M, Longo F, Scalzo D, Martini C, Villanueva J, et al. Simulation based design of innovative quick response processes in cloud supply chain management for “slow food” distribution, in theory, methodology, tools and applications for modeling and simulation of complex systems. In: 16th asia simulation conference and SCS autumn simulation multi-conference, AsiaSim/SCS AutumnSim 2016, Beijing, China, October 8-11, proceedings, Part III 16. Singapore, Springer 2016. p. 25–34.
5. Bruzzone AG, Ferraris GM, Ferrero F. Optimization based on innovative models for online food delivery and supply chain management. In: Proceeding of the 10th international food operations & processing simulation (FOODOPS) workshop; 2024.
6. Bhatt P. Perceived organizational culture across generation, tenure, and gender- an exploratory study. Organ Dev J 2020;38:9–20.
7. Tran V-D, Vu QH. Inspecting the relationship among E-service quality, E-trust, E-customer satisfaction and behavioral intentions of online shopping customers. Glob Bus Finance Rev 2019;24. https://doi.org/10.17549/gbfr.2019.24.3.29.
8. Chekembayeva G, Garaus M, Schmidt O. The role of time convenience and (anticipated) emotions in AR mobile retailing application adoption. J Retailing Consum Serv 2023;72. https://doi.org/10.1016/j.jretconser.2023.103260.
9. Annaraud K, Berezina K. Predicting satisfaction and intentions to use online food delivery: what really makes a difference? J Foodserv Bus Res 2020;23:1–19.
10. Ali S, Khalid N, Javed HMU, Islam DMZ. Consumer adoption of online food delivery ordering (OFDO) services in Pakistan: the impact of the COVID-19 pandemic situation. J Open Innov Technol Mark Complex 2020;7:10.
11. Dsouza D, Sharma D. Online food delivery portals during COVID-19 times: an analysis of changing consumer behavior and expectations. Int J Innovat Sci 2021;13:218–32.
12. Min H, Kim HJ, Agrusa J. Serving diverse customers: the impact of cultural intelligence on employee burnout, engagement, and job satisfaction. J Hospit Tourism Res 2023;47:503–27.
13. Yeo VCS, Goh S-K, Rezaei S. Consumer experiences, attitude and behavioral intention toward online food delivery (OFD) services. J Retailing Consum Serv 2017;35:150–62.
14. Hua G, Wang S, Cheng TCE. Price and lead time decisions in dual-channel supply chains. Eur J Oper Res 2010;205:113–26.
15. Wang Y, Zheng Y, Xue Y. Travel time estimation of a path using sparse trajectories. In: Proceedings of the 20th ACM SIGKDD international conference on knowledge discovery and data mining 2014. p. 25–34.
16. Wang HT. The construction of the strategy selection behavior of online food delivery platform based on the tripartite evolutionary game model. Asia Pac Manag Rev 2022. https://doi.org/10.1016/j.apmrv.2022.12.004.
17. Liu S, He L, Shen ZJM. On-time last-mile delivery: order assignment with travel-time predictors. Manag Sci 2021;67:4095–119.
18. Hildebrandt F, Ulmer MW. Supervised learning for arrival time estimations in restaurant meal delivery. Transp Sci 2020;56. https://doi.org/10.1287/trsc.2021.1095.
19. Gao C, Zhang F, Wu G, Hu Q, Ru Q, Hao J, et al. A deep learning method for route and time prediction in food delivery service. In: Proceedings of the 27th ACM SIGKDD conference on knowledge discovery and data mining 2021. p. 2879–89.
20. Salari N, Liu S, Shen Z-JM. Real-time delivery time forecasting and promising in online retailing: when will your package arrive? Manuf Serv Oper Manag 2022;24:1421–36.
21. Beardwood J, Halton JH, Hammersley JM. The shortest path through many points. Math Proc Camb Phil Soc 1959;55:299–327 1959.
22. Toth P, Vigo D. Vehicle routing: problems, methods, and applications, 2nd ed. Philadelphia: SIAM – Society for Industrial and Applied Mathematics; 2014.
23. Dijkstra EW. A note on two problems in connexion with graphs. Numer Math 1959;1:269–71.
24. Gass S, Fu M. Dijkstra’s algorithm, encyclopedia of operations research and management science. Berlin: Springer; 2013.
25. Chen Y, Wang H. Pricing for a last-mile transportation system. Transp Res B 2017;107:57–69.
26. Li J, Fang D, Li X. Dynamic batching and routing optimization in on-demand food delivery systems. Comput Ind Eng 2020;149:106829.
27. Siddhartha P, Doreswamy G. An optimization model for priority-based on-demand meal delivery system. In: International Conference on industrial engineering and engineering management, IEEM; 2022.
28. Yildiz B, Kara BY. Heterogeneous vehicle routing in urban last-mile delivery: balancing efficiency and sustainability. Transport Res E Logist Transport Rev 2022;159:102625.
29. Pearson K. Note on regression and inheritance in the case of two parents. Proc Roy Soc Lond 1895;58: 240–2.
30. Wilcoxon F. Individual comparisons by ranking methods. Biometrics Bull 1945;1:80–3.
31. Levene H. Robust tests for equality of variances. In: Olkin I, editor. Contributions to probability and statistics: essays in honor of harold hotelling. Stanford University Press; 1960:278–92 pp.
32. Kim WC, Mauborgne R. Blue ocean strategy, 2nd ed. Milan: Rizzoli Etas; 2021.

Supplementary Material: This article contains supplementary material (https://doi.org/10.1515/ijfe-2025-0028).