Meituan: Operational-Level On-Demand Food Delivery Data for the 2025 INFORMS TSL Data-Driven Research Challenge

Hai Wang[a], Lei Zhao[b*], Kaile Yan[b], Xiaoyi Wang[b], Yile Liang[c], Jinghua Hao[c]
[a] School of Computing and Information Systems, Singapore Management University
[b] Department of Industrial Engineering, Tsinghua University
[c] Meituan
[*] Corresponding author: lzhao@tsinghua.edu.cn

Abstract. The INFORMS Transportation Science and Logistics (TSL) Society and the journal *Transportation Science* host the First INFORMS TSL Data-Driven Research Challenge in 2024-2025. This challenge is supported by Meituan, China's largest on-demand food delivery platform, which provides a rich operational-level dataset to facilitate data-driven research on food delivery services. This article outlines the food delivery process from the perspective of the order lifecycle and offers a detailed description of the dataset, which contains 568,546 orders, 4,955 couriers, and 4,962 merchants, as well as records of key concepts such as "waybill" and "wave." It also presents a descriptive analysis of the dataset and highlights key observations, insights, and implications with respect to orders, couriers, merchants, and dispatches. Researchers are encouraged to leverage this dataset to address real-world challenges with both practical significance and academic innovation, using data-driven techniques, analytical models, and optimization methods.

Key words: on-demand food delivery, three-sided market, operational-level data, INFORMS TSL society, data-driven research

1. Introduction

On-demand food delivery service is a vibrant emerging industry market that has experienced significant growth in recent years. This growth is attributed to urbanization and the convenience of the service. The COVID-19 pandemic has further accelerated the adoption of food delivery services. According to Statista (2024), worldwide revenue (i.e., gross merchandise value) in the food delivery market reached USD 1,198.4 billion in 2024 and is expected to increase to USD 1,854.5 billion by 2029. The penetration rate was 25.2% in 2023 and is expected to rise to 28.2% by 2025. Regionally, Asia is leading the charge, with projected revenues of USD 717.6 billion by 2025 and an annual growth rate of 8.34%. China is expected to generate the highest revenue, reaching USD 500.5 billion in 2025. North America also shows robust potential, with projected revenues of USD 457.5 billion in 2025. Europe is likewise experiencing significant growth, although its market size remains relatively small, with Southern Europe projected to reach USD 25.9 billion in 2025. Across the globe, several food delivery companies have established themselves as significant players in their respective regional markets. In the United States, DoorDash leads the market with a 67% share, followed by Uber Eats at 23%. In China, the market is largely controlled by two major platforms, Meituan and Ele.me, which leverage their scale to provide competitive pricing and extensive services. In Southeast Asia, Grab holds the leading position, while in Europe, Just Eat Takeaway is among the largest players.

In the on-demand food delivery service, as shown in Figure 1, after a customer selects the desired food and places an order on the platform, the platform pushes the order information to the merchant and subsequently dispatches the order to a courier. The courier then picks up the meal from the merchant and delivers it to the customer.

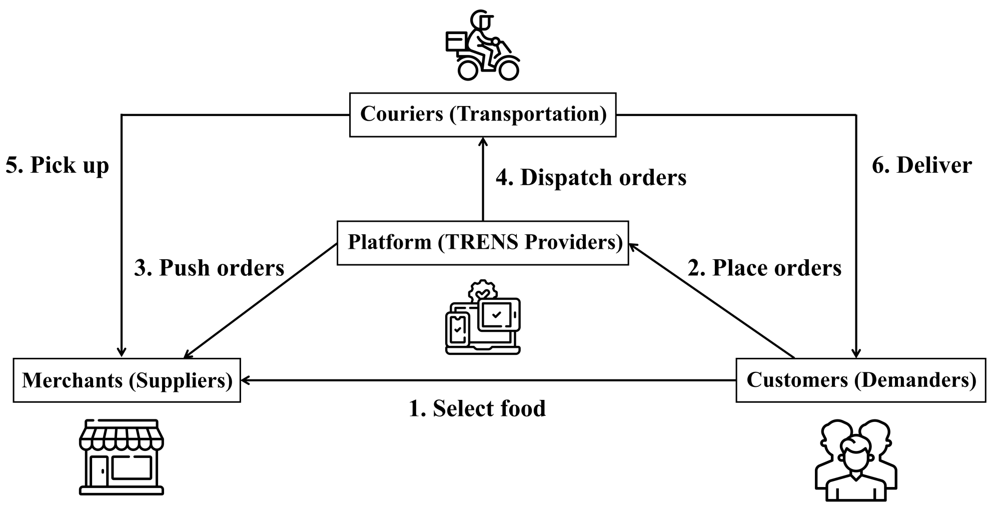


Figure 1 Model of food delivery service (adapted from Liang et al. 2024, with modifications)

On-demand food delivery service is a typical example of **TR**ansportation-**EN**abled **S**ervices (TRENS), which refers to the use of transportation systems to enhance and expand the delivery, accessibility, and effectiveness of non-transportation services (Agatz et al. 2024). TRENS involves four key stakeholders: demanders (i.e., customers), suppliers, transportation carriers, and TRENS providers. The food delivery platform (TRENS provider) serves as the central coordinator and manages complex interactions among the other three stakeholders. These multifaceted relationships engender various difficult tasks. On the platform-customer side, spatio-temporal demand estimation is critical, with significant implications for resource allocation. On the platform-merchant side, tasks include merchant recommendation and commission strategies. On the platform-courier side, the primary focus is the real-time dispatch of couriers. In addition, tasks such as designing incentives, ensuring courier safety, and evaluating the environmental impact of food packaging are also important. These efforts contribute to the sustainable development of the on-demand food delivery industry and create greater value for all stakeholders.

The INFORMS Transportation Science and Logistics (TSL) Society, in collaboration with Meituan, launches the First TSL Data-driven Research Challenge in 2024-2025 ("the TSL challenge" hereafter) to motivate data-driven research in the context of on-demand food delivery services. Meituan, the largest food delivery platform in China, provides a dataset ("the Meituan dataset" hereafter) of 568,546 orders placed by customers within a 50 km × 40 km area between October 17 and 24, 2022, which involves 4,955 delivery couriers and 4,962 merchants. The dataset also provides information at three selected dispatching decision epochs during the noon peak on each date over the eight days, with each epoch comprising approximately 600 orders awaiting dispatch and 2,500 candidate couriers. The rich dataset offers researchers a valuable opportunity to examine the complexities of food delivery systems.

The challenge aims to foster synergy between academic research and practical applications, which emphasize data-driven approaches that generate new insights into real-world food delivery operations. In this article, we (1) outline the food delivery process from the perspective of the order lifecycle; (2) describe the Meituan dataset in detail; and (3) highlight key observations, insights, and implications regarding orders, couriers, merchants, and dispatches.

2. The Food Delivery Process

Figure 2 illustrates the food delivery process from the perspective of the order lifecycle, from order creation to completion, in a typical on-demand food delivery service.

Step 1. Place an order. The customer selects the desired food offered by a merchant (restaurant) and places an order in the app of the platform.

Step 2. Create the order. The platform receives the order from the customer and creates a (delivery) order in its system.

Step 3. Push the order. The platform sends order information to the corresponding merchant, requesting that the meal be prepared. At the same time, the order information enters the platform's dispatch system.

Step 4. Start meal preparation. Upon receiving the meal request from the platform, the merchant starts to prepare the meal. (Note that the merchant may decline the request due to reasons such as stock shortages, resulting in the order's cancellation. However, since such rejections are rare in practice, they are excluded from the analysis in this paper).

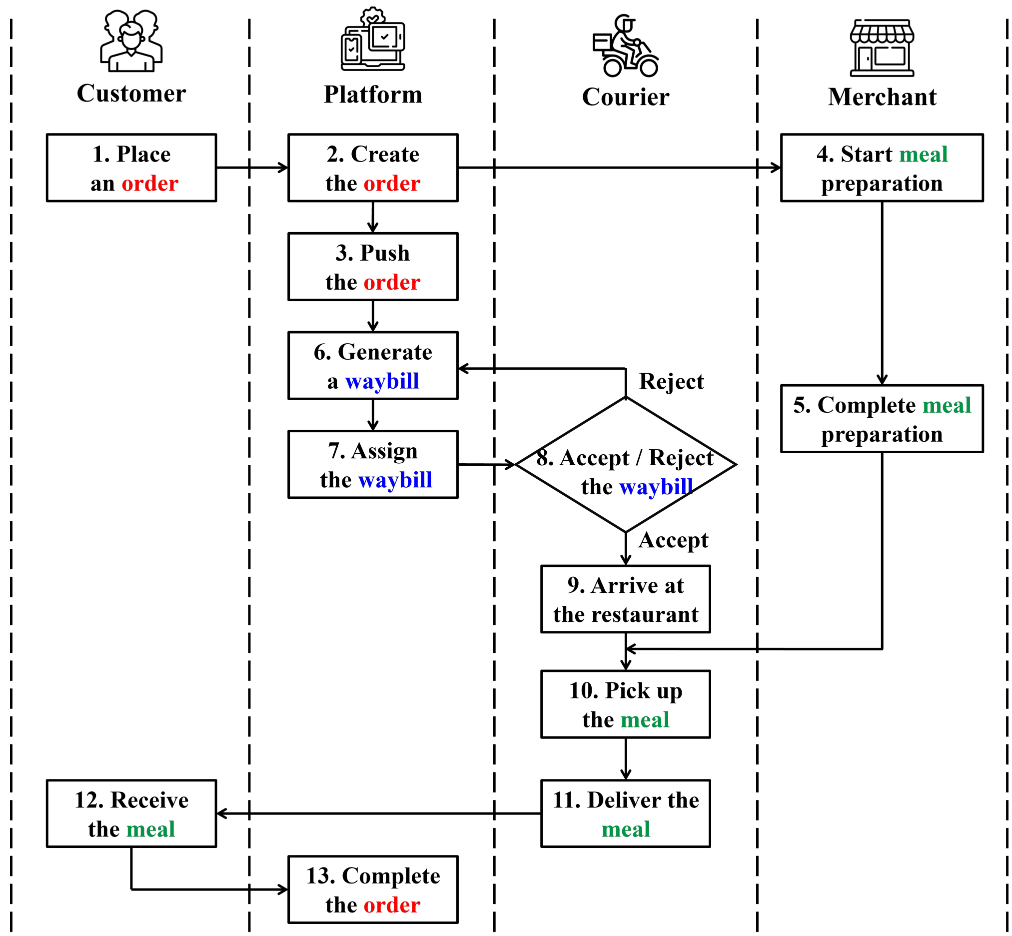


Figure 2 **Order lifecyle in a typical on-demand food delivery service**

Step 5. Complete meal preparation. The merchant completes the meal preparation, and the meal is ready for pickup.

Step 6. Generate a waybill. After order pushing, the dispatch system generates a waybill for the order.

Step 7. Assign the waybill. The dispatch system assigns the waybill to a suitable courier at an appropriate time. In this paper, the terms "assign" and "dispatch" are used interchangeably to denote the assignment of a waybill to a courier, regardless of whether the courier subsequently accepts or rejects it.

Step 8. Accept or reject the waybill. Upon receiving the assignment, the courier can either accept or reject it. (i) If the courier accepts the assigned waybill, the waybill proceeds and the order leaves the dispatch system. (ii) If the courier rejects the assigned waybill, the waybill is terminated, the order re-enters the dispatch system for reassignment with a new waybill generated (i.e., back to Step 6). In practice, some rejected waybills may be directed to an "order-snatching" pool for courier pickup, instead of being reassigned through the dispatch system. For simplicity, this paper does not consider the order-snatching mechanism.

Step 9. Arrive at the merchant. After accepting the assignment, the courier travels to and arrives at the merchant.

Step 10. Pick up the meal. The courier's pickup time depends on the meal's readiness. If the meal is ready upon the courier's arrival at the merchant (i.e., Step 5 is completed before Step 9), the courier picks up the meal and departs immediately. Otherwise, the courier waits at the merchant until the meal preparation is completed.

Step 11. Deliver the meal. The courier arrives at the customer's location and delivers the meal.

Step 12. Receive the meal. The customer checks the meal and confirms receipt through the app.

Step 13. Complete the order. Following the customer's confirmation, the platform completes the waybill and the order fulfillment process.

The operations of the on-demand food delivery system face three major challenges. First, the system operates under significant uncertainties, including customer demand occurrence, meal preparation time at merchants, courier availability and behavior, traffic conditions, and so on. Second, the system must balance the multiple objectives of different stakeholders, such as customers' expectations for timely delivery and fresh meals, merchants' desire for expedited order handling and business growth, and couriers' need for fair order assignments and adequate income. Last, the system must process a high volume of time-sensitive demand and make operational decisions within extremely short time frames (within minutes or seconds).

3. Data Description

In this section, we provide a detailed description of the Meituan dataset, which records order dispatch and food delivery activities over eight days between October 17 and October 24, 2022, in an anonymized midsize city in China. The dataset consists of four tables: (1) *waybills*, (2) *couriers*, (3) *dispatch orders*, and (4) *dispatch couriers*. The data can support research on decisions and performance in the order dispatch and delivery process, while research on pricing, recommendation mechanisms, and competition, etc., may not be well supported by these data. To ensure confidentiality, certain key identification information, such as user IDs, is anonymized.

In the following subsections, we provide detailed descriptions of each table.

3.1. The *Waybills* Table

The *Waybills* tables (Tables A.1 and A.2) provide information on 654,343 waybills associated with 568,546 orders between October 17 and October 24, 2022. Each waybill is uniquely identified by *waybill_id*, and each order is uniquely identified by *order_id*.

The table records the dates on which orders were created (labeled *dt*) and whether it was on a weekend (labeled *is_weekend*)—i.e., October 22 and October 23. It also specifies whether a waybill was accepted by the dispatched courier (labeled *is_courier_grabbed*). Specifically, once an order enters the dispatch system, the system generates a waybill and dispatches it to a courier. The courier may reject the waybill, in which case the order re-enters the dispatch system, a new waybill is generated, and the order is re-dispatched. Each dispatch of an order results in a new waybill associated with that order. As a result, a single order may correspond to multiple waybills, whereas each waybill is uniquely linked to one order and one dispatched courier.

The table includes the merchant ID (labeled *poi_id*), business district ID (labeled *da_id*), and courier ID (labeled *courier_id*) associated with each waybill. The orders are linked to 4,962 merchants distributed across 23 business districts. The system involves 4,955 couriers, 54 of whom did not accept any orders and rejected all dispatches.

The table indicates whether an order was pre-booked (labeled *is_prebook*). Orders are categorized into two types: on-demand and pre-booked. Pre-booked orders are placed by customers in advance with a scheduled delivery time later than that of typical on-demand delivery. After creation, a pre-booked order may follow one of the three paths: (a) it enters the dispatch system immediately and is dispatched to a courier who can deliver near the scheduled time; (b) it enters the dispatch system but is not dispatched until close to the scheduled delivery time; (c) it does not enter the dispatch system until close to the scheduled delivery time. In the dataset, only 3.9% of orders are pre-booked.

The table records a series of important timestamps in the food delivery process. Figure 3 illustrates these timestamps and their corresponding fields in the table, where *platform_order_time*, *order_push_time*, *dispatch_time*, *grab_time*, *fetch_time*, and *arrive_time* ("ATA" hereafter) represent the timestamps of actual events, while *estimate_arrived_time* ("ETA" hereafter) and *estimate_meal_prepare_time* ("EMR", estimated meal ready time, hereafter) are timestamps predicted by the platform based on order information. All timestamps are expressed in Unix format.

The order lifecycle comprises the following key events, each associated with a timestamp:

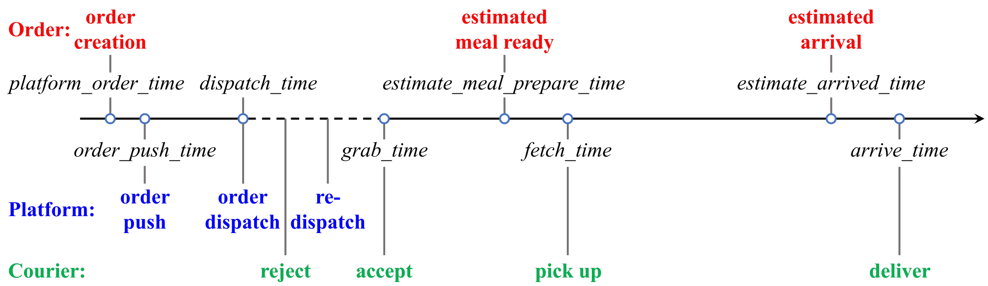


Figure 3 **Timeline of the food delivery process**

1. The customer places the order (labeled *platform_order_time*, corresponding to **Step 1** in Figure 2).

2. The platform pushes the order into the dispatch system (labeled *order_push_time*, corresponding to **Step 3**).

3. The platform dispatches the order to a courier (labeled *dispatch_time*, corresponding to **Step 7**). Note that the *dispatch_time* field in the dataset does not differentiate between the two types of dispatch discussed in **Step 8**).

4. The courier accepts the order (labeled *grab_time*, corresponding to **Step 8**).

5. The courier picks up the meal at the merchant's location (labeled *fetch_time*, corresponding to **Step 10**).

6. The courier delivers the meal to the customer (labeled *arrive_time*, corresponding to **Step 11**).

A waybill accepted by a courier includes all six timestamps listed above, while for a waybill rejected by a courier, the values of *grab_time*, *fetch_time*, and *arrive_time* are recorded as zero. Every waybill also contains two estimated timestamps—estimated arrival time (*estimate_arrived_time*) and estimated meal ready time (*estimate_meal_prepare_time*)—both of which are uniquely associated with the corresponding order ID. The field *estimate_arrived_time* denotes the promised delivery time based on the platform's predictions and other considerations. By Meituan's rule, *estimate_arrived_time* must be no earlier than 30 minutes after *platform_order_time*. If *arrive_time* exceeds *estimate_arrived_time*, this indicates a delay in delivery. The field *estimate_meal_prepare_time* represents the predicted meal ready time at the merchant, which may be either earlier or later than *fetch_time*.

The table also records geographic coordinates for several key events: *sender_lat*, *sender_lng*, *recipient_lat*, *recipient_lng*, *grab_lat*, and *grab_lng*. Specifically, *sender_lat* and *sender_lng* denote the latitude and longitude of the merchant associated with the order; *recipient_lat* and *recipient_lng* denote the latitude and longitude of the customer's specified location; *grab_lat* and *grab_lng* denote the latitude and longitude of the courier at the time of order acceptance. If a waybill is rejected by the courier, *grab_lat* and *grab_lng* are set to 0. All latitude and longitude values have been uniformly shifted to preserve confidentiality without affecting relative distance estimation.

3.2. The *Couriers* Table

The *Couriers* table (Table A.3) summarizes the delivery behaviors of all 4,955 couriers between October 17 and October 24, 2022, based on records of "waves." A *wave* starts when a courier in an idle state (i.e., with no orders on hand) accepts a new order and ends once the courier completes all orders on hand and returns to idle status. A wave is uniquely identified by a composite key consisting of date (labeled *dt*), courier (labeled *courier_ID*), and wave ID (labeled *wave_ID*). For a given courier on a given date, the wave ID serves as a unique identifier for that particular wave.

The table records the set of order IDs included in each wave (labeled *order_ids*), with each wave containing at least one order. A courier's behaviors during the eight days can therefore be represented as a sequence of waves interspersed with idle intervals.

The table also records the start time (labeled *wave_start_time*) and end time (labeled *wave_end_time*) of each wave. The *wave_start_time* corresponds to the earliest *grab_time* among the accepted waybills (with *is_courier_grabbed* = 1), while the *wave_end_time* corresponds to the latest *arrive_time* among the accepted waybills. The duration of each wave is calculated as $wave\_end\_time - wave\_start\_time$. Since each accepted waybill uniquely corresponds to an order in the system, we may use the terms "order" and "waybill" interchangeably.

3.3. The *Dispatch Orders* and *Dispatch Couriers* Tables

At each dispatch decision epoch, the dispatch system evaluates the orders awaiting assignment and the pool of candidate couriers. The Dispatch Orders table (Table A.4) and Dispatch Couriers table (Table A.5) record information at three selected decision epochs (labeled *dispatch_time*) during the noon peak on each date (labeled *dt*) between October 17 and October 24, 2022.

Each row in Table A.4 corresponds an order awaiting assignment at a given decision epoch (*dispatch_time*) on a given date (*dt*). Each row in Table A.5 corresponds a candidate courier (*courier_id*) at a given decision epoch (*dispatch_time*) on a given date (*dt*). Table A.5 also provides the geographic coordinates (*rider_lat* for latitude and *rider_lng* for longitude) as well as the current set of on-hand orders (labeled *courier_waybills*) for each candidate courier. All latitude and longitude values have been uniformly shifted (same as in Table A.2) to preserve confidentiality without affecting relative distance estimation.

4. Data Analysis: Orders

In this section, we analyze the order data and present key insights. We examine the spatial and temporal patterns of orders in Sections 4.1 and 4.2. In Section 4.3, we analyze the patterns of ETA and ATA. In Sections 4.4 and 4.5, we analyze the delivery punctuality of orders.

4.1. Spatial Distribution of Orders

Figure 4 presents a density heat map that depicts the spatial distribution of customer orders. Each point in the figure represents a grid of 500 meters from west to east along the x-axis and 400 meters from south to north along the y-axis. The color intensity of each point represents the number of orders per hour with customer locations in that grid, under logarithmic normalization. The results reveal three subdistricts (labeled as 1, 2, and 3 from north to south) with notably high concentrations of orders in the city.

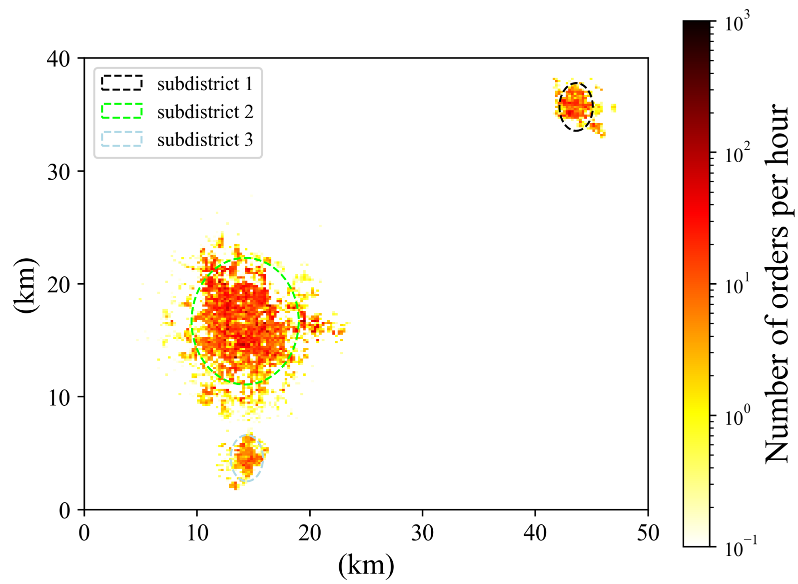
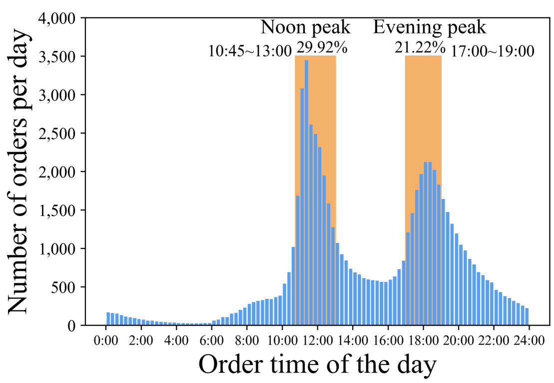


Figure 4 **Spatial distribution of orders (based on customer locations)**

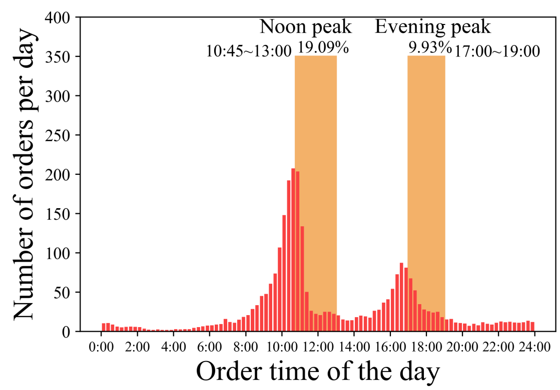
We use standard deviation ellipses to describe the range of each subdistrict. The standard deviation ellipse is a geographic statistical approach to analyze the spatial distribution and orientation of data. The ellipse is based on the standard deviation and covariance of the spatial data in different directions and covers a certain proportion of data points. In Figure 4, the 2-sigma standard deviation ellipses (the dashed ellipses) of the three subdistricts cover approximately 98% of all orders. The order density near the center of each subdistrict is high and decreases toward the edge. The three subdistricts correspond to ellipse areas of 9.81 km^2, 83.65 km^2, and 9.19 km^2, respectively, with subdistrict 2 being the largest.

4.2. Temporal Distribution of Orders

Figure 5 presents the daily temporal distribution of orders. The x-axis represents the time of day in 15-minute intervals (e.g., 13:00-13:15), and the y-axis represents the number of orders placed within each interval (defined by *platform_order_time*). Figures 5(a) and 5(b) show the temporal distribution of on-demand orders and pre-booked orders, respectively. Note that the y-axis scales differ between the two subfigures because on-demand orders are many more than pre-booked orders.



(a) On-demand orders



(b) Pre-booked orders

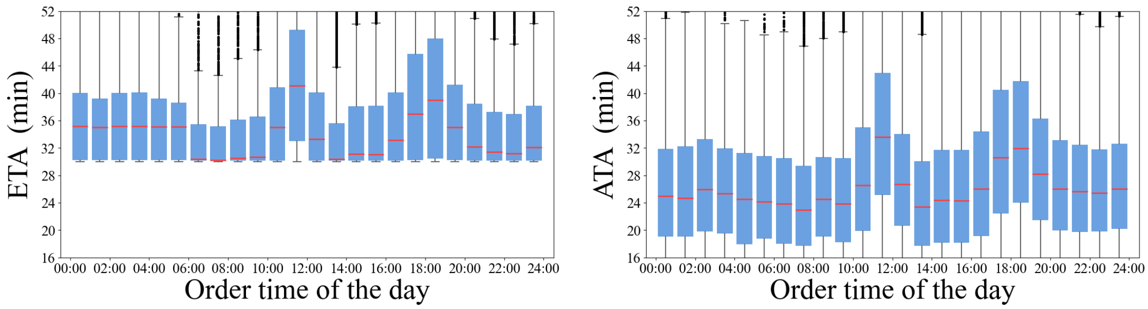
Figure 5 Temporal distribution of orders

We observe two significant peaks, noon and evening. For on-demand orders, the noon peak occurs between 10:45 and 13:00 and the evening peak between 17:00 and 19:00. The concentration of orders during the noon peak is higher than that during the evening peak. Pre-booked orders follow a similar pattern but the peaks are slightly earlier than those of the on-demand orders, possibly due to customers pre-booking orders slightly ahead of the meal time. In the rest of the paper, we focus our analysis on on-demand orders only (in the dataset, only 3.9% of orders are pre-booked).

4.3. ETA and ATA

Estimated Time of Arrival (ETA) refers to the estimated delivery time (*estimate_arrived_time*), and *Actual Time of Arrival* (ATA) refers to the actual delivery time (*arrive_time*). When there is no ambiguity, we also use ETA to denote the time interval from order placement (*platform_order_time*) to the estimated delivery time, and ATA to denote the time interval from order placement to the actual delivery time.

Figure 6 presents box plots of the daily temporal distributions of ETA and ATA for on-demand orders. The x-axis represents the time of day in one-hour intervals (e.g., 13:00-14:00), and the y-axis represents the distributions of ETA or ATA for orders placed within each interval.



(a) ETA (b) ATA

Figure 6 Temporal distribution of ETA and ATA

The platform imposes a minimum bound of 30 minutes for ETA. The average ETA is 37.8 minutes, and the average ATA is 29.6 minutes, which results in an average difference of about eight minutes. Similar to the temporal distribution of orders in Section 4.2, we observe noon and evening peaks for both ETA and ATA. Furthermore, the ETA and ATA during the noon peak are slightly longer than those during the evening peak.

4.4. Delivery Delay

Delivery delay is the difference between ATA and ETA (i.e., *arrive_time* - *estimate_arrived_time*). Note that a negative delivery delay indicates that the actual delivery time (ATA) is earlier than ETA.

Figure 7 presents a histogram of the delivery delays for on-demand orders. The x-axis represents the delivery delay in one-minute intervals, and the y-axis represents the average number of orders per day within each interval.

About 85.2% of orders have a negative delivery delay, which indicates that most orders are delivered earlier than ETA. Similar to the 8-minute difference observed between ETA and ATA in Figure 6, the average delivery delay is -8.2 minutes, with a standard deviation of 8.6 minutes.

4.5. Late Delivery Ratio

In practice, the platform may offer couriers a time buffer when measuring delivery punctuality. For example, Meituan offers an 8-minute buffer; that is, if the ATA of an order is within 8 minutes after the ETA, it is not considered a late delivery, and there is no penalty to the courier.

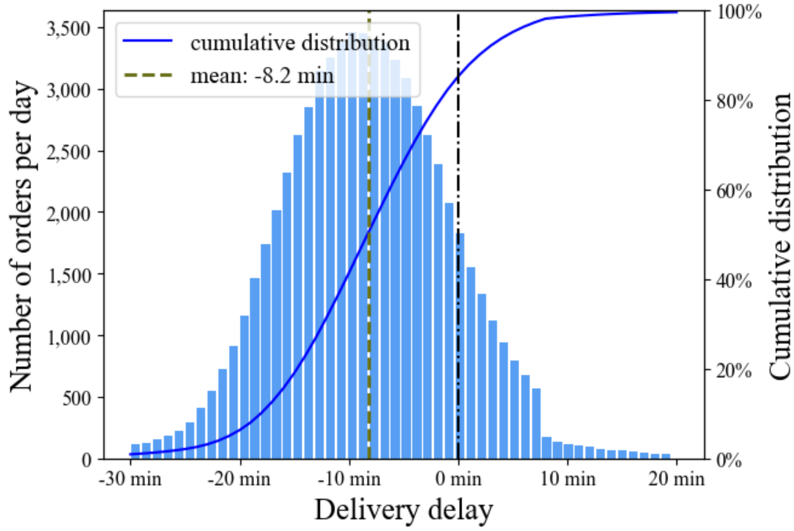
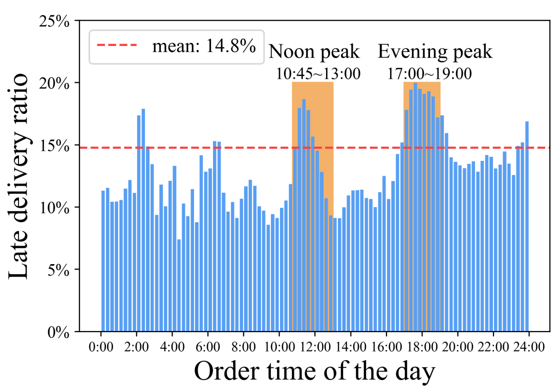
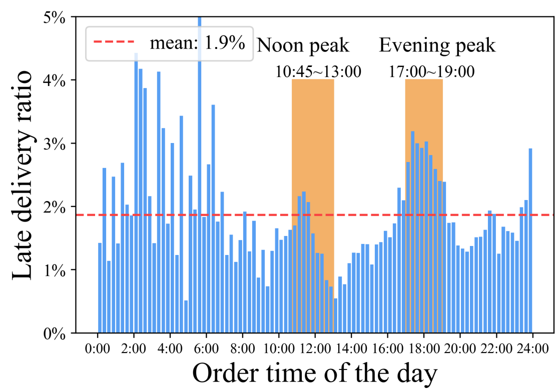


Figure 7 Distribution of delivery delays

Figure 8 presents histograms of the late delivery ratios for the on-demand orders under buffer times of zero and eight minutes. The x-axis represents the time of day in 15-minute intervals, and the y-axis represents the late delivery ratio measured as the proportion of late delivery orders among all orders placed within each interval.



(a) 0-minute buffer (no buffer)



(b) 8-minute buffer

Figure 8 Temporal distribution of late delivery ratios

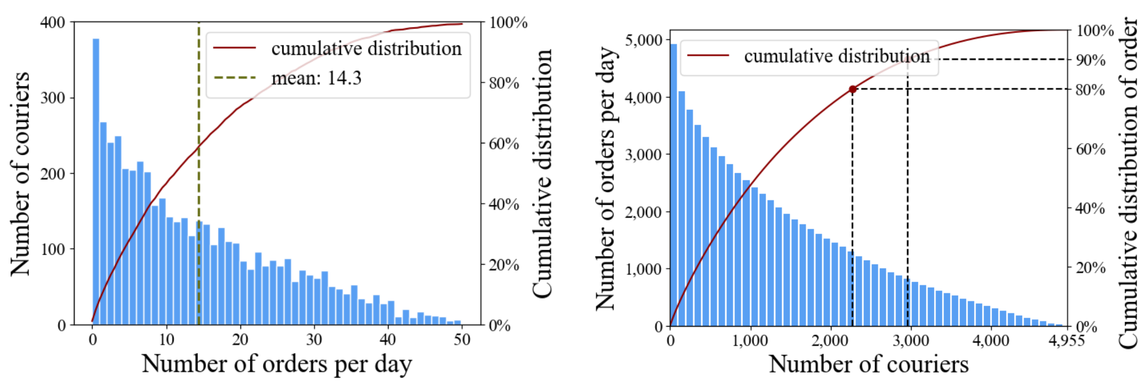
The average late delivery ratio is 14.8% without a buffer, decreasing to 1.9% with an 8-minute buffer. Similar to Figures 5(a) and 6, we observe a noon peak between 10:45 and 13:00 and an evening peak between 17:00 and 19:00. The late delivery ratio during the evening peak is higher than that during the noon peak. We also observe that the late delivery ratio fluctuates and is high during the early hours of the day (e.g., 2:00 to 7:00).

5. Data Analysis: Couriers

In this section, we analyze the courier data and present key insights. In Section 5.1, we examine the distribution of orders across couriers. In Section 5.2, we analyze the distribution of workdays and their relationship with the number of orders per workday. In Section 5.3, we introduce the concept of "waves" and analyze the associated data. In Section 5.4, we analyze the courier delivery punctuality. In Section 5.5, we present an illustrative example of a courier's trajectory within a wave and provide observations on courier behavior.

5.1. Number of Orders per Day

Figure 9 presents the distribution of the number of orders completed per day by couriers. Figure 9(a) shows the corresponding histogram, and Figure 9(b) shows the Pareto diagram.



(a) Histogram (b) Pareto diagram

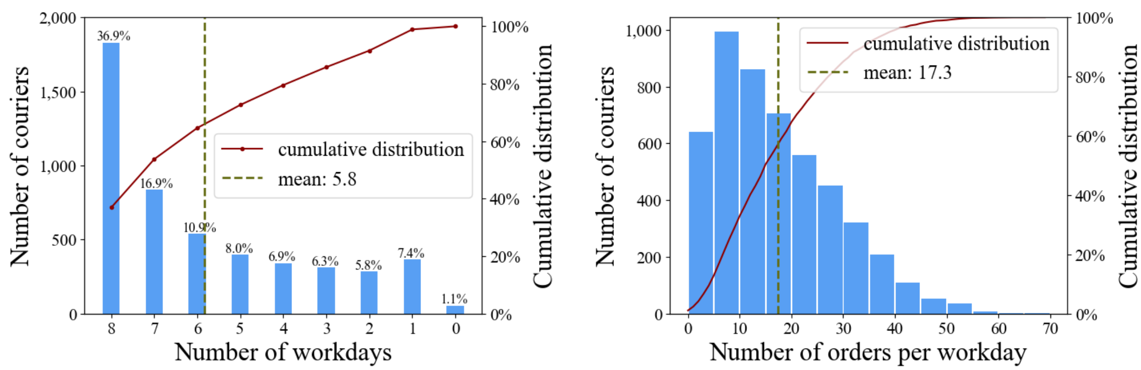
Figure 9 Distribution of the number of orders completed per day across couriers

In Figure 9(a), the x-axis represents the number of orders completed per day, and the y-axis represents the number of couriers who completed that number of orders. The average number of orders per day across couriers is 14.3, with a standard deviation of 12.0. Notably, 378 couriers delivered, on average, fewer than one order per day.

In Figure 9(b), the x-axis represents the cumulative number of couriers in 100-courier intervals, and the y-axis represents the total number of orders completed per day by the couriers within each interval. The results indicate that 45.9% of couriers account for 80% of all orders, and 59.8% of couriers account for 90% of all orders. In contrast, the remaining 40.2% of couriers contribute only 10% of all orders.

5.2. Workday

Figure 10(a) presents the bar chart of couriers' workdays over the eight days in the Meituan dataset. We observe that 36.9% of couriers worked all eight days. The average number of workdays of couriers is 5.8, with a standard deviation of 2.4. Figure 10(b) presents a histogram of the number of orders completed per workday. The average number of orders completed *per workday* is 17.3, with a standard deviation of 11.5. For comparison, the average number of orders *per day* is 14.3, as shown in Figure 9(a).



(a) Number of workdays (b) Number of orders per workday

Figure 10 Distributions of number of workdays and number of orders per workday

Figure 11 shows the relationship between couriers' workdays and the number of orders completed per workday. The red line in each boxplot represents the median. The Pearson correlation coefficient (0.4965) and the t-test ($p < 0.001$) support a significant positive correlation, which indicates that couriers who work more days tend to complete more orders per workday.

5.3. Wave

In Section 3.2, we defined the "wave" concept. Figure 12 illustrates an example of two consecutive waves for a courier (*courier_id* = 2) on a given day (*dt* = '20221022'). The first wave (*wave_id* = 3) starts at 12:43:55, when the courier (with no on-hand orders) accepts two orders (Waybill 368603 and Waybill 375191). The wave ends at 13:29:16, when the courier delivers the last order (Waybill 587526). The *wave duration* is defined as the time interval between the start and end times of the wave. Figure 13 shows all the waves of this courier on that day.

Figure 14 presents histograms of wave durations and the number of orders per wave. In Figure 14(a), the average wave duration is 37.2 minutes, with a standard deviation of 27.6 minutes. About 50.2% of waves last 30 minutes or less, and 86.6% last one hour or less. In Figure 14(b), the

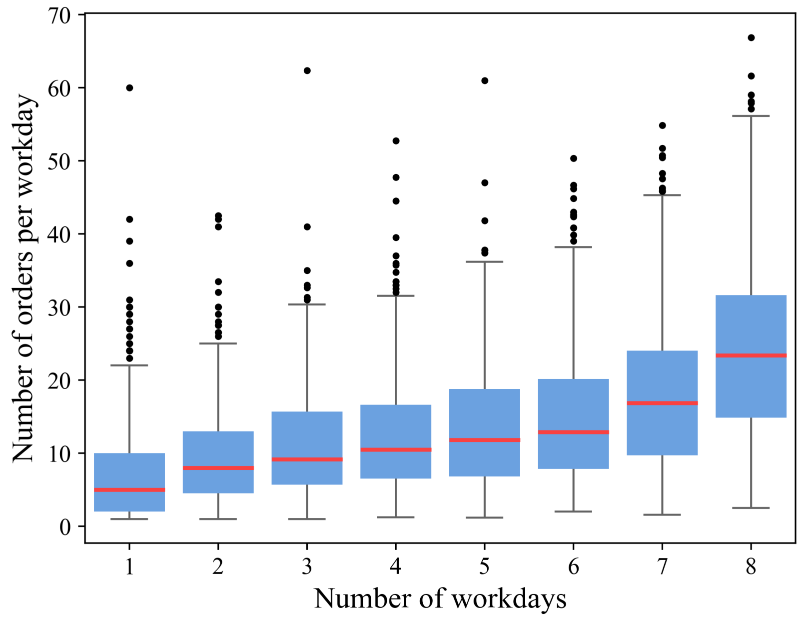


Figure 11 Relationship between number of workdays and number of orders per workday

average number of orders in a wave is 2.7, with a standard deviation of 2.6. Specifically, 39.4% of waves contain only one order, 77.2% contain three or fewer orders, and 89.6% contain five or fewer orders.

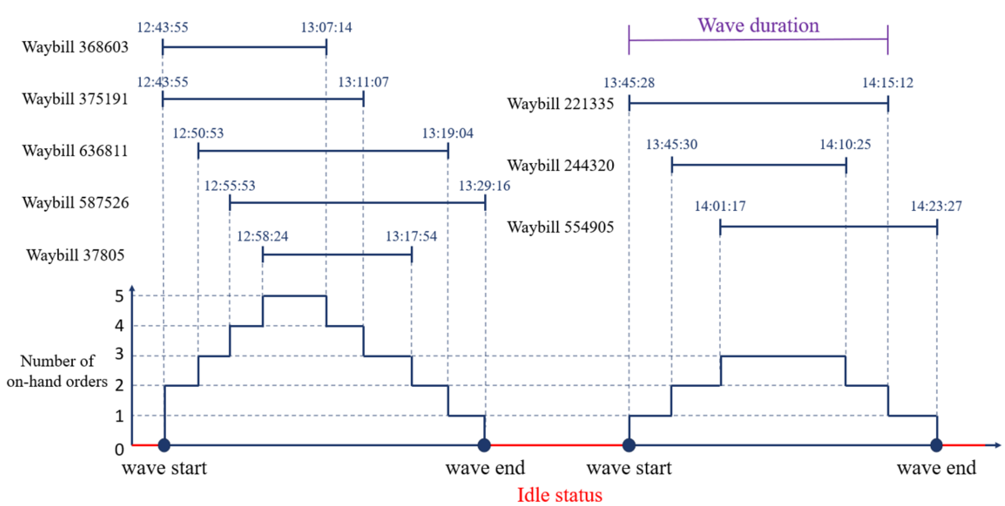


Figure 12 Example of two consecutive waves for a courier on a day

A courier's *wave hours* within a single workday refer to the total duration of all waves on that day, with the courier remaining idle between consecutive waves. Figure 15 presents the distributions of couriers' wave hours and the number of orders completed per wave hour. The average wave hours

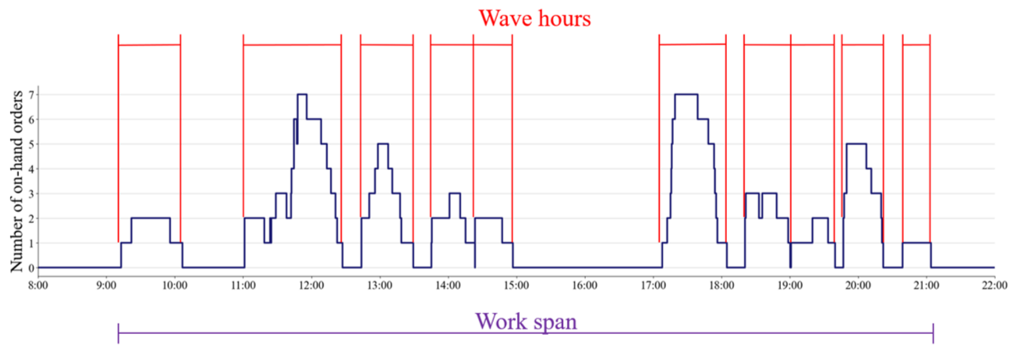
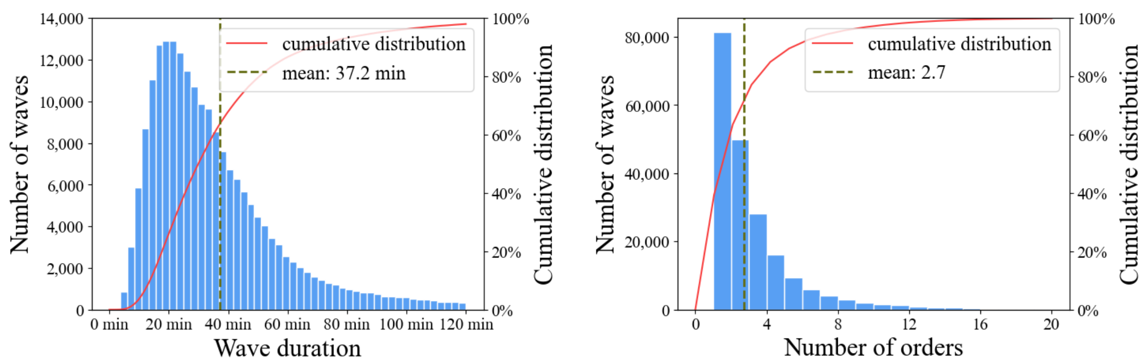


Figure 13 **Example of all waves for a courier on a day**



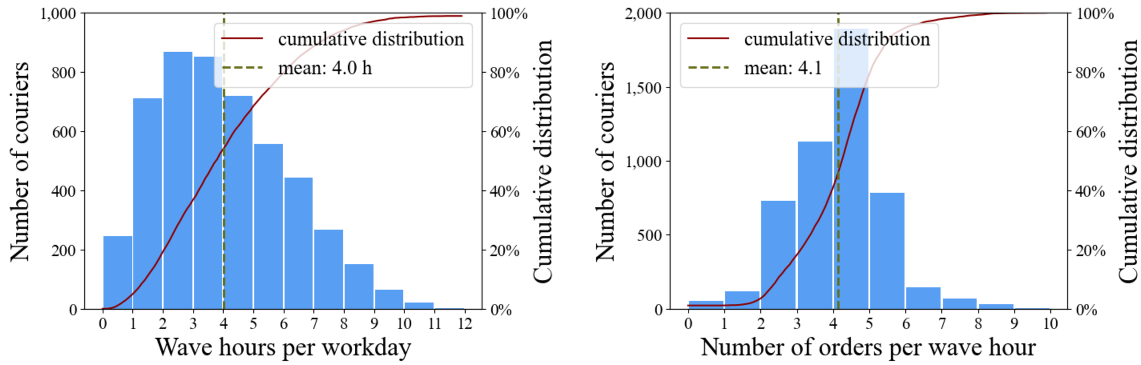
(a) Distribution of wave duration (b) Distribution of number of orders per wave

Figure 14 **Distributions of wave duration and number of orders per wave**

per day across all couriers is 4.0 hours, with a standard deviation of 2.2 hours. The average number of orders per wave hour is 4.1, with a standard deviation of 1.3. These results indicate substantial variation in both couriers' active work time (wave hours per day) and work density (number of orders per wave hour).

Figure 16 presents the relationship between couriers' workdays and their daily wave hours. The red line in each boxplot represents the median. The Pearson correlation coefficient (0.4901) and the t-test ($p < 0.001$) support a significant positive correlation, which indicates that couriers who work more days also tend to work more actively during the workday (longer wave hours).

A courier's *work span* within a single workday refers to the time interval from the start time of the first wave to the end time of the last wave on the day. Figure 17(a) presents the distribution of work spans across all couriers. The average work span per workday is 7.9 hours, with a standard deviation of 4.2 hours. Figure 17(b) shows a heat map illustrating the relationship between couriers' work spans and wave hours. The Pearson correlation coefficient (0.7623) and the t-test ($p < 0.001$)



(a) Wave hours per workday (b) Number of orders per wave hour

Figure 15 **Distributions of wave hours per day and number of orders per wave hour**

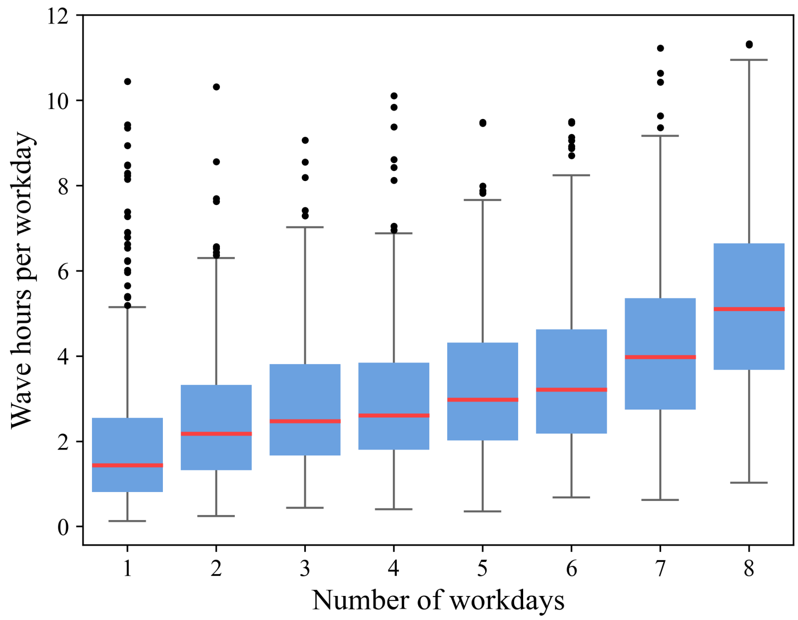
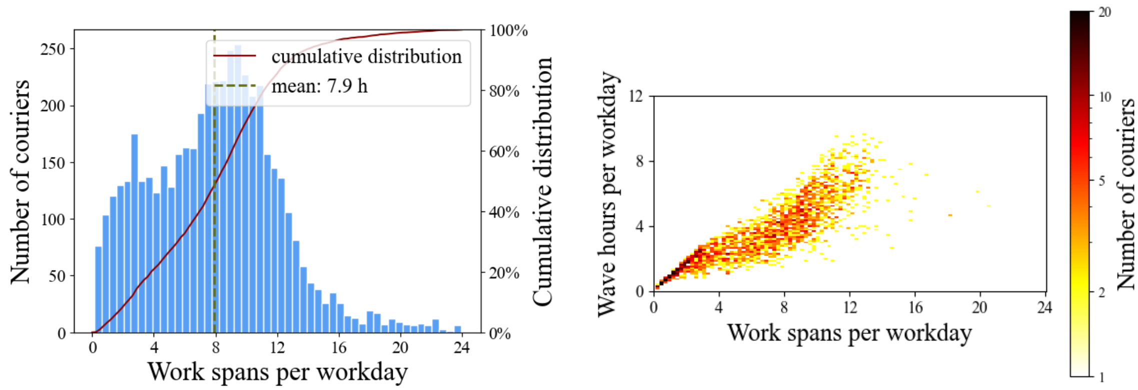


Figure 16 **Relationship between workdays and wave hours per workday**

support a significant positive correlation, which indicates that couriers who work longer (longer work spans) tend to work more actively (longer wave hours).

Figure 18 presents the distribution of the ratios between wave hours and work spans per workday. The average wave hours-work span ratio across all couriers is 55.8%, with a standard deviation of 19.1%. On average, couriers spend slightly more than half of their work spans actively delivering orders.



(a) Distribution of work spans per workday (b) Relationship with wave hours per workday

Figure 17 Distribution of work spans and relationship with wave hours

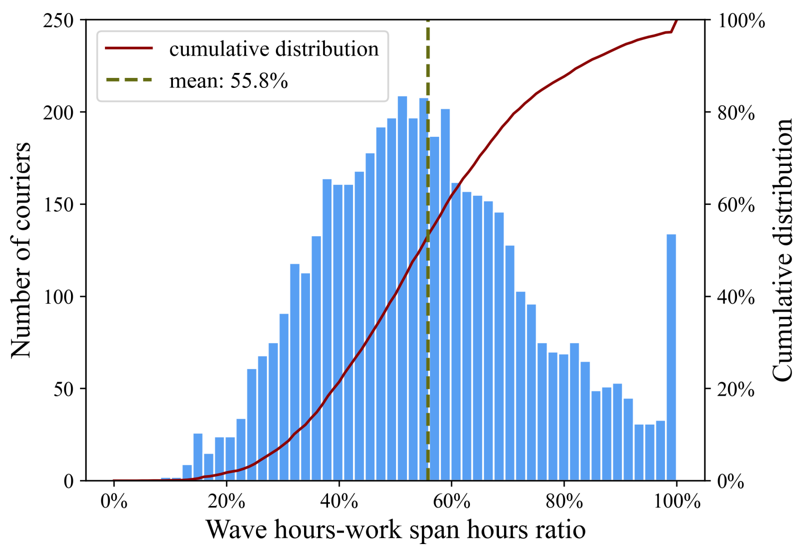
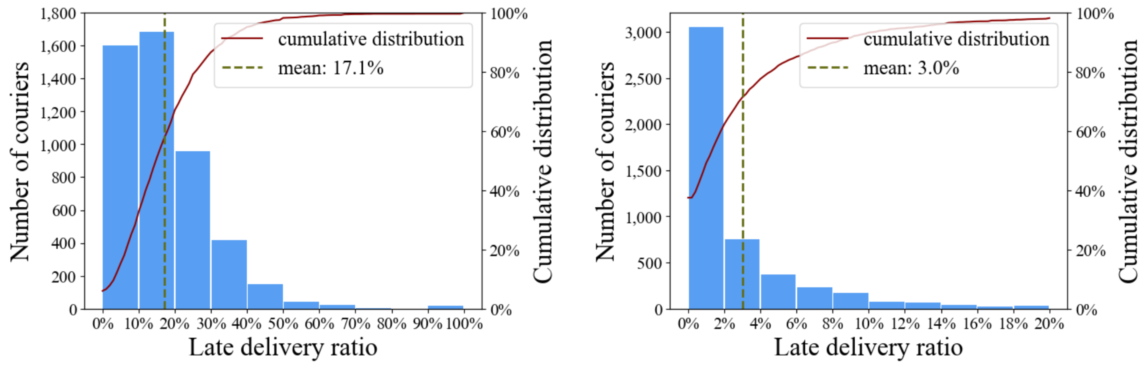


Figure 18 Distribution of wave hours-work span ratios

5.4. Late Delivery Ratio

Figure 19 presents a histogram of late delivery ratios among couriers, without a buffer (Figure 19(a)) and with an 8-minute buffer (Figure 19(b)). The bin width is 10% in Figure 19(a) and 2% in Figure 19(b).

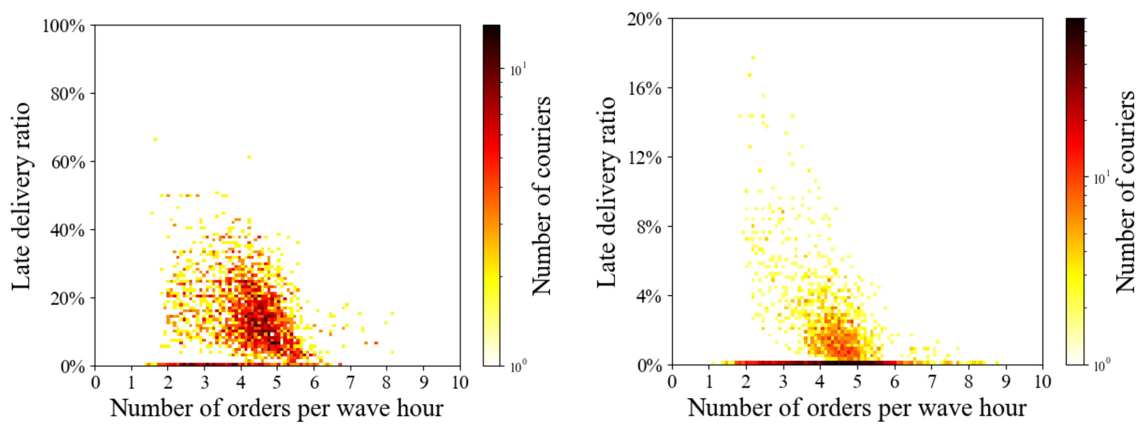
Without a buffer, only 6.0% of couriers achieved zero late deliveries; the average late delivery ratio across couriers is 17.1%, with a standard deviation of 13.1%. With an 8-minute buffer (the practice adopted by Meituan), 37.5% of couriers achieved zero late deliveries; the average late delivery ratio decreases to 3.0%, with a standard deviation of 6.2%.



(a) 0-minute buffer (no buffer) (b) 8-minute buffer

Figure 19 Distribution of late delivery ratios across couriers

Figure 20 illustrates the relationship between the number of orders completed per wave hour and the late delivery ratio among couriers. The color intensity of each grid represents the number of couriers in that grid, under logarithmic normalization. After excluding data from couriers with zero late deliveries, the Pearson correlation coefficients (-0.3551 for the 0-minute buffer and -0.5156 for the 8-minute buffer) and the t-test ($p < 0.001$) support significant negative correlations between the two variables.



(a) 0-minute buffer (no buffer) (b) 8-minute buffer

Figure 20 Relationship between number of orders per wave hour and late delivery ratio

5.5. Courier Trajectory

Figure 21 illustrates an example of a courier's trajectory within a wave. Specifically, it shows the trajectory within the sixth wave of the courier (*courier_id* is 2) on October 22, 2022 (*dt* =

‘20221022’), with detailed information provided in Table B.1 in the appendix. The figure also includes two zoomed-in views: the larger zoomed-in view (to the right of the main map) highlights the starting points of the courier’s trajectory at the top right corner; the smaller zoomed-in view (at the bottom of the main map) highlights the delivery points of the courier’s trajectory at the bottom left corner.

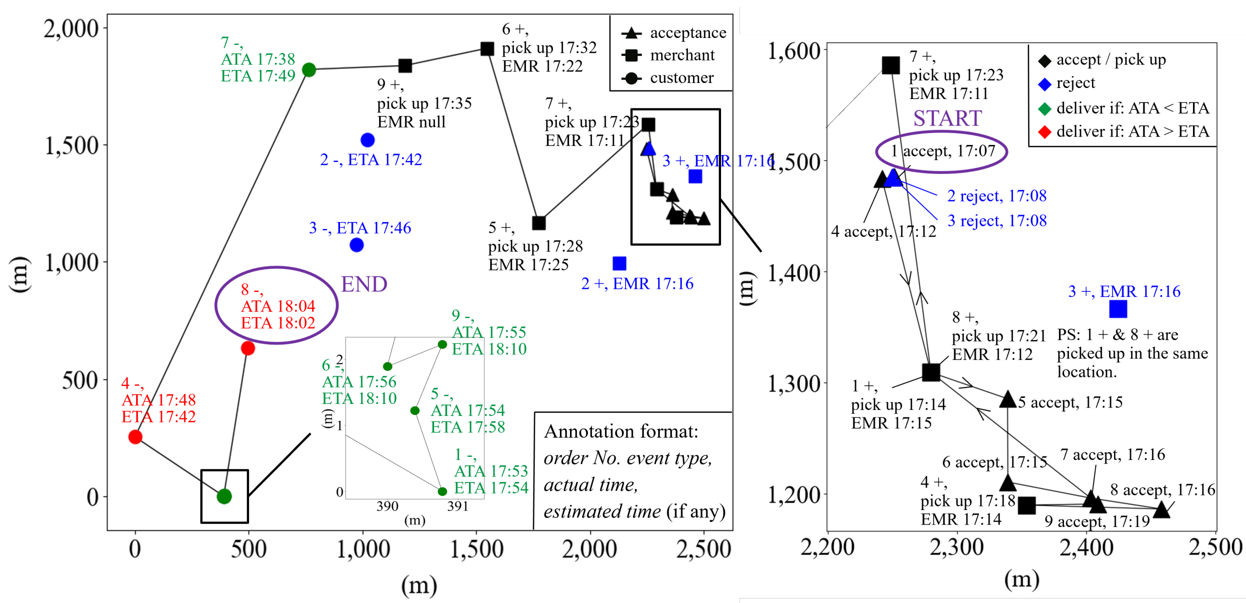


Figure 21 **Example of a courier’s trajectory within a wave**

Each event location is labeled in the format *order number, event type, actual time, and estimated time (if available)*. The starting and ending locations are marked with “START” (in the larger zoomed-in map) and “END” (in the main map), respectively. Three shapes denote different types of locations: A *triangle* represents the courier’s location at order acceptance, a *square* represents the order pickup location (i.e., the merchant’s location), and a *circle* represents the order delivery location (i.e., the customer’s location). We use the “+” symbol for pickups and “-” symbol for deliveries. Four colors further differentiate the locations: **green** indicates an early delivery (ATA < ETA), **red** indicates a delayed delivery without buffer (ATA > ETA; both “delayed” deliveries in this example remain within the 8-minute buffer), **blue** indicates the merchant’s and customer’s locations of an order rejected by the courier, and **black** indicates all other locations.

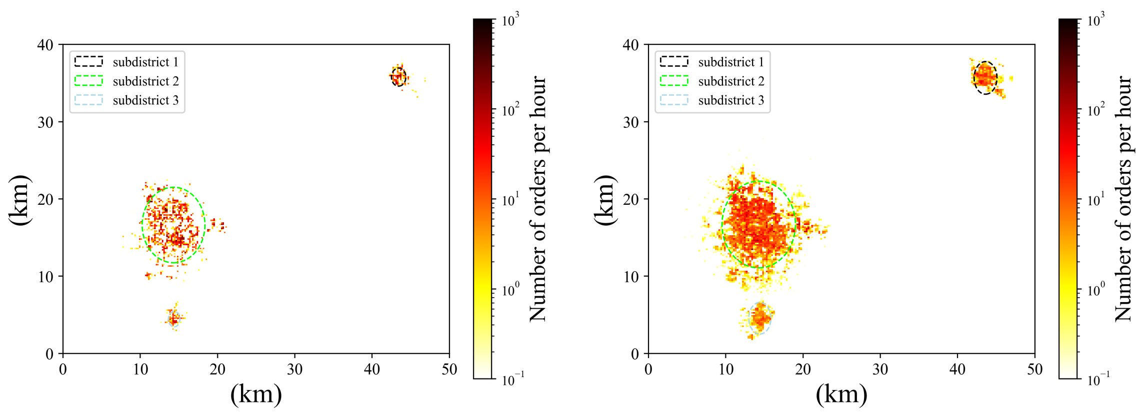
We make several interesting observations. First, the courier accepted orders early in the wave and then proceeded with pickups and deliveries. Second, the courier accepted orders with nearby delivery locations (e.g., orders 1, 5, 6, and 9). Third, the courier tended to batch pickups before proceeding with deliveries. Courier behaviors warrant further exploration, and a deeper understanding of such behavior could enhance order dispatch strategies.

6. Data Analysis: Merchants

In this section, we analyze the merchant data and present key insights. In Section 6.1, we examine the spatial distribution of merchants. In Section 6.2, we analyze the distribution of orders across merchants. In Section 6.3, we evaluate the service ranges of merchants. In Section 6.4, we assess courier pickup punctuality at merchants.

6.1. Spatial Distribution of Merchants

Figure 22 presents heat maps of the spatial distributions of merchant and customer locations. Similar to Figure 4, each point in the heat maps corresponds a grid of 500 meters from west to east and 400 meters from south to north. The color intensity of each point represents the number of orders per hour with merchant locations (Figure 22(a)) or customer locations (Figure 22(b)) in that grid, under logarithmic normalization. Note that Figure 22(b) is the same as Figure 4, replicated here for comparison purposes.



(a) Spatial distribution of merchants

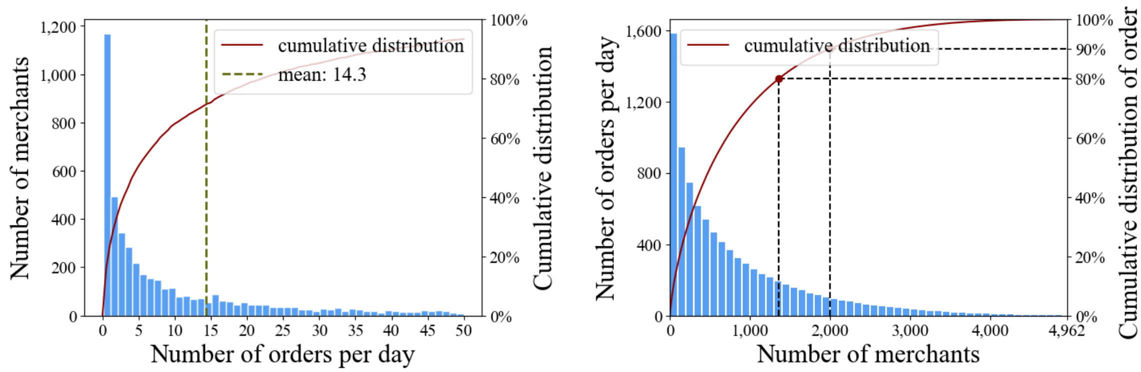
(b) Spatial distribution of customers

Figure 22 Spatial distribution of merchants and customers

Again, we use 2-sigma standard deviation ellipses to delineate the ranges of the three subdistricts, labeled 1, 2, and 3 from north to south. The three ellipses of merchants cover areas of 5.16 km^2, 73.89 km^2, and 3.60 km^2, respectively. The three ellipses of customers cover areas of 9.81 km^2, 83.65 km^2, and 9.19 km^2, respectively. These results indicate that merchant locations are more spatially concentrated than customer locations.

6.2. Number of Orders per Day

Figure 23 presents the distribution of the number of orders completed per day by merchants. Figure 23(a) shows the histogram, and Figure 23(b) shows the Pareto diagram.



(a) Histogram (b) Pareto diagram

Figure 23 Distribution of the number of orders per day across merchants

In Figure 23(a), the x-axis represents the number of orders per day, and the y-axis represents the number of merchants in each bin. The average number of orders per day per merchant is 14.3, with a standard deviation of 23.8. Notably, 78.2% of merchants handle fewer than 20 orders per day.

In Figure 23(b), the x-axis represents the cumulative number of merchants in 100-merchant intervals, and the y-axis represents the total number of orders completed per day by the merchants within each interval. The results show that 27.4% of merchants account for 80% of all orders, and 40.2% of merchants account for 90% of all orders. In contrast, the remaining 59.8% of merchants contribute only 10% of all orders.

6.3. Service Range of Merchants

Figure 24 presents a histogram of the distances between customers and merchants across orders. The average distance is 2.0 km, with a standard deviation of 1.3 km. For 93.8% of all orders, the customer–merchant distance is within 4 km.

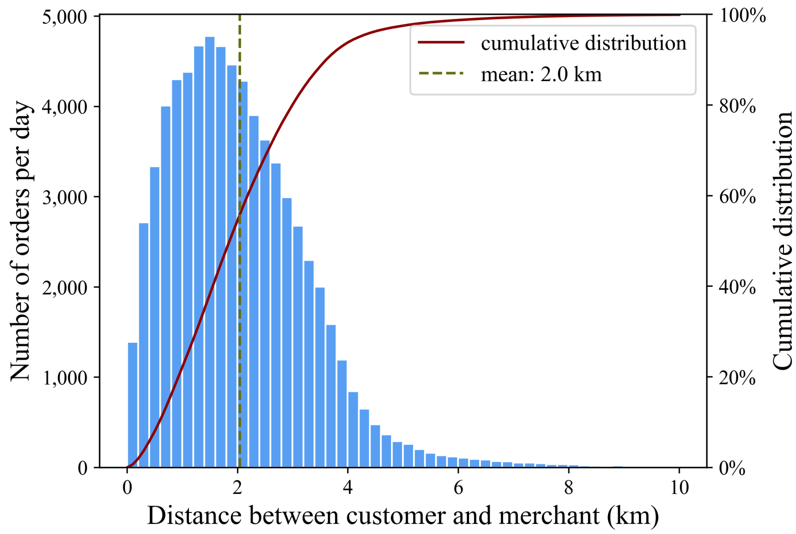


Figure 24 **Distribution of customer-merchant distances across orders**

6.4. Fetch Delay

The *fetch delay* of an order is defined as the difference between the *actual* pickup time (*fetch_time*) and the *estimated* meal ready time (*estimated_meal_prepare_time*). A positive value indicates that the courier picked up the meal after the estimated meal ready time, while a negative value indicates a pickup before the estimated meal ready time.

Figure 25 presents a histogram of fetch delays across orders. The x-axis represents *fetch delay* in 1-minute intervals. The average fetch delay is 2.7 minutes, with a standard deviation of 8.5 minutes. Approximately 53.3% of orders exhibit positive *fetch delay*, which suggests that couriers generally arrive at merchants around the estimated meal ready time.

Figure 26 presents the temporal distribution of *fetch delay ratios*. The x-axis represents the time of day in 15-minute intervals, and the y-axis represents the fetch delay ratio, that is, the proportion of orders with positive fetch delay among all orders picked up in each interval. The average fetch delay ratio is 53.3%. Similar to Figures 5 and 8, we observe a noon peak between 10:45 and 13:00 and an evening peak between 17:00 and 19:00. The fetch delay ratios during the noon peak are higher than those during the evening peak. Further, we examine the relationship between fetch delay (as a proxy for pickup punctuality) and delivery delay (as a proxy for delivery punctuality). The Pearson correlation coefficient (0.3799) and the t-test ($p < 0.001$) support a significant positive correlation.

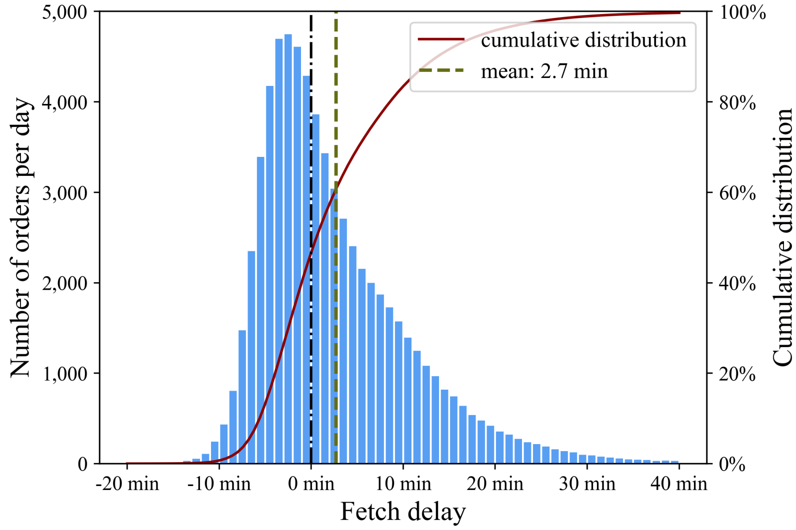


Figure 25 **Distribution of fetch delays**

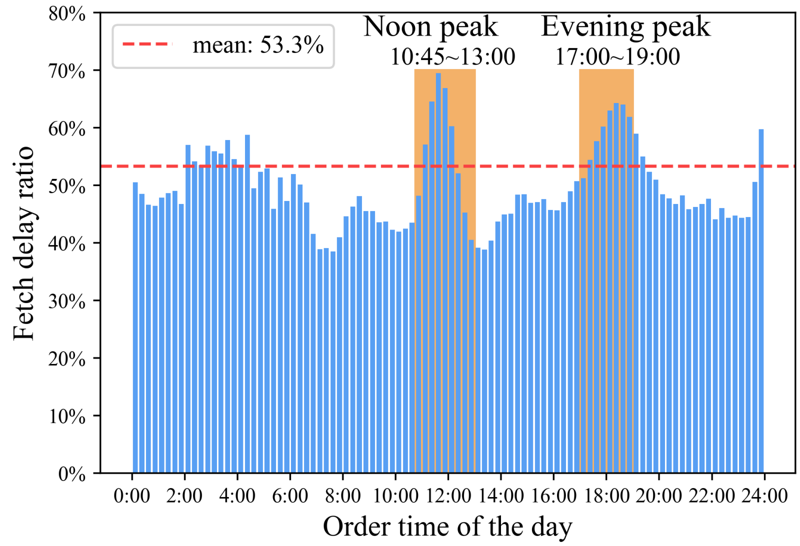


Figure 26 **Temporal distribution of fetch delay ratios**

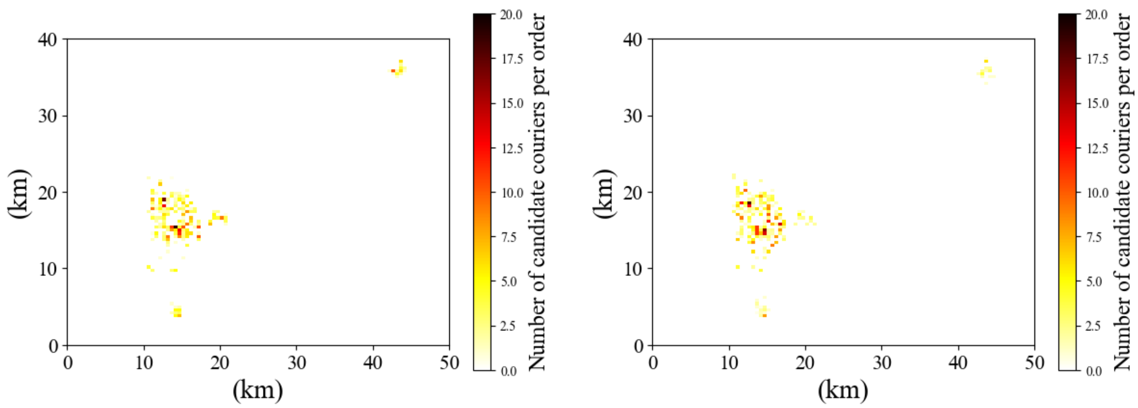
7. Data Analysis: Dispatch

The Dispatch Orders table (Table A.4) and Dispatch Couriers table (Table A.5) provide information at three selected decision epochs (labeled *dispatch_time*) during the noon peak on each date (labeled *dt*) between October 17 and October 24, 2022. At each decision epoch, there are on average 623.0 on-demand orders awaiting dispatch, with a standard deviation of 33.9. The average number of candidate couriers at each decision epoch is 2,585.2, with a standard deviation of 54.9 and a range of 198.

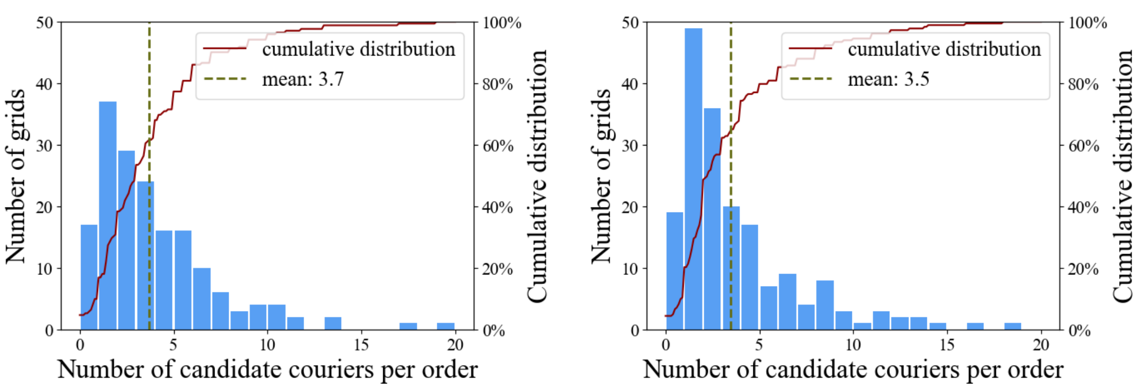
In this section, we analyze the data at these decision epochs and present key insights. In Section 7.1, we examine the spatial balance between supply and demand using the number of candidate couriers per order during the noon peaks of two selected days. In Section 7.2, we analyze statistics on dispatch times and rejection counts. In Section 7.3, we evaluate the distances between merchants and dispatched couriers. In Section 7.4, we assess the status of candidate couriers, including their number of on-hand orders and time to the earliest ETA.

7.1. Spatial Balance between Delivery Demand and Supply

Figure 27 presents heat maps and histograms of the number of candidate couriers per order at the decision epochs of 2022-10-17 11:27 and 2022-10-18 11:27. Each point in the heat maps corresponds to a grid of 500 meters from west to east and 400 meters from south to north.



(a) Heatmap 2022-10-17 11:27 (b) Heatmap 2022-10-18 11:27



(c) Histogram 2022-10-17 11:27 (d) Histogram 2022-10-18 11:27

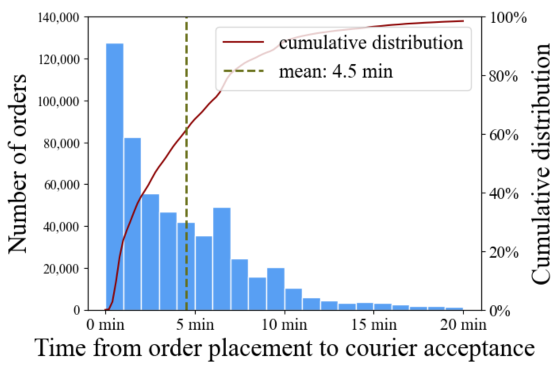
Figure 27 Spatial distribution of candidate-courier-to-order ratios

As shown in Figures 27(a) and 27(b), 77.3% and 79.8% of grids contain fewer than five candidate couriers per order, respectively. Some grids contain more than ten candidate couriers per order, which reveals substantial variation in courier-order ratios across space.

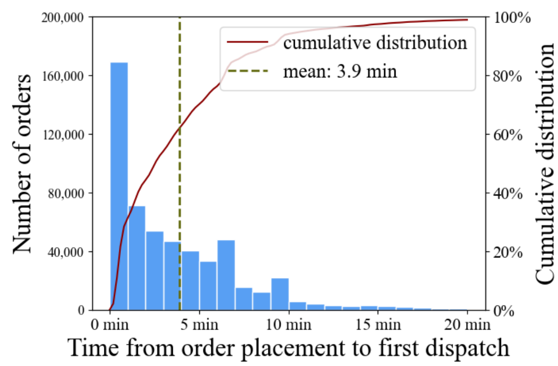
In Figure 27(c), the average number of candidate couriers per order is 3.7, with a standard deviation of 3.1. In Figure 27(d), the average is 3.5, with a standard deviation of 3.2. The relatively high standard deviation indicates strong spatial heterogeneity in courier-order ratios.

7.2. Dispatch Time and Rejection Count

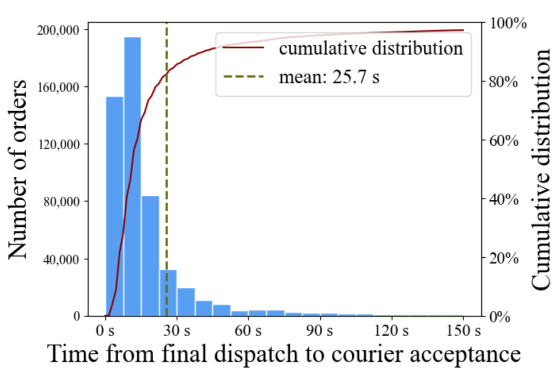
Next, we analyze order dispatch times and rejection counts. Figure 28 presents histograms of (i) the time from order placement (*platform_order_time*) to courier acceptance (*grab_time*), (ii) the time from order placement to the first dispatch, (iii) the time from the final dispatch to courier acceptance, and (iv) the rejection counts of all orders.



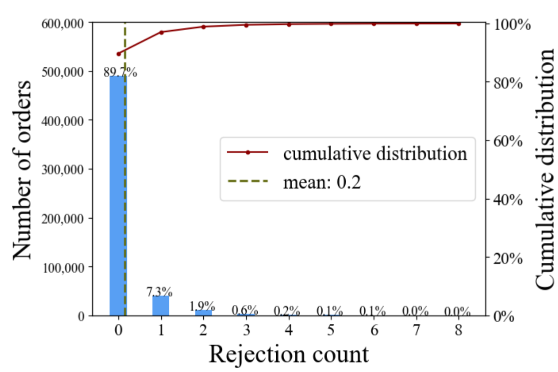
(a) Time from order placement to courier acceptance



(b) Time from order placement to the first dispatch



(c) Time from the final dispatch to courier acceptance



(d) Rejection count

Figure 28 Distributions of dispatch times and rejection counts of all orders

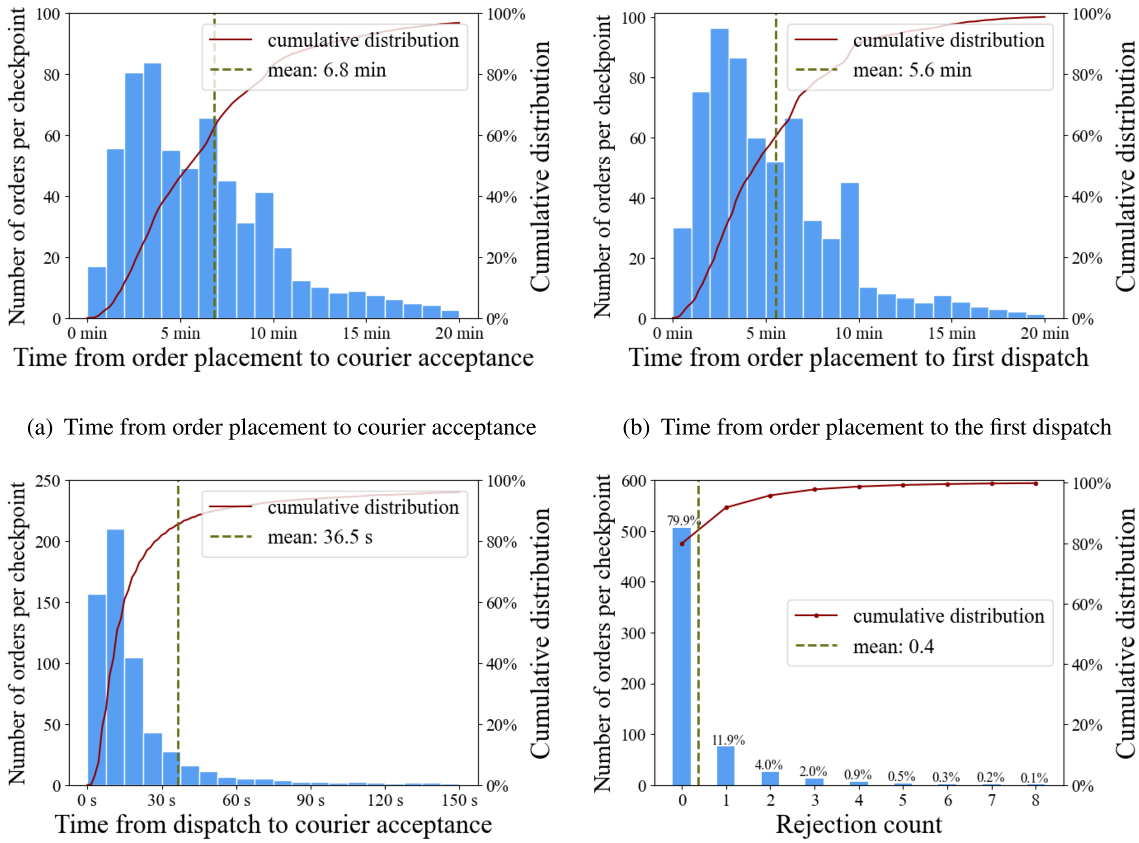
We observe that within ten minutes of order placement, 94.1% of orders were dispatched, and 91.5% were accepted by couriers. The average time from order placement to the first dispatch is

3.9 minutes, with a standard deviation of 4.7 minutes (Figure 28(b)), while the average time from order placement to courier acceptance is 4.5 minutes, with a standard deviation of 5.1 minutes (Figure 28(a)). Further, the average time from the final dispatch to courier acceptance is 25.7 seconds, with a standard deviation of 71.6 seconds; notably, 93.1% of orders were accepted by couriers within 60 seconds of the final dispatch (Figure 28(c)). As shown in Figure 28(d), most orders were accepted by couriers after very few dispatch attempts. Specifically, 89.7% of orders were successfully dispatched on the first dispatch attempt, and 97.0% of orders were accepted by couriers within two dispatch attempts, although some orders were rejected as many as 16 times. The very low rejection rate in Figure 28(d) explains the close similarity between the histograms in Figures 28(a) and 28(b).

Figure 29 presents histograms of (i) the time from order placement to courier acceptance, (ii) the time from order placement to the first dispatch, (iii) the time from the final dispatch to courier acceptance, and (iv) the rejection counts—similar to Figure 28. Here, we restrict the analysis to the orders at the 24 decision epochs (around 11:25, 11:27, and 11:30 each day), which capture dispatches during the noon peak hours.

Compared with Figures 28(a) and 28(b), the proportion of orders dispatched within 10 minutes decreases from 94.1% to 90.3%, and the proportion accepted within 10 minutes decreases from 91.5% to 83.0%. The average time from order placement to the first dispatch increases from 3.9 minutes to 5.6 minutes, with the same standard deviation of 4.7 minutes (Figure 29(b)), while the average time from order placement to courier acceptance increases from 4.5 minutes to 6.8 minutes, with the standard deviation increasing from 5.1 to 6.1 minutes (Figure 29(a)). Further, the average time from the final dispatch to courier acceptance increases from 25.7 seconds to 36.5 seconds, with the standard deviation increasing from 71.6 to 122.9 seconds. Nevertheless, the proportion of orders accepted by couriers within 60 seconds of the final dispatch remains unchanged at 93.1% (Figure 29(c)). As shown in Figure 29(d), the proportion of orders successfully dispatched on the first dispatch attempt decreases significantly from 89.7% to 79.9%, and the proportion accepted within two dispatch attempts decreases from 97% to 91.8%.

These differences between Figure 28 and 29 highlight longer dispatch holding times, delays in acceptance, and increased rejection rates during noon peak hours, possibly due to high demand density and low supply-demand ratio at noon.



(a) Time from order placement to courier acceptance

(b) Time from order placement to the first dispatch

(c) Time from the final dispatch to courier acceptance

(d) Rejection Count

Figure 29 Distributions of dispatch times and rejection counts of orders at the 24 decision epochs

7.3. Distance between Merchant and Dispatched Courier

If an order awaiting dispatch at a decision epoch is dispatched within 180 seconds (regardless of whether it is accepted or rejected by the dispatched courier), we assume that the dispatch decision is based on the information available at that epoch. Figure 30 presents a histogram of the distances between merchants and dispatched couriers, averaged over the 24 decision epochs. The bin width is 200 meters. It also presents a scatter plot of the rejection ratios along the right vertical axis.

The average distance between merchants and dispatched couriers is 0.9 km, with a standard deviation of 0.7 km. In 92.4% of dispatches, the dispatched courier is located within 2 km of the merchant. The average rejection ratio is 19.8%. We observe a clear trend in which the platform generally avoids dispatching orders to couriers located far from merchants. Interestingly, the rejection ratio is high at short distances (less than 1 km), decreases until around 3 km, and then increases thereafter. It is important to note that the merchant-courier distance is only one of several factors influencing courier's order acceptance or rejection decision.

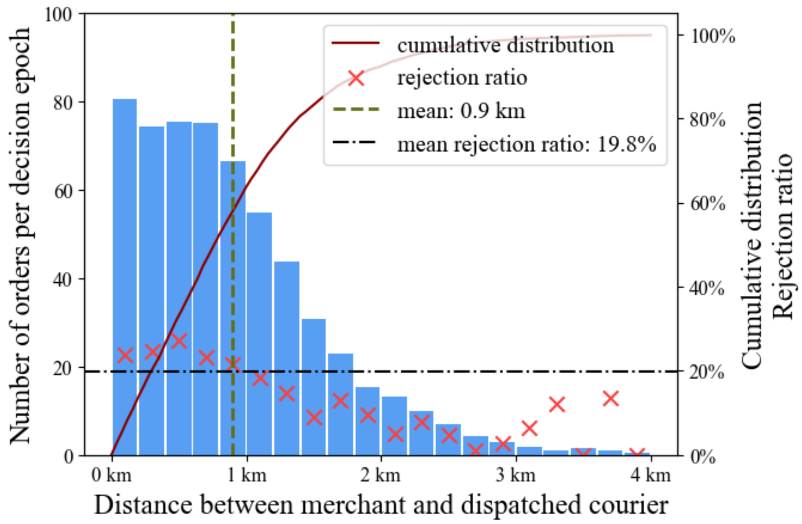


Figure 30 **Distribution of distances between merchants and dispatched couriers**

7.4. Status of Candidate Couriers

If a candidate courier at a decision epoch is dispatched at least one order within 180 seconds of that epoch (regardless of whether the courier accepts or rejects the order), we assume that the dispatch decision is based on the information available at that epoch, including the courier's status. We refer to such couriers as *dispatched candidate couriers*. Among them, those who reject at least one assigned order are referred to as *rejecting candidate couriers*.

Figure 31 presents a bar chart of the number of on-hand orders of candidate couriers, averaged over the 24 decision epochs. It also presents scatter plots of the dispatch ratios and rejection ratios, where *dispatch ratio* is defined as the proportion of dispatched candidate couriers among all candidate couriers, and *rejection ratio* is defined as the proportion of rejecting candidate couriers among dispatched candidate couriers.

The average number of on-hand orders is 2.0, with a standard deviation of 1.9. The average *dispatch ratio* is 15.6%, and the average *rejected ratio* is 17.2%. Notably, 30.1% of candidate couriers have no on-hand orders at the decision epochs. For these couriers, the dispatch ratio is low, and the rejection ratio is high. One possible explanation is that some of these couriers were actually resting while remaining online. The system may have learned this behavior, as reflected in the low dispatch ratio directed toward them.

After excluding candidate couriers without on-hand orders, the Pearson correlation coefficient (-0.9667) and the t-test ($p < 0.001$) support a significant negative correlation between the number of on-hand orders and dispatch ratio, which indicates that the platform is less likely to dispatch

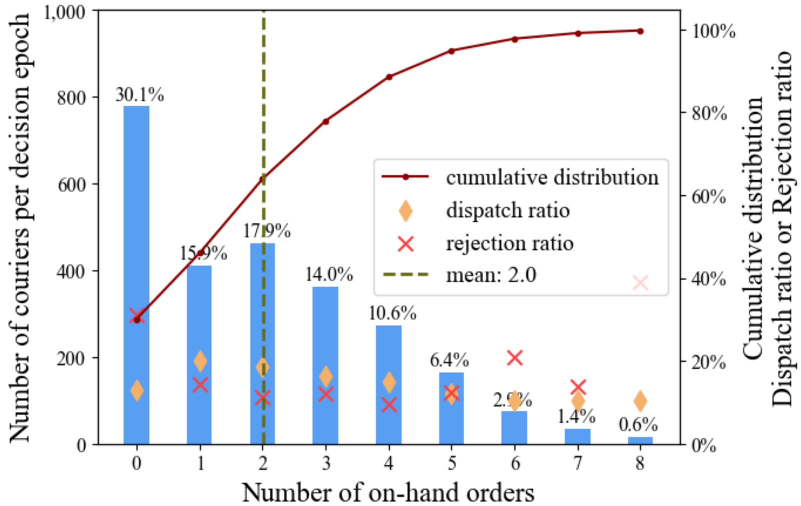


Figure 31 **Distribution of the number of on-hand orders of candidate couriers**

orders to candidate couriers who already have multiple on-hand orders. We observe no clear trend in the rejection ratio, consistent with the findings in Figure 30.

For a candidate courier with at least one on-hand order at a decision epoch, the *time to the earliest ETA* is defined as the time from the decision epoch to the earliest ETA (*estimate_arrived_time*) among the on-hand orders. Figure 32 presents a histogram of times to the earliest ETA, averaged over the 24 decision epochs, with a bin width of 5 minutes. Scatter plots of the dispatch ratios and rejection ratios are also presented.

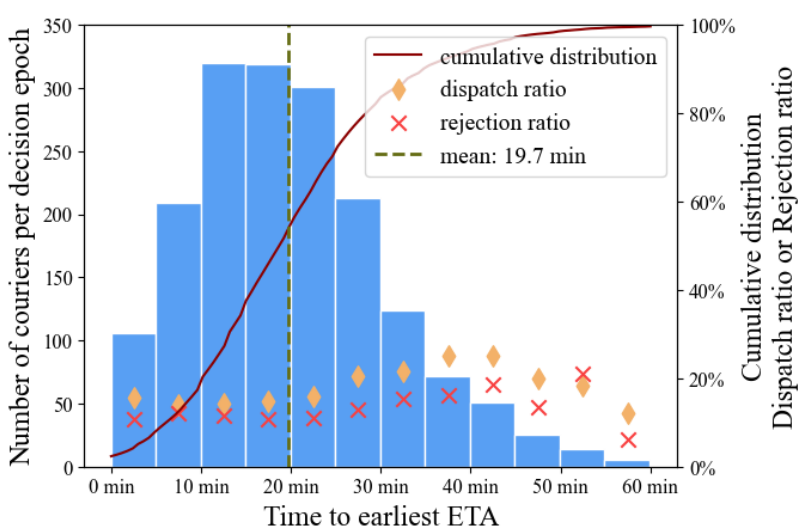


Figure 32 **Distribution of candidate couriers' time to the earliest ETA**

The average time to the earliest ETA is 19.7 minutes, with a standard deviation of 11.7 minutes. When the time to the earliest ETA is less than 45 minutes, the dispatch ratio is positively correlated with it, supported by the Pearson correlation coefficient (0.9091) and the t-test ($p < 0.001$). Similarly, the rejection ratio is also positively correlated with the time to the earliest ETA, supported by the Pearson correlation coefficient (0.8655) and the t-test ($p = 0.003$). When the time to the earliest ETA exceeds 45 minutes, both the dispatch ratio and rejection ratio decrease as the time to the earliest ETA increases. However, these patterns are not statistically significant, possibly due to the limited sample size.

8. Conclusions

This article introduces the dataset for the First INFORMS TSL Data-Driven Research Challenge, provided by Meituan, the largest on-demand food delivery platform in China. The dataset comprises 568,546 orders placed by customers within a 50 km × 40 km service area between October 17 and 24, 2022, which involves 4,955 delivery couriers and 4,962 merchants. It captures the complete lifecycle of these orders from creation to completion. The dataset also records information at three selected dispatching decision epochs during the noon peak on each date over the eight days, with each decision epoch comprising approximately 600 orders awaiting dispatch and 2,500 candidate couriers.

Based on the **TR**ansportation-**EN**abled **S**ervices (TRENS) framework (Agatz et al. 2024), we outline the process of a typical on-demand food delivery service from the perspective of the order lifecycle. We then provide a detailed descriptive analysis of orders (waybills), couriers, merchants, and dispatches, and present key insights from these analyses and observations. Researchers are encouraged to leverage this dataset to address real-world challenges in the complex operational process of on-demand food delivery, combining practical significance with academic innovation through data-driven techniques, analytical models, and optimization methods.

Acknowledgments

We gratefully acknowledge the journal *Transportation Science*, the INFORMS TSL Society, and Meituan for their support in making the Data-Driven Research Challenge possible. We also thank the Challenge Committees for their dedicated service.

References

Agatz N, Cho SH, Sun H, Wang H, 2024 *Transportation-enabled services: Concept, framework, and research opportunities*. *Service Science* 7(4):1–21.

Liang Y, Luo H, Duan H, Li D, Liao H, et al, 2024 *Meituan's real-time intelligent dispatching algorithms build the world's largest minute-level delivery network*. *INFORMS Journal on Applied Analytics* 54(1):84–101.

Meituan, 2024 *TSL-Meituan challenge_background and data_20240321*. Accessed from meituan.com on February 25, 2025.

Statista, 2024 *Online food delivery services market size, share, and trends 2024 to 2029*. Last accessed on February 21, 2025.

Appendix A. Description of Tables in the Dataset

Table A.1 Description of the *Waybills* Table, Part 1 (adapted from Meituan (2024), with modifications)

Field	Description	Data type	Sample value
waybill_id	Waybill unique identifier	Long	654338
order_id	Order unique identifier	Long	57635
is_courier_grabbed	Whether waybill is accepted by courier	Boolean	1
dt	Date of order creation	String	'20231212'
is_weekend	Whether order date is at weekend	Boolean	1
poi_id	Merchant unique identifier	Int	578
da_id	Business district unique identifier	Int	12
courier_id	Courier unique identifier	Int	1159
is_prebook	Whether order is pre-booked	Boolean	1
platform_order_time	Order creation time (Unix)	Long	1702357786 (2023-12-12 13:09:46)
order_push_time	Time when order enters dispatch system (Unix)	Long	1702357786 (2023-12-12 13:09:46)
dispatch_time	Waybill dispatching time (Unix)	Long	1702357786 (2023-12-12 13:09:46)

Appendix B. Wave Information on the Example of Courier Trajectory in Section 5.5

Table B.1 presents detailed information on the example of the courier trajectory shown in Figure 21 in Section 5.5. Specifically, it records the details of the 6th wave of the courier (*courier_id* is 2) on October 22, 2022 (*dt* = '20221022'), derived from the original *waybills* and *couriers* tables.

The wave starts at 17:07:48 and ends at 18:04:49, during which the courier accepts seven orders and rejects two orders (orders 2 and 3). An *event* is defined as one of four actions: order accepted (grab), order rejected (reject), order

Table A.2 Description of the *Waybills* Table, Part 2 (adapted from Meituan (2024), with modifications)

Field	Description	Data type	Sample value
grab_time	Time when courier accepts order (Unix)	Long	1702357786 (2023-12-12 13:09:46)
fetch_time	Time when courier fetches food (Unix)	Long	1702357786 (2023-12-12 13:09:46)
arrive_time	Actual food arrival time (Unix)	Long	1702357786 (2023-12-12 13:09:46)
estimate_arrive_time	Promised food arrival time (Unix)	Long	1702357786 (2023-12-12 13:09:46)
estimate_meal_prepare_time	Estimated food ready time (Unix)	Long	1702357786 (2023-12-12 13:09:46)
sender_lat	Merchant latitude (shifted)	Long	39996108
sender_lng	Merchant longitude (shifted)	Long	116481447
recipient_lat	Customer latitude (shifted)	Long	39996108
recipient_lng	Customer longitude (shifted)	Long	116481447
grab_lat	Courier latitude when accepting order (shifted)	Long	39996108
grab_lng	Courier longitude when accepting order (shifted)	Long	116481447

Table A.3 Description of the *Couriers* Table (adapted from Meituan (2024), with modifications)

Field	Description	Data type	Sample value
dt	Date of wave	String	'20231212'
courier_id	Courier unique identifier	Int	1159
wave_id	Wave unique identifier	Int	12
wave_start_time	Wave start time (Unix)	Long	1702357786 (2023-12-12 13:09:46)
wave_end_time	Wave end time (Unix)	Long	1702357786 (2023-12-12 13:09:46)
order_ids	Set of order IDs in wave	Set	(57635, 57636, 57637)

Table A.4 Description of the *Dispatch Orders* Table (adapted from Meituan (2024), with modifications)

Field	Description	Data type	Sample value
dt	Date of check time	String	'20231212'
dispatch_time	Check time of dispatch system (Unix)	Long	1702357786 (2023-12-12 13:09:46)
order_id	Order unique identifier	Long	57635

Table A.5 Description of the *Dispatch Couriers* Table (adapted from Meituan (2024), with modifications)

Field	Description	Data type	Sample value
dt	Date of check time	String	'20231212'
dispatch_time	Check time of dispatch system (Unix)	Long	1702357786 (2023-12-12 13:09:46)
courier_id	Courier unique identifier	Int	1159
rider_lat	Courier latitude when checking (shifted)	Long	39996108
rider_lng	Courier longitude when checking (shifted)	Long	116481447
courier_waybills	Set of courier's on-hand order IDs when when checking	Set	(57635, 57636, 57637)

picked up (fetch), or order delivered (arrive). The wave consists of 23 events, as listed in Table B.1. Note that the "order number" in Table B.1 refers to the dispatch sequence number of the orders within the wave, rather than the unique identifier (*order_id*).

Table B.1 Wave information on the example of the courier trajectory in Figure 21

Event ID	Time	Order Number	Action
1	17:07:48	1	grab
2	17:08:12	2	**reject**
3	17:08:43	3	**reject**
4	17:12:22	4	grab
5	17:14:33	1	fetch
6	17:15:17	5	grab
7	17:15:49	6	grab
8	17:16:20	7	grab
9	17:16:52	8	grab
10	17:18:36	4	fetch
11	17:19:13	9	grab
12	17:21:51	8	fetch
13	17:23:29	7	fetch
14	17:28:36	5	fetch
15	17:32:26	6	fetch
16	17:35:34	9	fetch
17	17:38:58	7	arrive
18	17:48:26	4	arrive
19	17:53:32	1	arrive
20	17:54:08	5	arrive
21	17:55:10	9	arrive
22	17:56:21	6	arrive
23	18:04:49	8	arrive