How to Enhance Customer Satisfaction of Food Delivery Business

Insights from Logistics Analytics

Customer Satisfaction in *logistics* comes from the effort of *rider*, *restaurant* and *platform*

- My order is accepted by the restaurant and courier.
- My order arrives within the expected time.

- Be faster in meal preparation

- Faster in riding
- Become city/area expert

- **Pick the right courier to assign the order to.**
- **Assist rider to on their way of delivery.**
- **Assist restaurant to improve efficiency in meal preparation planning.**
- **Manage customer expectation by better estimation**

Logistic process breakdown

Online

Stage 1: An Order is accepted by one *courier*
Reduce Order Rejection Rate

Offline

Stage 2: An Order is delivered to customer
Improve On-time Rate

Executive Summary

We examined factors impacting customer satisfaction: on-time delivery and order acceptance in Meituan's food delivery service, with a focus on peak-hour challenges. Through data analysis, we found:

1. Peak-hour workload, distance and traffic, past performance are the key factors related to the delay of delivery.
2. Time of the day and rider's behaviour are the key factors related to the acceptance rate.

According to the findings, my main suggestions to Meituan are to

1. Balance the workload of the riders during assignment
2. Solicit more riders during peak hours

Storyline and Methodology

- Process overview at high level
  - Decompose the process to steps, highlight stage(s) that might be bottleneck
  - Formulate initial hypothesis to decide the segments for further investigation
- Segmentation of data to explore patterns
  - E.g. Segment by time, proximity (location), workload
- Hypothesis testing for root causes
  - E.g. Longer travel time of riders around dinner time might be due to evening peak hour traffic
- Recommendations and impact projection based on findings.

BQ 1: What are the root causes of PtoD and how to improve?

Decomposition of PtoD (1): From Order Placement to Order Preparation

Stage 1: An Order is accepted by one *courier*

	Time to enter dispatch system	Order is assigned to the first rider	Time to wait until one rider accepts the order
Main Related Factors	• Real-time efficiency of IT infrastructure	• Calculation Time of the Algorithm	• Order-specific factors • Estimated time for delivery • Traffic & weather • Current Workload

Decomposition of PtoD (2): From Order Preparation to Customer’s Dining Table

Stage 2: An Order is delivered to Customer

Order Preparation Time at Restaurant	Rider’s Waiting Time at Restaurant	Rider’s Travel Time to Customer

Main Related Factors

Order Preparation Time at Restaurant

- Restaurant Factors:
  - Kitchen efficiency
  - menu complexity
  - preparation method
- Order-Specific Factors:
  - Order size
  - Special requests
- Time Factors:
  - Peak hours
  - Holiday and events

Rider’s Waiting Time at Restaurant

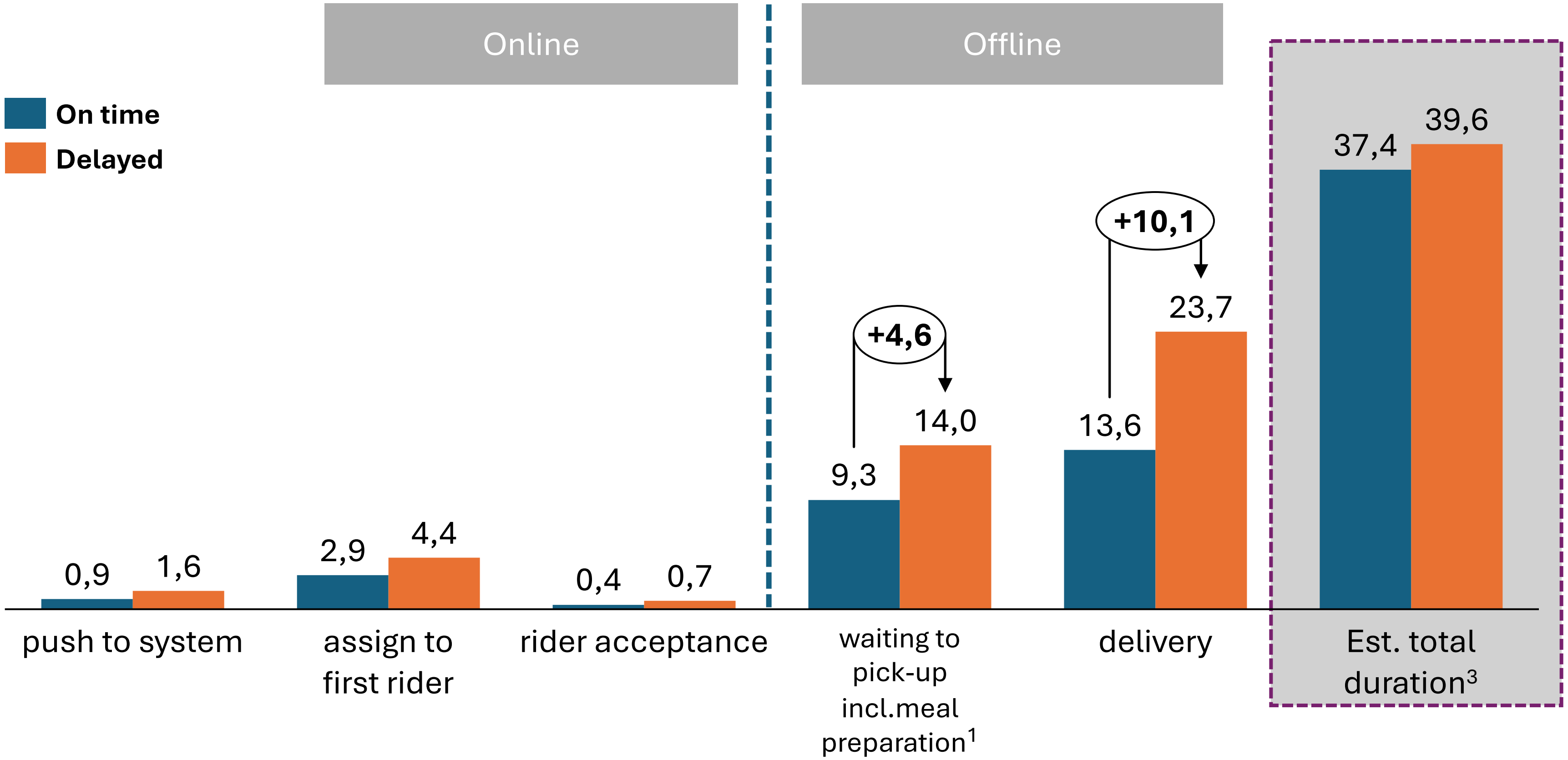
- Order Preparation Time
- Riding time to pick-up point:
  - Distance
  - Traffic & Weather
  - Current workload
  - Complexity of *Pick-up* location e.g. shopping mall
  - Experience and Familiarity

Rider’s Travel Time to Customer

- Distance
- Traffic & Weather
- Current workload
- Complexity of *drop-off* location e.g. old residential complex, school campus
- Experience and Familiarity

Delayed delivery (~15%) is *mainly* caused by the time spent from meal preparation to delivery steps

Time spent on each step for the entire PtoD process for on-time and delayed delivery for *non-prebooked* orders
unit: minute



Key Initial Hypotheses

Based on the factors that may affect each step, the delay might be caused by[2]

a. Traffic jams
b. Spike of orders at restaurants
c. Heavier workload of riders
d. Distance to restaurants/customer
e. Incapability of riders/restaurants

1. I didn't distinguish the time of meal preparation and waiting to pick-up after arrival, because the the meal preparation time is estimated.
2. Inefficiency restaurants and riders will also cause the delay, but what the platform can intervene is rather limited.
3. The delayed order have the minutes of delay: average: 4.8min, median: 3.2min.

Recap: Issue Tree of possible root causes of delay

- Longer waiting time to **pick-up meal**
  - Meal preparation time gets longer
    - More orders to prepare at the same time
    - Restaurant incapability
  - Longer time to arrive at pick-up point
    - Traffic jams during peak hours
    - Other orders to pick-up or deliver
    - Long distance to travel
    - Rider incapability

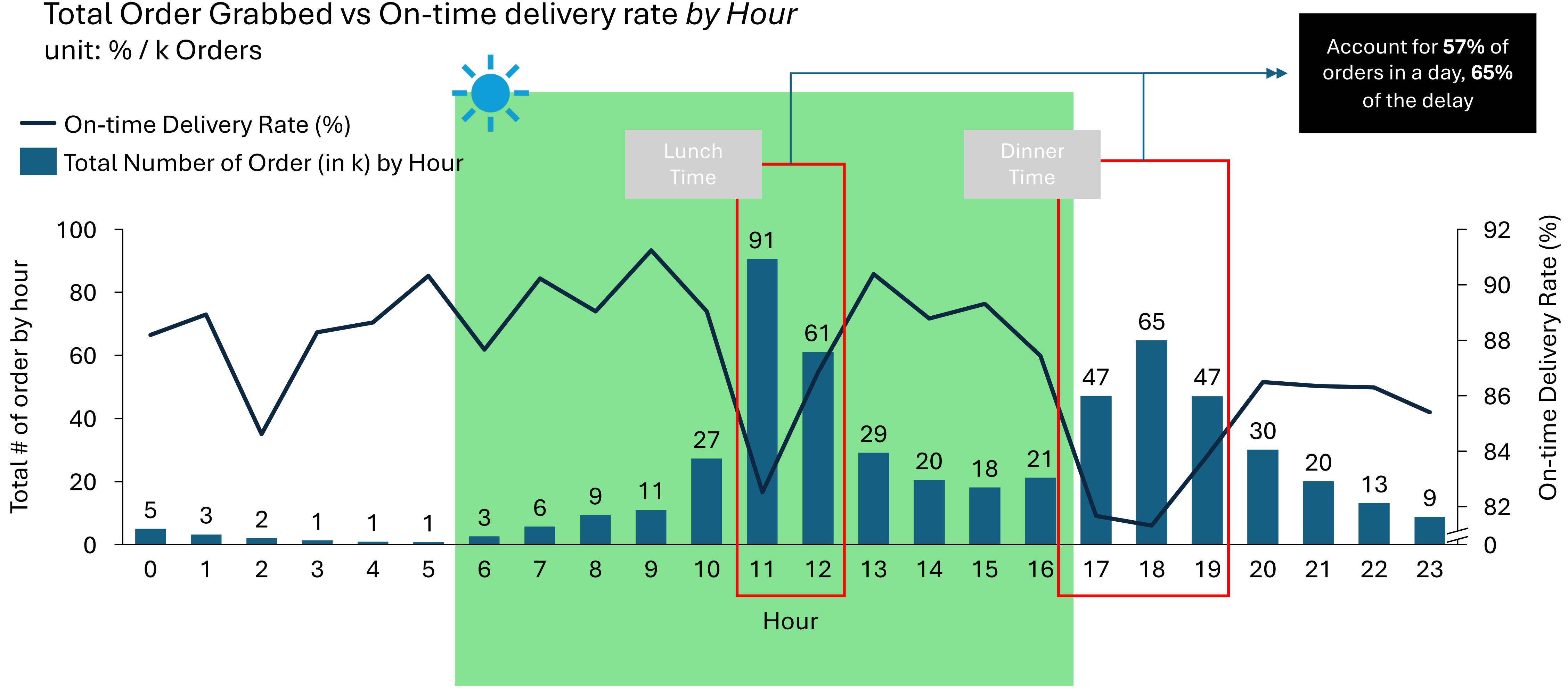
- Longer time for **delivery to customer**
  - Traffic jams during peak hours
  - Other orders to deliver before arrival
  - Long distance to travel
  - Rider incapability

Hypotheses in red are *time-invariant*.

Hypotheses in blue are *time-relevant*.

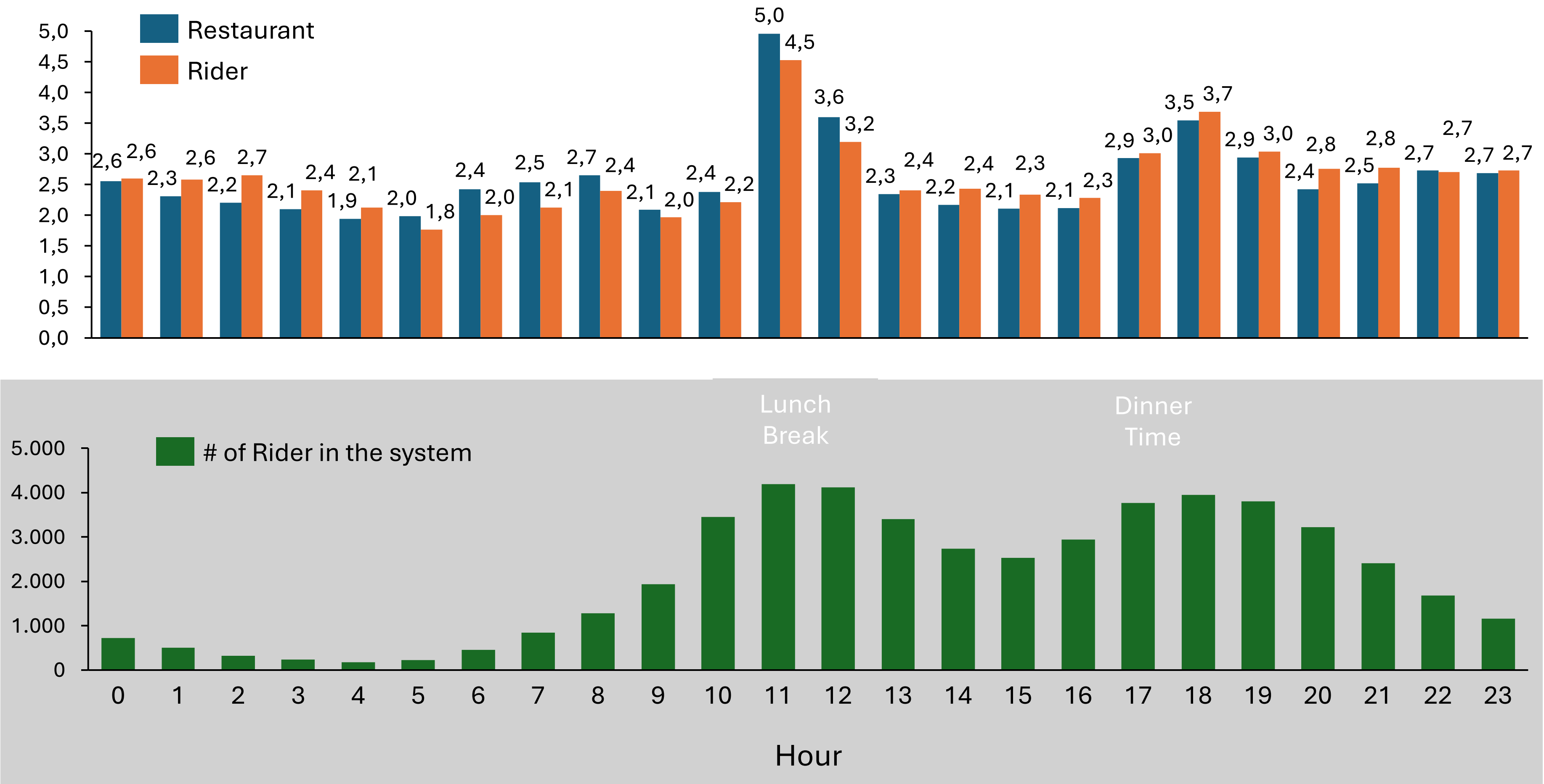
During Peak dining hour, the rate of on-time delivery drops, **dinner** peak is even *worse* than **lunch** peak.

Total Order Grabbed vs On-time delivery rate *by Hour*
unit: % / k Orders



During the peak hour, both restaurants and riders have surged workload

Avg. hourly orders (grabbed hour) to handle by restaurant and rider
unit: # of Orders

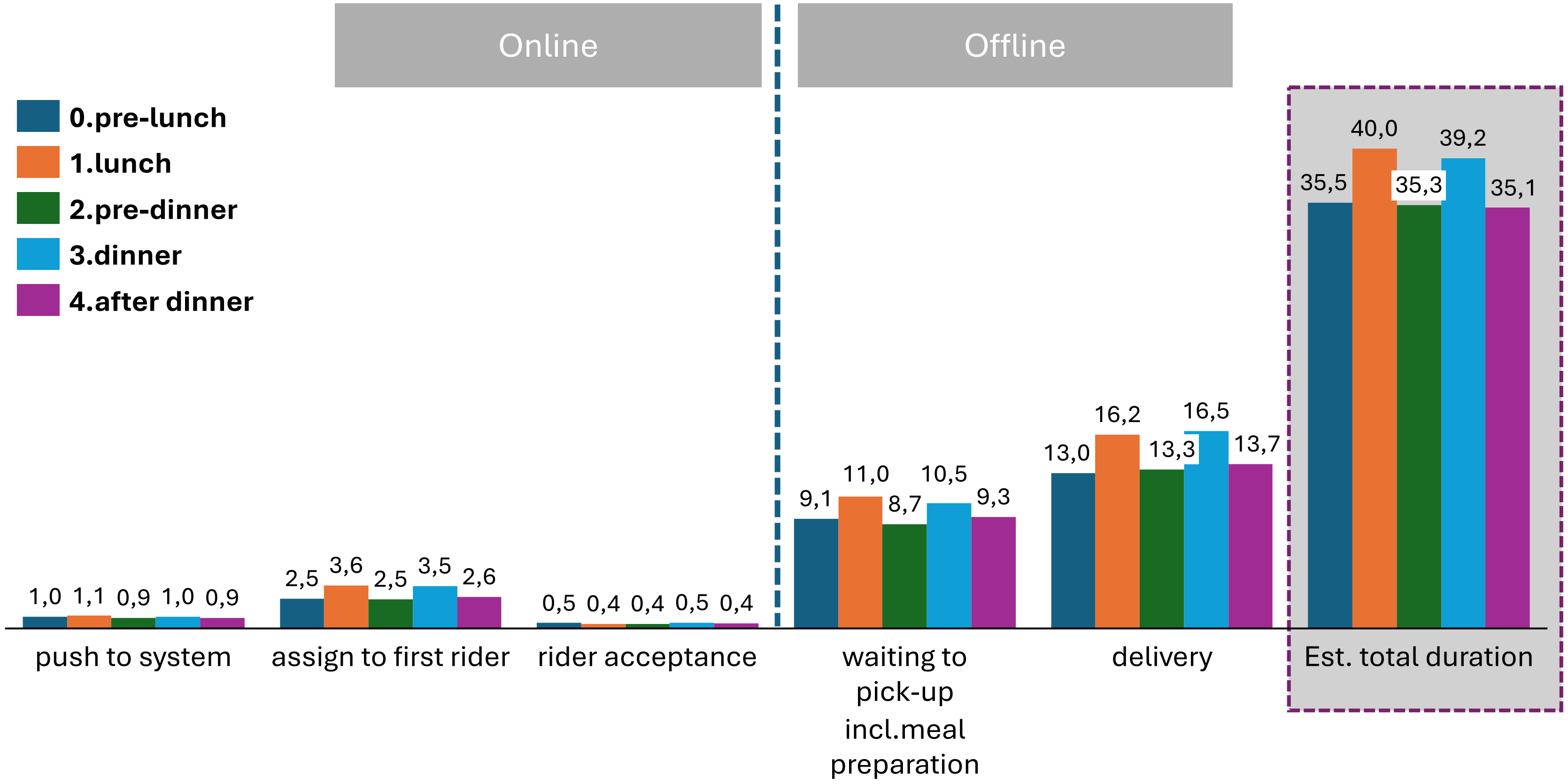


Key Conclusions

When there is a spike in demand, the number of riders does not increase proportionally, this leads to surge in workload during the peak hours.

During Peak Dining Hours, it takes longer from meal preparation to delivery.

Time spent on each step for the entire PtoD process for on-time and delayed delivery by time segment
unit: minute



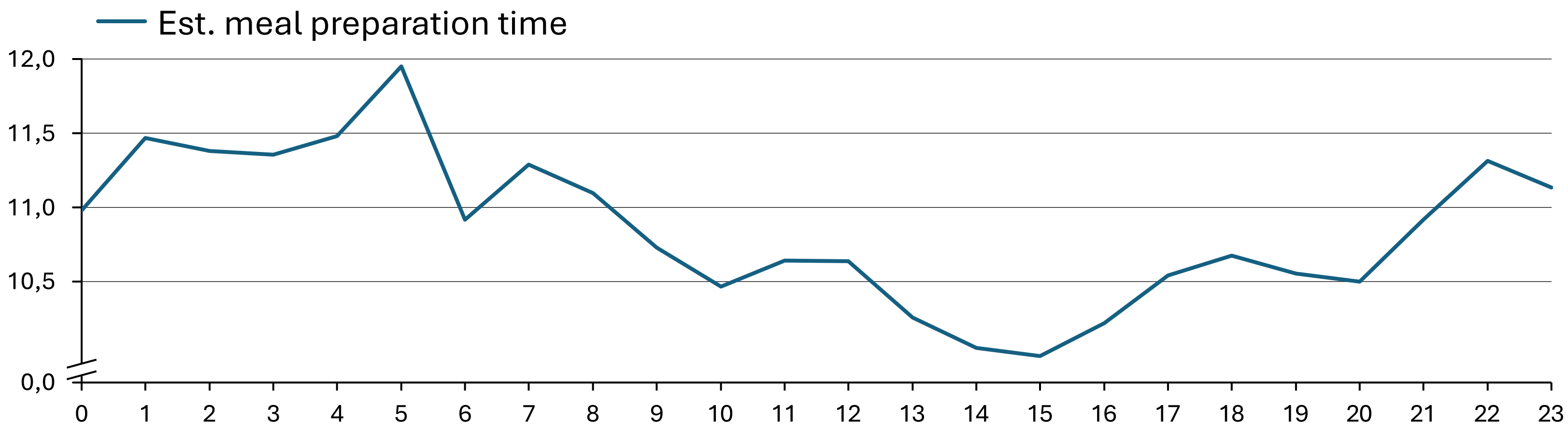
Key Conclusions

Peak hour makes some difference in rider acceptance, time to order pick-up and delivery, and the platform has also taken these into consideration by giving a relatively longer estimated time of total duration.

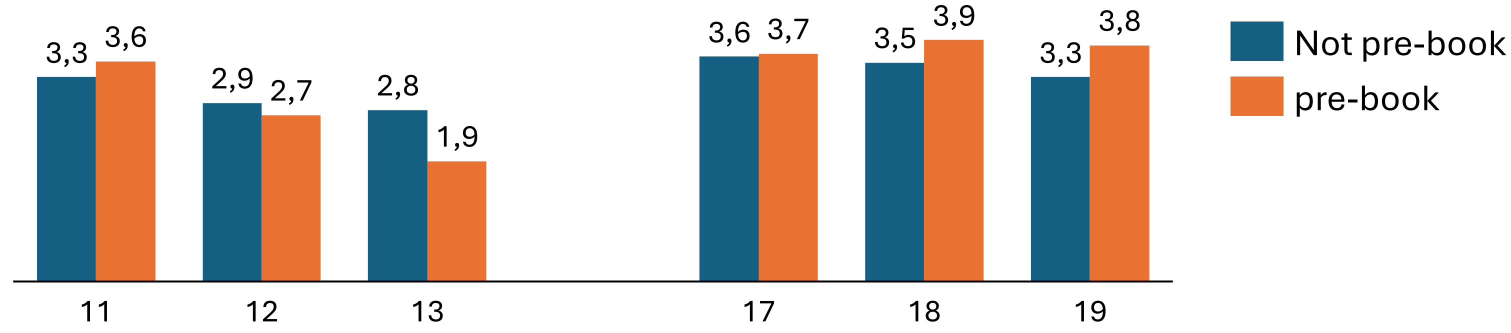
1. I didn't distinguish the time of meal preparation and waiting to pick-up after arrival, because the the meal preparation time is estimated.

Hypothesis 1: Meal preparation takes longer due to spike in demand.

Estimated meal preparation time (filtered only 1-120min)
unit: minute



Median minutes delayed of pre-book(4%) vs ad hoc orders in peak hours
unit: min



Key Conclusions

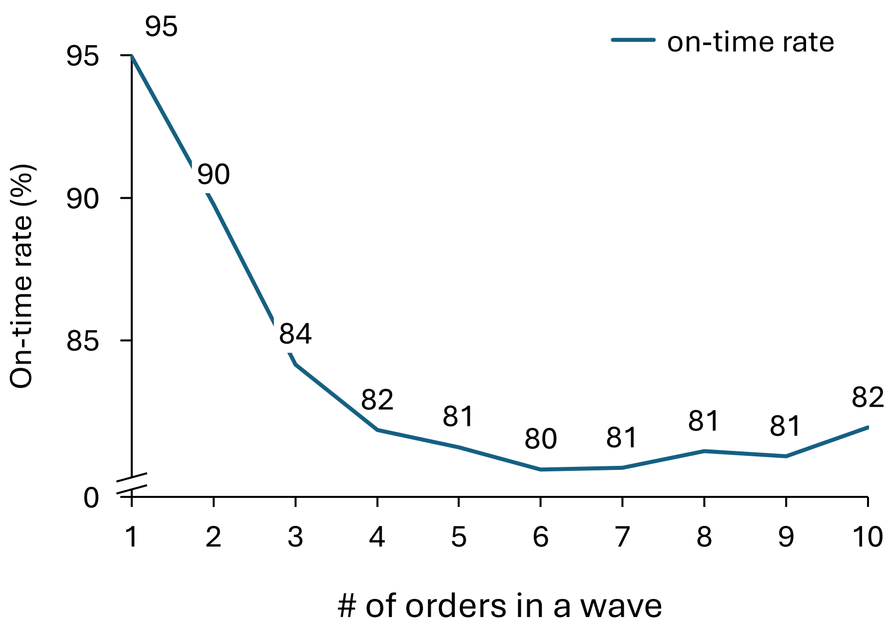
(We don't have exact data that gives when the order is ready for pick-up, so the estimated preparation time is used.)

Meal preparation does not *seem to be* an obvious bottleneck that causes the delay.

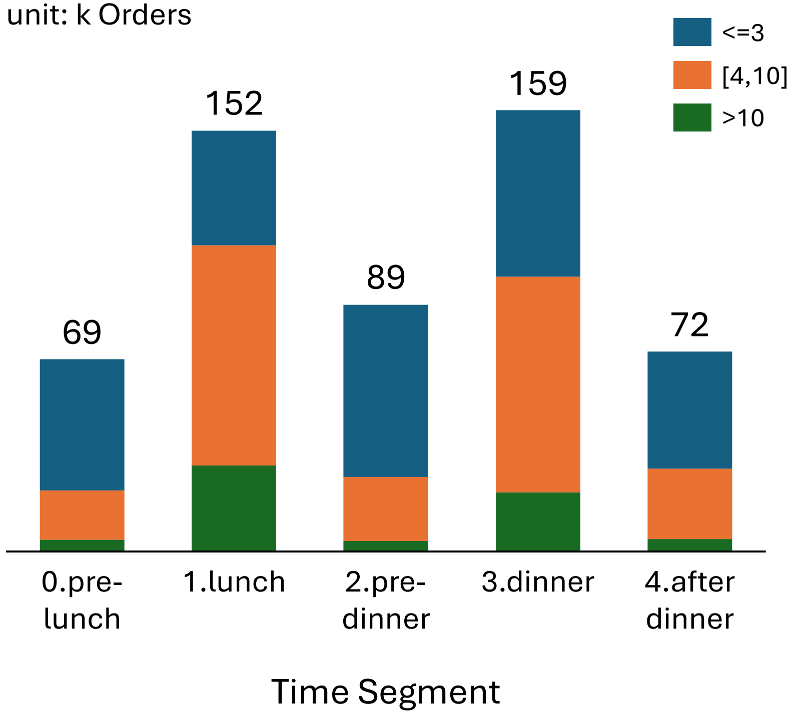
Pre-book option that is supposed to assist restaurant to better plan their capacity also does not help in reduce the delay.

Hypothesis 2: More orders in the same wave can cause more delays

Plot 1: Avg. on-time rate vs # of orders in a wave
unit: %



Plot 2: # of orders in wave distribution by time segment
unit: k Orders



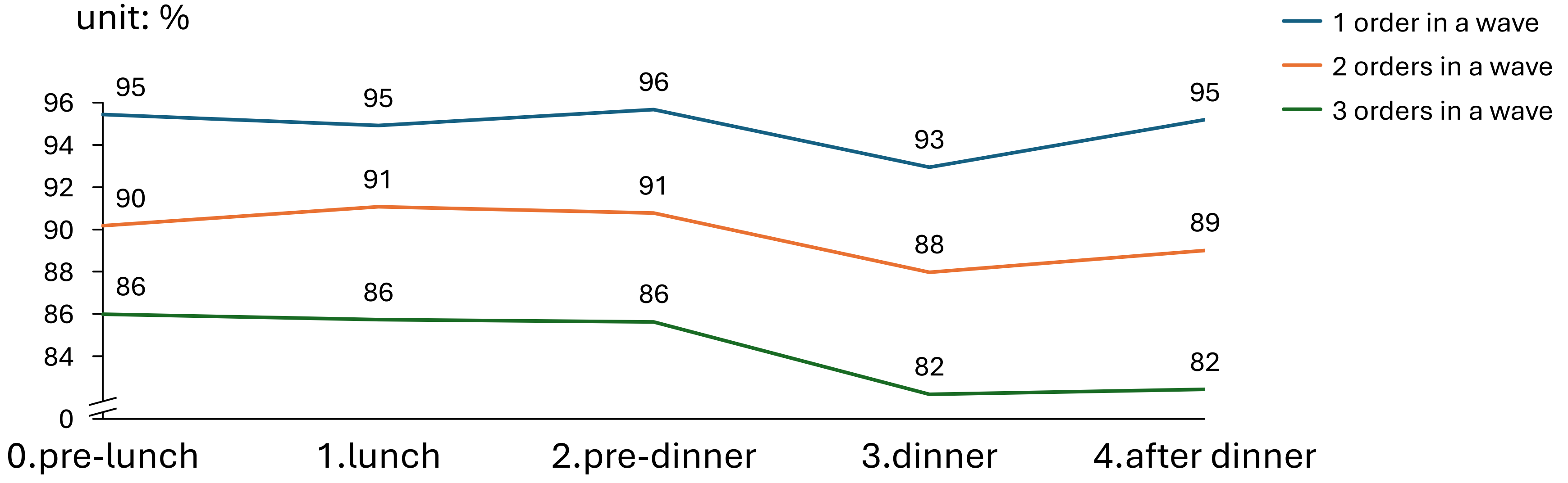
Key Conclusions

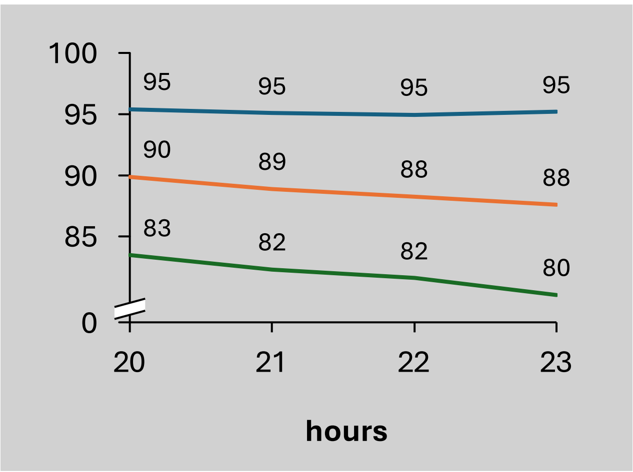
Riders tend to pick more orders in a wave during peak hours, and more orders in a wave are likely to cause delay in delivery.

The workload is more intensive in *lunch peak hour*, but the on-time rate is *slightly higher* than dinner peak.

Hypothesis 3: Traffic jams can cause more delays

Avg. on-time rate of 1,2,3 of orders in a wave by time segment
unit: %





During lunch peak hour, the delay is due to the more orders in a wave of couriers. *If the workload in one wave of courier is light*, the on-time rate resembles non-peak hours.

Key Conclusions

Looking at the drop in on-time rate in dinner time, it might be due to

a. Traffic
b. Evening fatigue

There can possible be *additive* effect of workload in one wave and evening fatigue.

Hypothesis 4: Delay is caused by the incapability of rider/restaurant.

Impact of Past Performance[1] on On-Time Rates of following days for Riders & Restaurants

	On-time order	Delayed order	Difference
	86%	82%	-4%
	86%	79%	-7%

Key Conclusions

Compared to orders delivered on time, delayed orders are more likely to be dispatched by riders and restaurant who are less punctual.

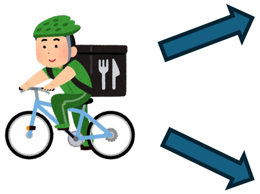
For those delayed orders:
The riders on avg. have **7%** *historical* on-time rate lower than orders arrived on time.

The restaurants have **4%** *historical* on-time rate lower than orders arrived on time.

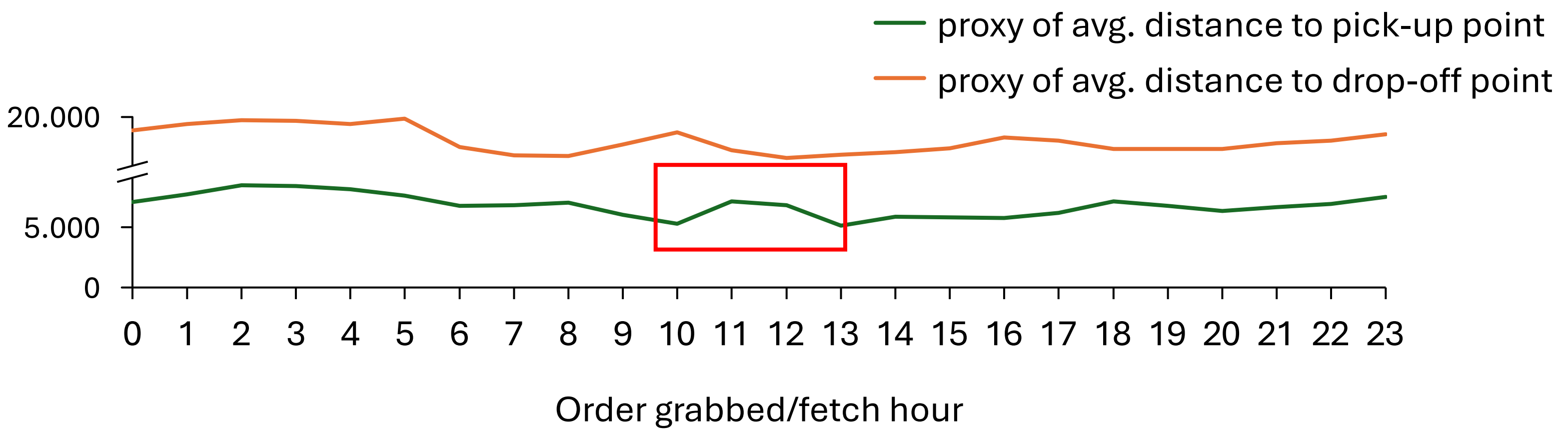
1. I use past 5-day on-time rate as the proxy for past performance.

Hypothesis 5: Distance can affect the on-time rate

Impact of (Euclidean) Distance[1] on On-Time Rates



	On-time order	Delayed order	Difference
Pick-up (restaurant)	6293	8031	+28%
Drop-off	16936	20635	+22%



For those delayed orders:
The the Euclidean distance for pick-up and drop-off are both more than 20% higher than the on-time delivered orders.

During lunch peak, riders will be assigned to orders that are relatively further in terms of the distance to the pick-up point.

1. Distance is a proxy of distance as the data has been sanitized. Note here Euclidean distance is not real distance on the route for delivery, it is just a proxy. The distance may not be the real distance a rider travels as they have multiple orders to deliver in one wave.

Conclusions to BQ 1

- Delivery is delayed due to the longer time takes getting to the restaurant and customer, and amongst the main causes, workload of riders in the wave is what the platform can actively intervene.
    - Encourage more riders to work during peak hours to relieve the increased demand by incentives.
    - For riders only have one order on the current wave, try to assign them one more order, but if a rider has more than 3 orders in the wave, try not to assign more orders to them.
- Pick riders with better past on-time rate when assigning the order to, especially for customers who already had several historical orders delayed.
- Give more buffer in estimated time of delivery during peak hours to manage the expectation of customers. E.g. if we extend estimated time of delivery by 3 min, the on-time rate will be ~92%.

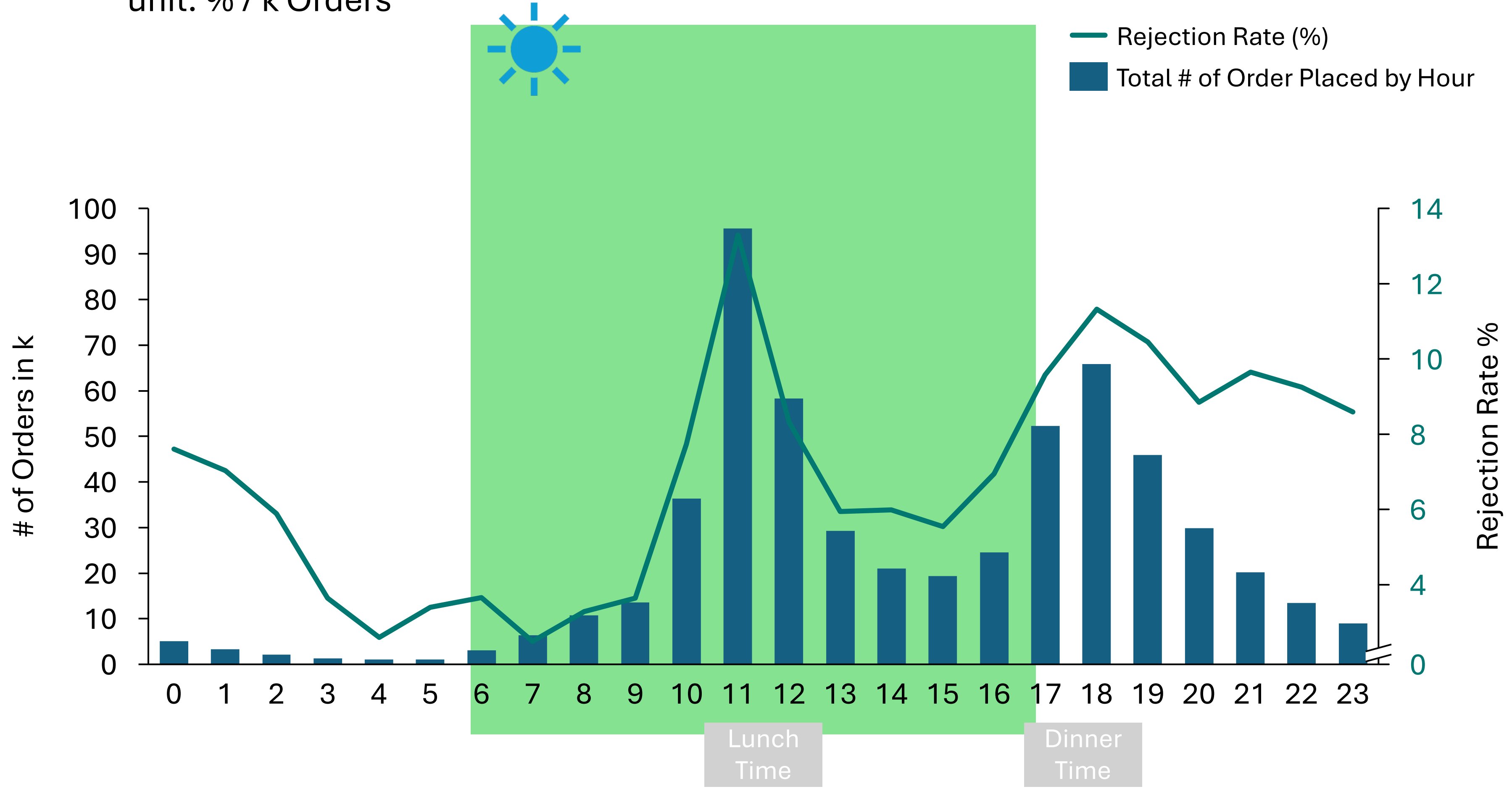
BQ 2: how to improve the order-courier assignment algorithm in order to mitigate the impacts of courier rejection?

Issue Tree of possible reasons of assignment rejection

- Time-Related
  - Peak hour – more uncertainties
  - Time of the day (day vs night) – riders are not vampire
- Rider-specific
  - Preference based on experience / behaviour
  - Fatigue – existing/expected workload
- Order-Specific
  - Estimated time for delivery of rider vs platform
  - Location, Distance – insufficient data
  - Order Type e.g. size, special requests – no supporting data

Rejection of Assignment[1] (13%) is more frequent during the **night** and **peak hours**

Order Placement by Hour vs Rejection rate
unit: % / k Orders



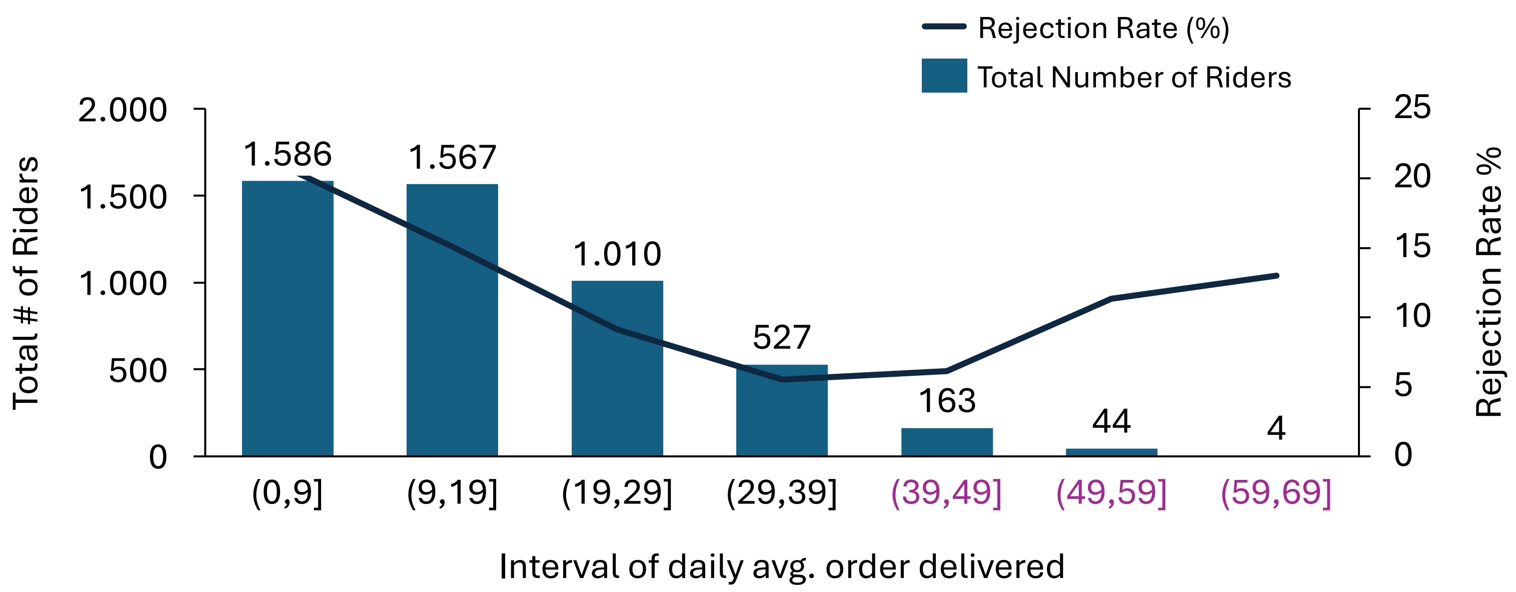
Key Conclusions

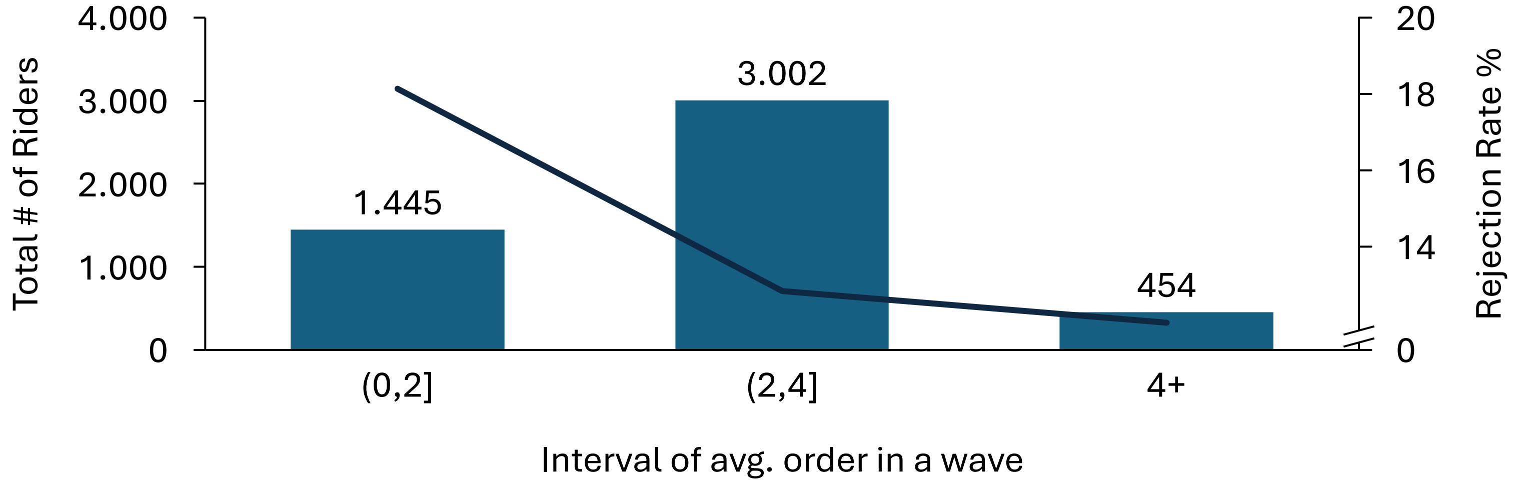
Night hours and peak hours might lead to higher rejection rate of orders due to more uncertainties, and riders' rest hours.

Early morning orders have the lowest rejection rate probably is because of the start of the day after they get up.

1. Rejection Rate: Weekday - 12.8% vs Weekend – 13.3%.

Hard-working riders tend to reject less, **conservative** riders tend to reject more





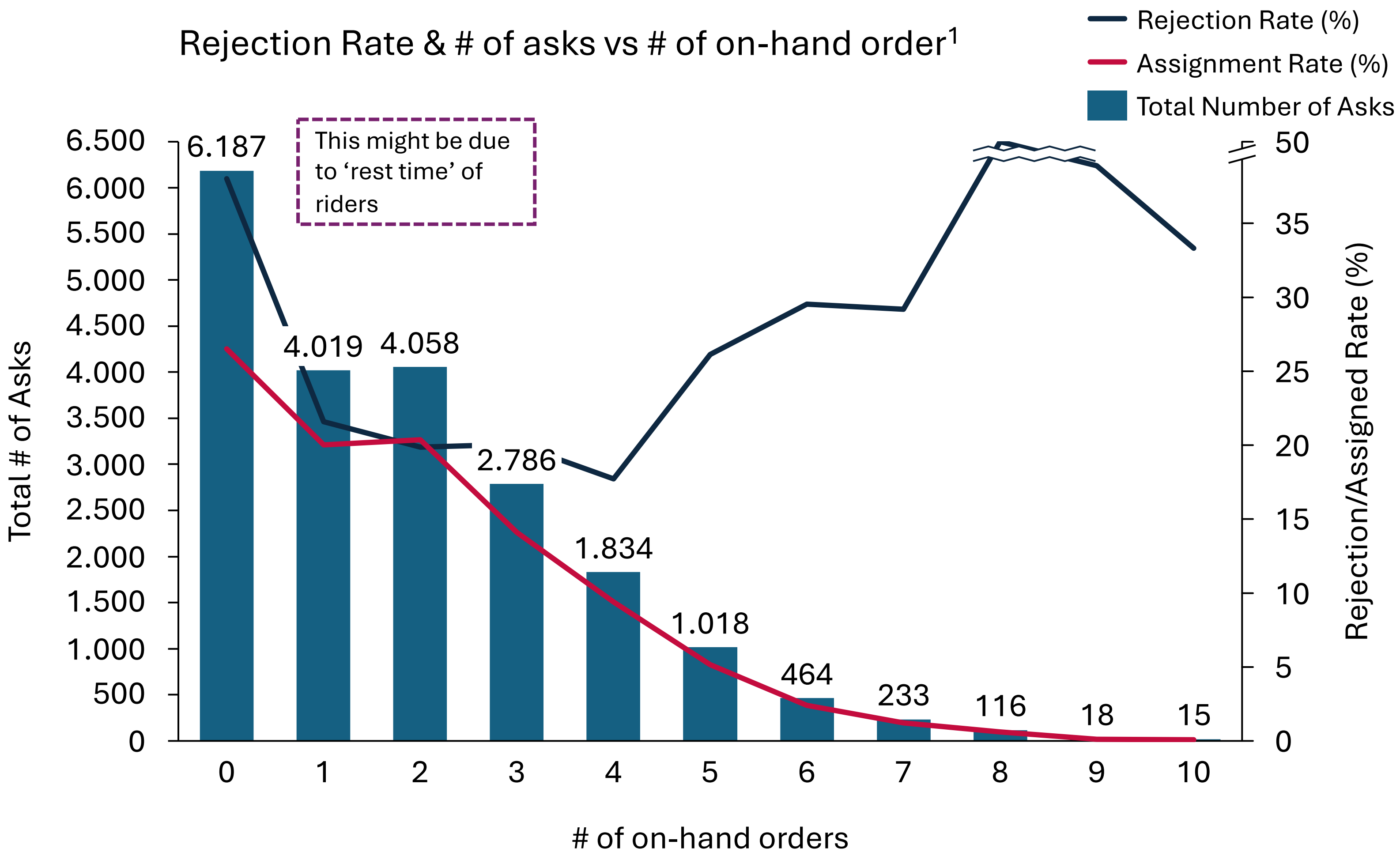
Key Conclusions

Rejection rate is also related to rider's behaviour.

Less hard-working riders <=9 orders a day (vs avg. 17 orders per day) tend to reject more often; Top performers (4%) may play smart in rejecting orders.

Riders on avg. having <= 2 orders (vs avg. 2.6 orders in a wave) in a wave tend to reject more, it might be due to risk-averse behaviour, e.g. new riders.

More on-hand orders can lead to a higher rejection rate



Key Conclusions

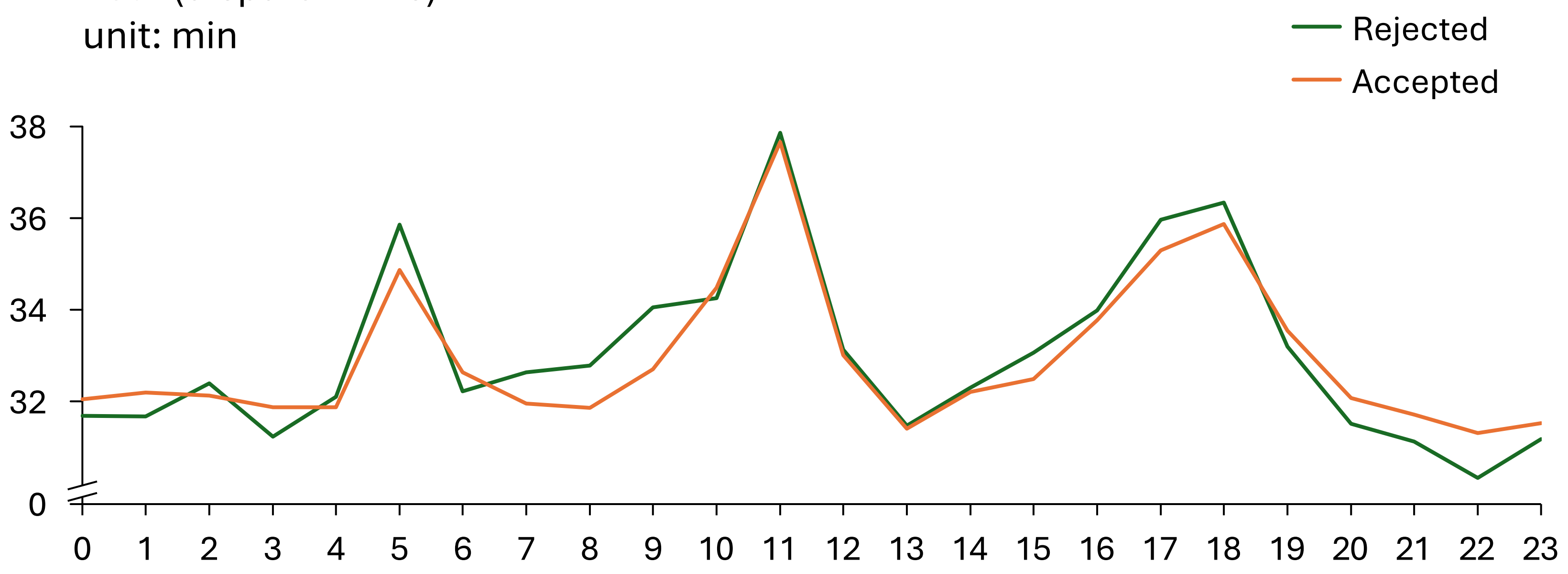
If the workload is heavy (with more than 4 orders to be delivered), couriers may tend to reject the assigned order.

But the system tends to assign more orders to those who are 'in rest', because they are idle.

1. Waybill data inner joined with info data on order_id , joined with rider data on dispatch_time to get this plot, but waybill only captures orders dispatched at 11am partially, the overall rejection rate is 26% vs 14% (info data), which might be due to sampling bias.

Estimated travel time is **NOT** an obvious factor related to rejection

Estimated travel time of rejected/accepted orders by hour (dispatch time)
unit: min



Key Conclusions

For orders that are grabbed by rider and rejected, throughout the day, we don’t spot apparent difference in estimated travel time for delivery between the two.

Conclusions to BQ 2

Rejection Patterns:

- Time-Related
  - Peak hour is more common than non-peak hours
  - Night is more common than day
- Rider-specific
  - Having more than 4 orders on hand is more likely to reject
  - Less hard-working riders are more likely to reject
  - Risk-averse riders are more likely to reject

Suggestions:

- Increase the probability of assigning to riders with 1 or 2 orders at hand instead of assigning to those having 0 orders at hand.
- Give more incentives to riders during peak-hour or night to increase the willingness of acceptance.

Next steps to take for improving PtoD

As we are not able to investigate all the possible factors related like complexity of location due to lack of data.

If we can do segmentation on locations of destinations for delayed orders, e.g. orders delivered to hospital, campus, high-end neighbourhood, we may find some patterns and assist drivers if they have orders with those destinations.

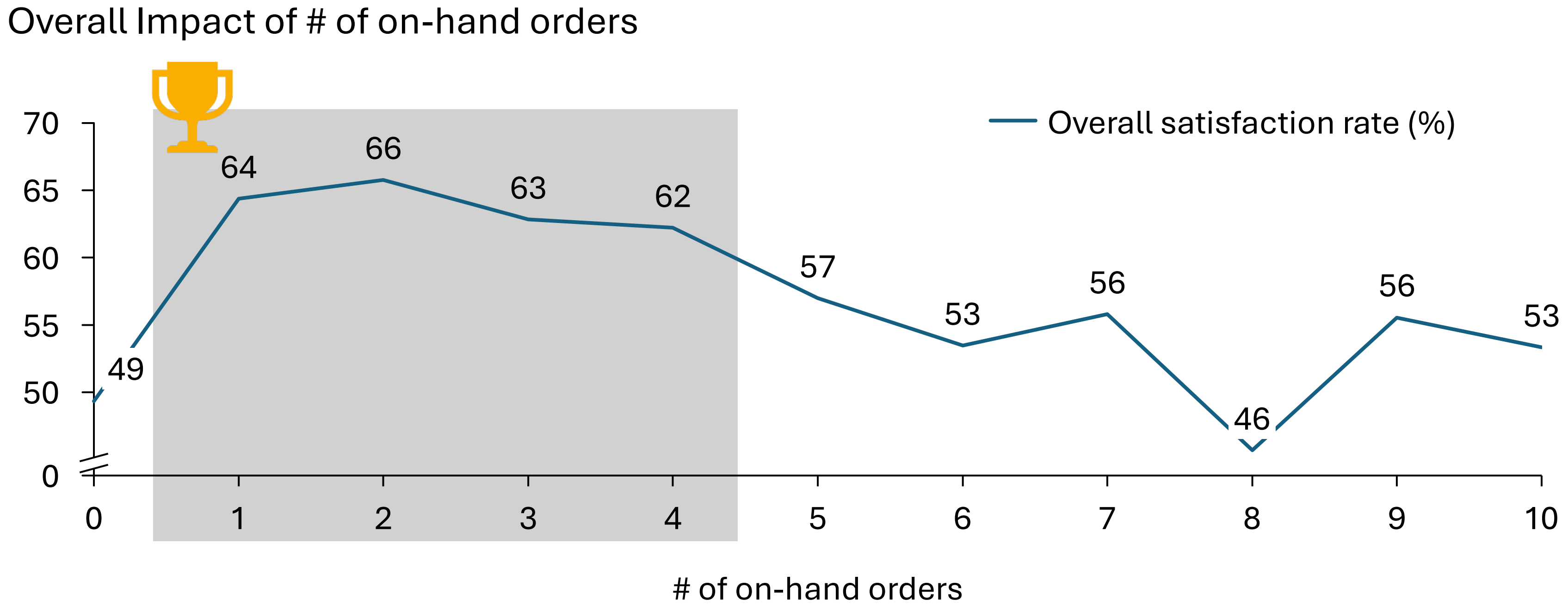
For those underperforming riders (e.g. new riders) we may provide trainings to them before being onboard.

Local Optimum vs Global Optimum

As we know that riders having more orders on a wave will have higher acceptance rate but lower on-time rate, therefore, when doing optimization, the global objective function to be optimized must take both factors into account to find the global optimum.

Order Acceptance and Delivery on-time rate are not separated tasks. The real satisfaction is coming from the joined probability of both:

*Pseudo Customer Satisfaction = P(order accepted) * P(order delivered on-time)*



Use Explainable AI to approach this problem

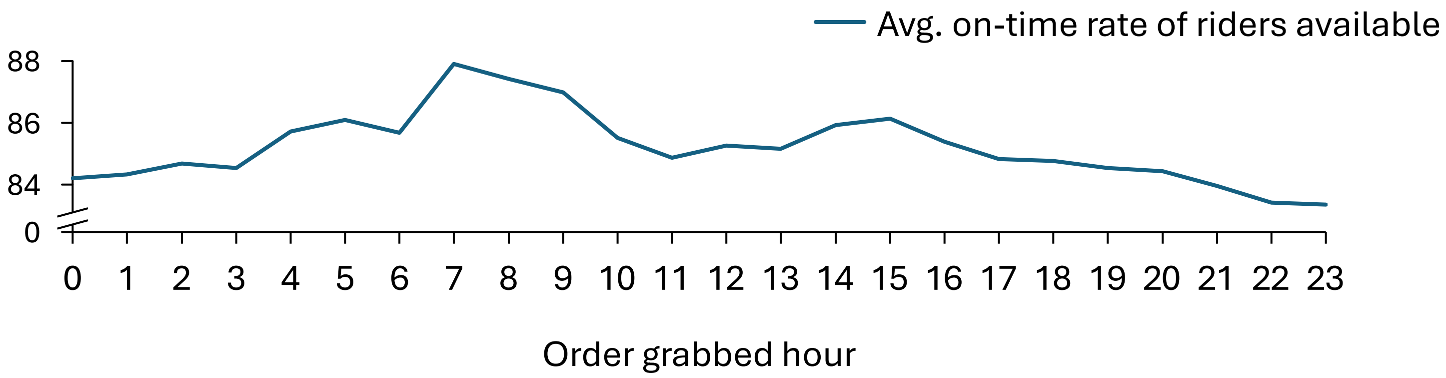
- Collect features:
  - **Time** e.g. weekday, hour, peak-hour, night
  - **Courier** e.g. daily avg. order delivered, rejection rate, working days in a week
  - **Order** e.g. restaurant/cuisine type, pick-up point building type, drop-off point building type
  - **Courier-order** interaction related e.g. current orders in the wave, distance to travel
- Build model e.g. LightGBM (does not require independence between explanatory variables)
- View the Shapley value for each explanatory variable to understand feature impacts.

The End

Hypothesis: Delay is caused by the incapability of rider/restaurant.

Impact of Past Performance[1] on On-Time Rates of following days for Riders & Restaurants

	On-time order	Delayed order
	86%	82%
	86%	79%



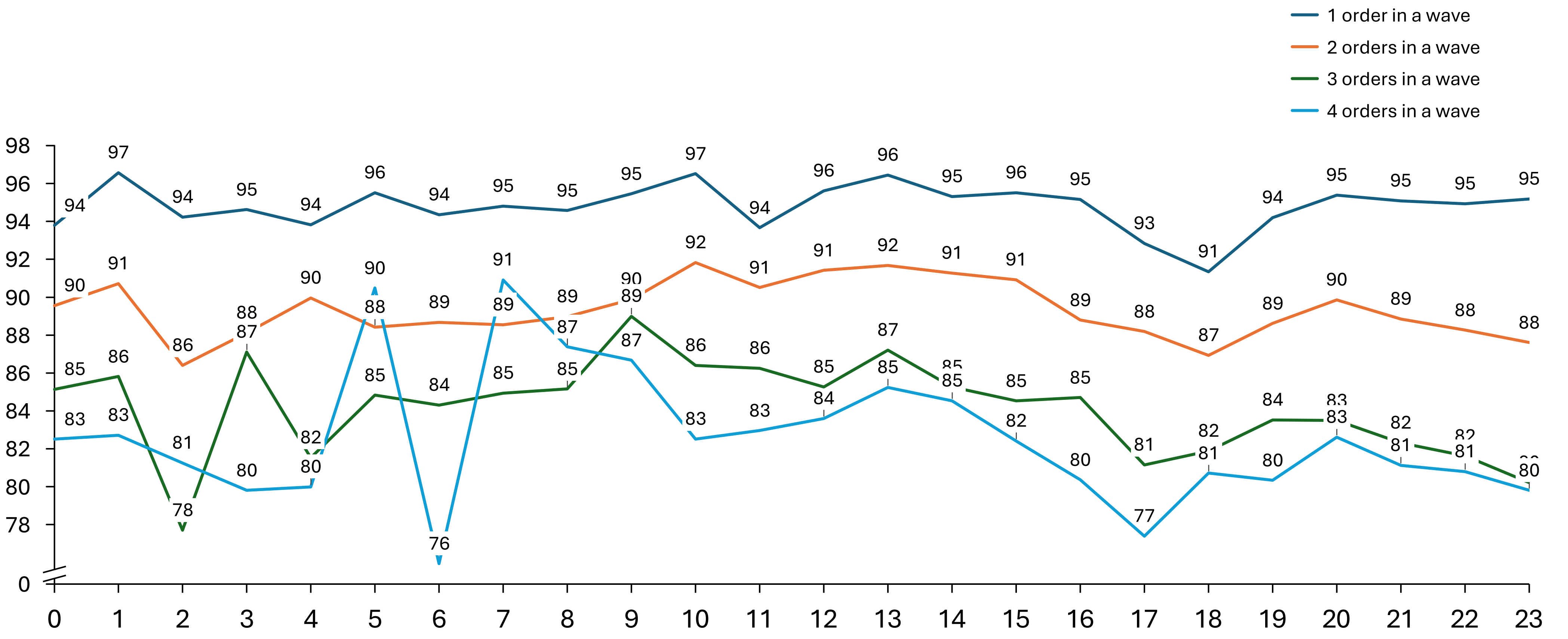
Key Conclusions

Compared to orders delivered on time, delayed orders are more likely to be dispatched by riders and restaurant who are less punctual. For those delayed orders:
The riders on avg. have **7%** on-time rate lower than orders arrived on time.
The restaurants have **4%** on-time rate lower than orders arrived on time.

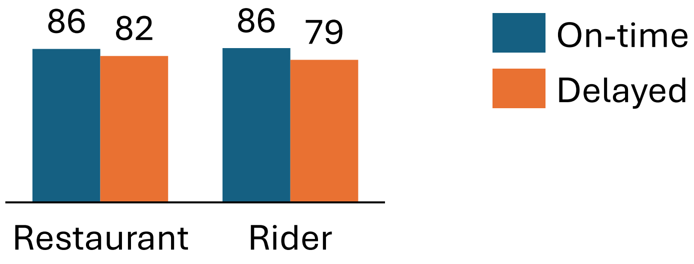
'Moring birds' tend to have better past performance; It is more likely to be assigned to a better performer if you have a morning order .

1. I use past 5-day on-time rate as the proxy for past performance.

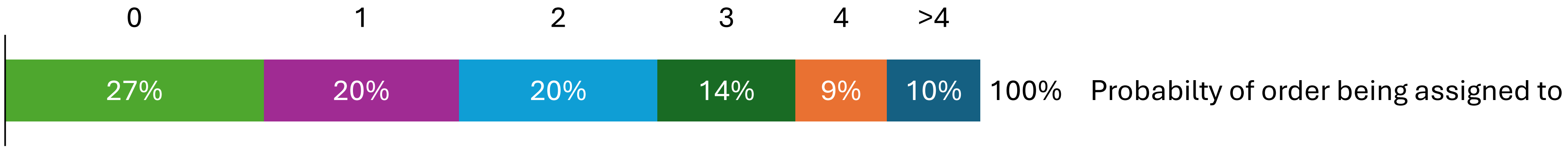
Backup Slides



Impact of Past Performance[1] on On-Time Rates of following days for Riders & Restaurants
unit:%

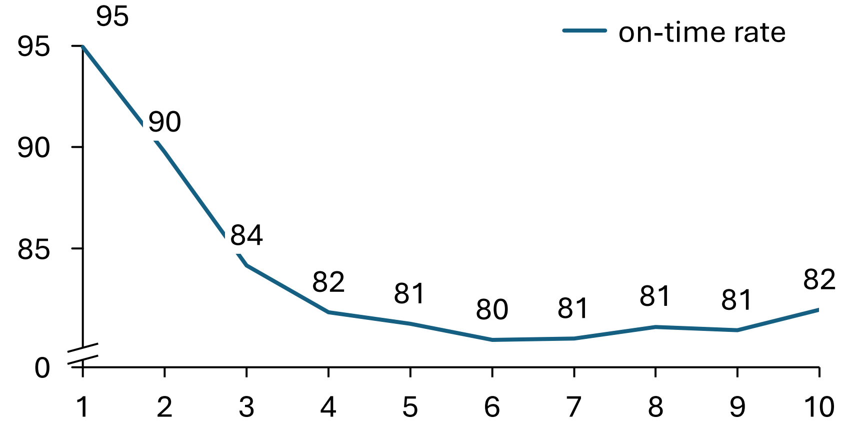


Likelihood of order being assigned given the current workload unit:%

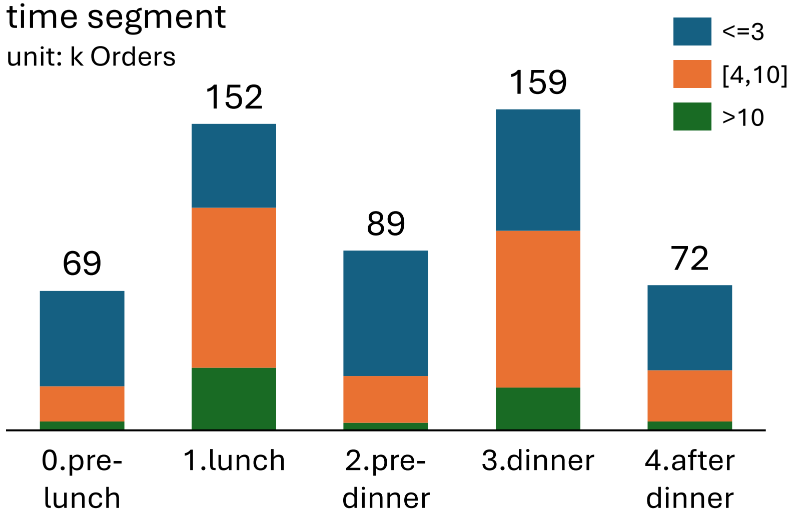


Hypothesis 2: More orders in the same wave can cause more delays

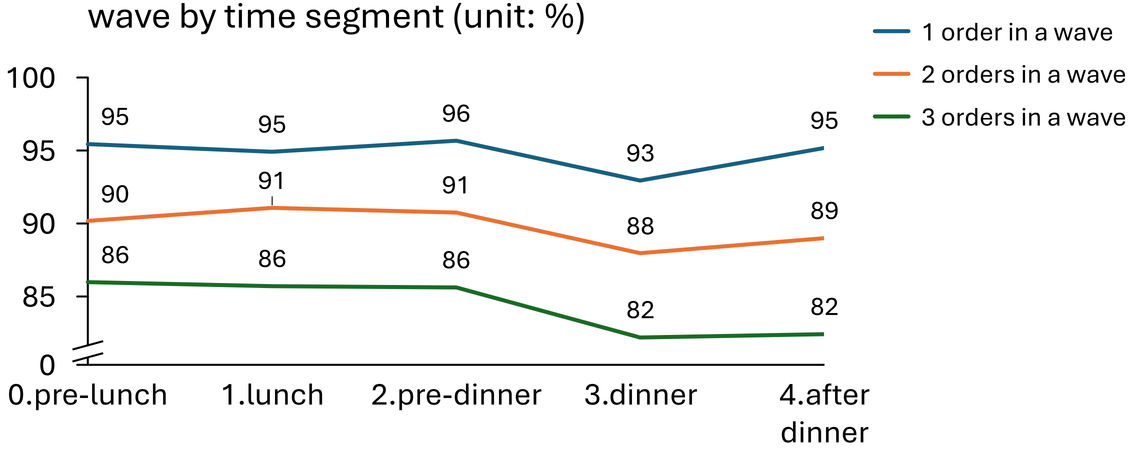
Plot 1: Avg. on-time rate vs # of orders in a wave (unit: %)



Plot 2: # of orders in wave distribution by time segment
unit: k Orders



Plot 3: Avg. on-time rate vs 1,2,3 of orders in a wave by time segment (unit: %)



During lunch peak hour, the delay is due to the more orders in a wave of couriers. *If the workload in one wave of courier is light*, the on-time rate resembles non-peak hours.

Key Conclusions

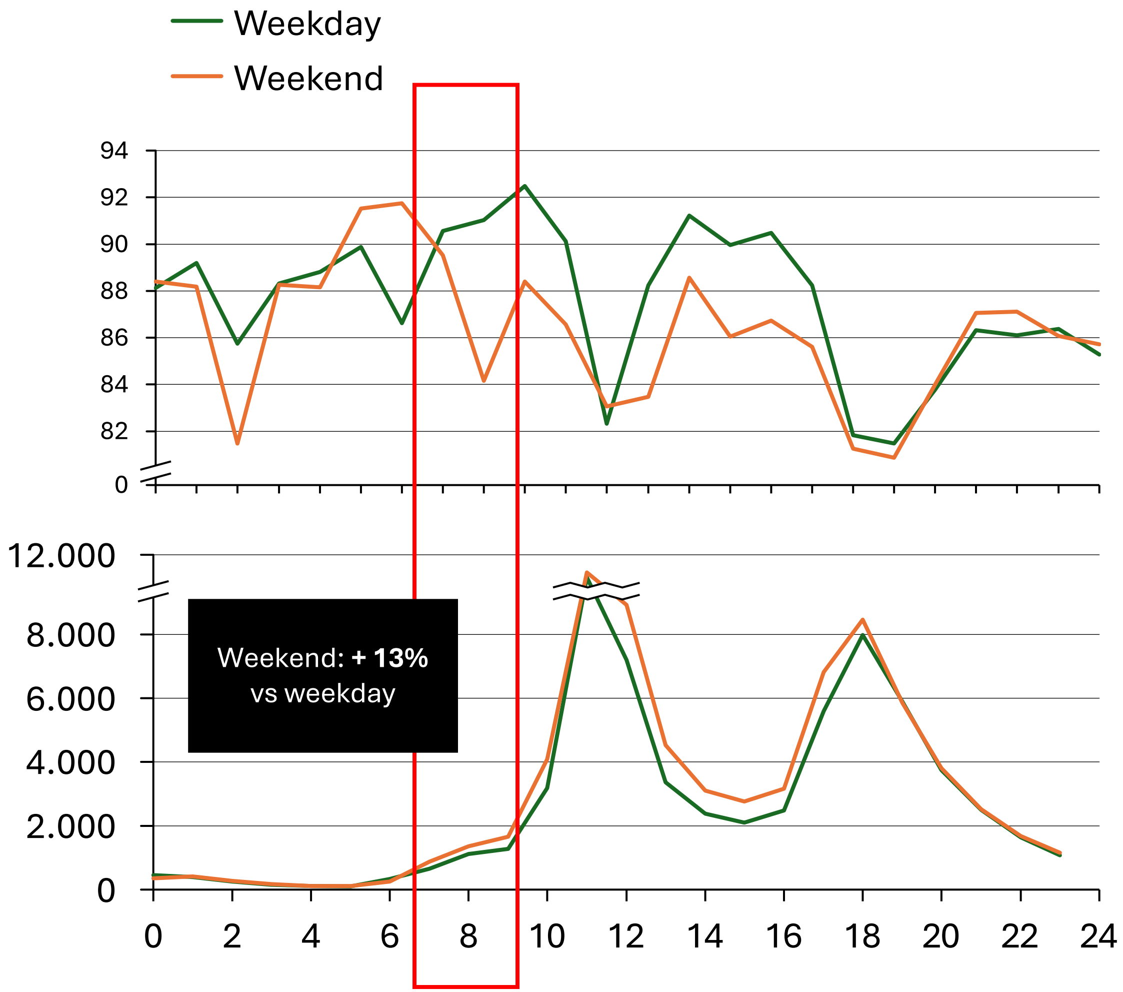
If we want to improve the efficiency for delivery in lunch peak hour, we can focus on reducing the workload of riders.

Looking at the drop in on-time rate in dinner time, it might be due to

a. Traffic
b. Evening and Rider fatigue

Hypothesis 3: Peak hour traffic jam can cause more delays

On-time Rate & Avg. # of Order Placement by Hour (Weekday vs Weekend)
unit: % / Orders



	Mon-Fri	Sat/Sun
7am – 9am	91%	88%
11am – 12pm	84%	82%
5pm – 7pm	82%	81%
Non-peak hours	88%	86%
Overall	85%	84%

Key Conclusions

The peak hour in weekdays does not cause the delay of delivery, so traffic may not be a key reason, otherwise we probably would see some increase in on-time delivery at weekends.

But it's worth noting that in China that traffic jam is heavier during evening rush hour than morning rush hour.

Issue Tree of possible root causes

- Longer waiting time to **pick-up meal**
  - Meal preparation time gets longer
    - 1 More orders to prepare at the same time
  - Longer time to arrive at pick-up point
    - 2 Traffic jams during peak hours
    - 3 Other orders to pick-up or deliver (workload)
    - Long distance to travel

- Longer time for **delivery to customer**
  - 2 Traffic jams during peak hours
  - 3 Other orders to deliver before arrival (workload)
  - Long distance to travel

	Weekday	Weekend
7am – 9am	2	
11am – 12pm	1 3	1 3
5pm – 7pm	1 2 3	1 2 3
Non-peak time		