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The Study on Optimization of Rider Resource Allocation and Performance Evaluation Based on Data-Driven Approach

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Abstract: *This study explores the key factors affecting delivery rider performance, with a focus on the impact of different contexts such as holidays, adverse weather, and peak periods on rider performance. By analysis riders' personal characteristics (such as age and work experience) and external environmental factors (such as weather), the study identifies performance differences among different rider groups in various contexts. The research finds that riders with 1-2 years of registration tenure exhibit the highest daily work rates, while riders from Heilongjiang perform better in all contexts compared to those from other provinces. Additionally, the study examines the impact of rider fatigue on timely delivery rates, revealing a significant correlation between continuous work hours, rest days, and rider performance. This research provides specific recommendations for optimizing rider resource allocation and improving service quality.*

Keywords: *Delivery Rider Performance; Contextual Factors; Rider Fatigue; Resource Optimization*

1. Introduction

With the rapid development of mobile internet and the express delivery industry, food delivery platforms have become an indispensable part of modern urban life. In China, platforms like Meituan provide users with convenient and efficient food delivery services day after day through large-scale fleets of delivery riders. As a key component of platform operations, the performance of delivery riders directly impacts delivery efficiency, user experience, and the platform's market competitiveness. However, there are significant performance differences among riders, which are influenced not only by their personal characteristics such as age, gender, and work experience, but also by external factors such as weather, holidays, and peak work periods. Therefore, identifying the key factors affecting rider performance through systematic data analysis and optimizing rider resource allocation in different contexts has become a critical issue for food delivery platforms.

In China, the online food delivery industry has experienced rapid growth. According to the latest market data, in 2024, the market size of the Chinese online food delivery industry reached 1.6357 trillion yuan, and it is expected to further grow to 1.9567 trillion yuan by 2027[1]. As the industry continues to evolve, competition among platforms has become increasingly fierce. Enhancing platform competitiveness through improved delivery efficiency and optimized user experience has become the core issue of industry development. Despite this, food delivery scenarios are complex and variable, and riders' performance is influenced by multiple factors. The performance differences among riders in different contexts, especially during holidays, bad weather, and other special circumstances, highlight the necessity of optimizing delivery resource allocation. In response to this backdrop, this study employs a data-driven analysis method to explore the key factors affecting rider performance. It aims to reveal the performance differences among various rider groups in different contexts and propose corresponding optimization strategies. The study focuses on analyzing the impact of personal attributes such as age, work experience, and place of origin, as well as external factors such as holidays, peak periods, and weather, on rider performance. Through in-depth analysis of rider operational data from Meituan, this paper provides theoretical foundations and practical guidance for platform rider scheduling and resource allocation in different contexts, thereby improving delivery efficiency and service quality and enhancing the platform's market competitiveness.

The main goals of the research are: first, to identify the key influencing factors of rider performance;

second, to analyze the differences in rider performance under different scenarios (such as holidays, peak periods, and bad weather); and third, to propose strategies for optimizing rider resource allocation based on data analysis results, enhancing platform operational efficiency and user satisfaction. Through this research, platforms can not only more accurately allocate rider resources but also build an intelligent, efficient, and differentiated delivery service system amidst fierce market competition, laying a solid foundation for the platform's long-term sustainable development.

2. Literature review

With the rapid development of the on-demand delivery industry, the delivery efficiency and service quality of riders have gradually become important indicators for measuring the success of delivery platforms. Numerous scholars and industry professionals have started focusing on various factors that affect rider performance, particularly in terms of delivery efficiency, punctuality, and work quality[2]. This section will review domestic and international research findings on delivery efficiency, rider performance, and external situational factors, with a focus on the impact of personal characteristics, external environmental factors, and their interactions on delivery performance.

2.1 The Rapid Development and Challenges of the On-Demand Delivery Industry

In recent years, with the widespread use of smartphones and mobile payments, the on-demand delivery industry has seen rapid global growth. According to reports from platforms such as Alibaba and Meituan, the scale of the Chinese delivery market has been expanding year by year[3]. Particularly, in first- and second-tier cities where the market is approaching saturation, the demand for convenient delivery services has significantly increased in lower-tier markets[4]. However, despite the vast market potential, improving delivery efficiency and ensuring service quality still face multiple challenges. The work performance of delivery riders directly determines the punctuality rate, customer satisfaction, and overall service level of the platform. Therefore, how to improve rider efficiency and optimize resource allocation has become a key research focus in both academia and industry.

2.2 Weather Conditions and Rider Performance

Extreme weather conditions such as heavy rain, floods, and high temperatures are well-documented as factors that disrupt logistics operations, leading to delays and increased risk of damage to goods. In a study by Kidwai and Maqbool, weather disruptions were found to negatively affect the performance of postal and private delivery services in Uttar Pradesh[5], India. These disruptions include road blockages, infrastructure damage, and health risks to delivery personnel. Additionally, Ramadhani et al. propose a model integrating historical weather data to optimize delivery routes, reducing operational costs and minimizing environmental impact[6]. Similarly, Seethapathy emphasizes how weather-related sales predictions are vital for optimizing inventory and reducing delays in supply chain operations[7] .

2.3 Peak Hours and Delivery Efficiency

The behavior of delivery riders varies significantly between peak and non-peak hours, directly influencing delivery efficiency and service quality. High-demand periods, such as lunch and dinner hours, lead to increased workload and greater time pressure on riders. Gabriel et al. show that during peak periods, riders are often forced to take faster but riskier routes, leading to an increased likelihood of accidents and delays[8] . This not only affects the punctuality of deliveries but also compromises the quality of service provided. Thus, understanding rider behavior during peak periods is essential for crafting effective scheduling strategies that prioritize rider safety and customer satisfaction.

2.4 Public Holidays and Delivery Performance

Public holidays, especially during major promotions like the "Double 11" shopping festival or Chinese New Year, significantly impact the workload of delivery riders. Tian discusses how promotional periods create a surge in demand, leading to longer working hours and reduced delivery performance[9] . This increase in demand often leads to fatigue, which in turn lowers punctuality and service quality. Consequently, platforms like Meituan face challenges in balancing the high workload with rider health and safety during these periods. To mitigate these challenges, Tian suggests that platforms should integrate dynamic scheduling and incentive systems to manage rider workload more effectively during

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peak periods[10] .

2.5 Rider Demographics and Performance

Rider demographics such as age, gender, and work experience also influence delivery performance. Studies show that younger riders tend to be more adept at using technological tools such as navigation apps, while older riders bring valuable experience and local road knowledge . However, younger riders are often found to have higher turnover rates, possibly due to the temporary nature of their employment. On the other hand, older riders may have a steadier performance but are less flexible in adapting to rapidly changing technological systems. Understanding these demographic differences is key to designing optimized training and resource allocation strategies for delivery platforms[11].

2.6 Fatigue and Safety Issues

The physical and mental health of riders is an underexplored yet critical factor in determining delivery efficiency. Studies indicate that long hours and irregular schedules can lead to fatigue, which impairs cognitive function and reaction times, increasing the risk of accidents . This is particularly pertinent in the context of platforms, where riders often work under high-pressure conditions with minimal rest. Nycz et al. highlight the importance of using technology and performance feedback systems to support healthcare initiatives for delivery personnel . Platforms must not only monitor work hours but also integrate fatigue-reducing interventions, such as mandatory rest periods and psychological support, to ensure the safety and well-being of their riders[12].

In conclusion, the existing body of literature emphasizes the multifaceted factors influencing delivery performance, including environmental conditions, peak periods, public holidays, and demographic characteristics. These factors, when analyzed in conjunction with rider performance metrics, can help platforms like Meituan optimize their operations. By incorporating advanced data analysis techniques such as machine learning and real-time monitoring, platforms can better manage resources, improve safety, and enhance customer satisfaction.

3. Data Description

3.1 Data processing

This study will conduct an in-depth analysis of delivery rider performance based on data provided by the delivery platform, considering multiple dimensions such as the riders' personal backgrounds and external environments. Our goal is to uncover the core characteristics of rider performance through data preprocessing and descriptive statistical analysis, and further analyze factors such as rider performance identification and the moderating effects of weather conditions on performance. Ultimately, we aim to propose strategies to optimize the capacity structure based on the research findings, ensuring the provision of optimal delivery services in various scenarios.

First, we will clean and preprocess the collected rider data, including removing outliers, filling missing values, and normalizing the data, to ensure the quality and accuracy of the analysis. This step is crucial for the reliability of the subsequent analysis, as the quality of the data directly impacts the accuracy and validity of the results. Next, through descriptive statistical analysis, we will reveal the basic characteristics of rider performance, including attendance, working hours, delivery efficiency, user experience contributions, and retention time. This analysis will help us understand the overall rider performance and lay the foundation for further in-depth analysis. Additionally, we will analyze the performance differences of riders under different weather conditions, exploring how weather factors affect their delivery efficiency and service quality. This analysis will help us understand the impact of weather on rider performance.

We will conduct an in-depth analysis of the rider's personal background, including birthplace, age, experience, fatigue level, etc., and explore how these factors affect the rider's performance. This analysis will help us understand the impact of the rider's personal background on their performance and provide insights for optimizing the rider structure. In addition to the rider's personal background, we will also analyze external environmental factors such as holiday conditions, city tier, and consumer demand, and examine how these factors influence the rider's delivery performance. This analysis will help us understand the impact of the external environment on rider performance and provide references for optimizing delivery services.

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As shown in Figure1, it illustrates the multifactor analytical framework constructed in this paper. The left-hand “Rider Personal Factors” module aggregates intrinsic attributes such as riders’ birthplace, age, work experience, and fatigue; the lower “Customer Impact Factors” module encompasses external contextual variables such as holidays and weather conditions; and the right-hand “Rider Delivery Outcome” module corresponds to the primary performance metrics employed in this study. The arrows indicate how personal attributes and environmental contexts jointly affect the final delivery performance, providing a clear logical pathway for subsequent model specification and resource optimization.

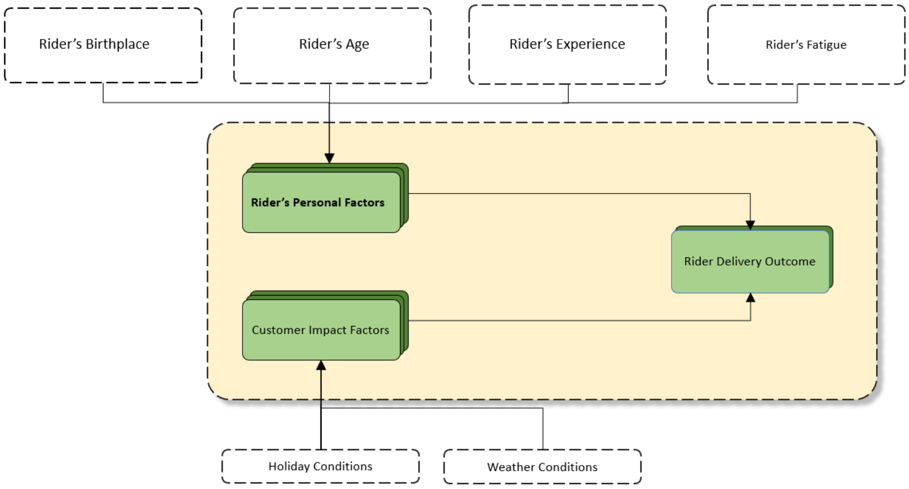

Figure 1 Technical Roadmap

3.2 Variable Description

Table 1 Variable Descriptions

Variable Name	Variable Meaning
Rider ID	Represents the identification number of the rider
Date	Represents the date of the rider’s workday
Completed Orders	Represents the number of orders completed by the rider
Rejected Orders	Represents the number of orders rejected by the rider
Working Hours	Represents the total working hours of the rider for the day
Current Age	Represents the current age of the rider
Registration Date	Represents the rider's registration date on the platform
Gender	Represents the rider's gender
Birthplace	Represents the rider’s birthplace province
Weather Conditions	Represents the weather conditions when the rider is working
Temperature	Represents the temperature during the rider's working hours
Actual Sensory Temperature	Represents the perceived temperature during the rider’s working hours
Air Humidity	Represents the air humidity on the rider’s working day
Wind Force	Represents the wind strength during the rider’s working day

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Precipitation Intensity	Represents the level of precipitation on the rider's working day
Total Working Days	Represents the total number of days the rider worked during the month
Accepted Orders	Represents the total number of orders accepted by the rider
Completed Rate	Represents the rate at which the rider completes accepted orders
Daily Completed Orders	Represents the daily completed orders of the rider
Rider Experience	Indicates the total experience of the rider
Is Continuous Work Period	Indicates whether the rider worked continuously or took breaks during the month
Cumulative Completed Orders	Represents the total number of orders completed without breaks in the month
Rest Days	Indicates whether the rider took a rest day (e.g., no orders)
Monthly Completed Orders	Represents the total number of orders completed by the rider in a month
Monthly Completion Rate	Represents the completion rate of the rider for the month
Average Rejected Orders	Represents the average number of rejected orders by the rider per day

3.3 Rider Distribution by Birthplace

Table2 Rider Distribution by Birthplace

Birthplace	Number of Riders	Percentage
Hebei Province	2435	70.31%
Heilongjiang Province	469	13.54%
Liaoning Province	167	4.82%
Jilin Province	106	3.06%
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As shown in Table 1, the distribution of riders' registered provinces is mainly concentrated in Hebei and Heilongjiang provinces. Among them, Hebei has 2,435 riders, accounting for 70.31%, and Heilongjiang has 469 riders, accounting for 13.54%. Liaoning has 167 riders, accounting for 4.82%. Jilin has a total of 106 riders, accounting for 3.06%.

Table 2 shows where the rider come from. Riders from other provinces are relatively fewer, with most provinces having fewer than 100 riders, and their proportions are also lower. This indicates that the rider population is primarily from Hebei and Heilongjiang, with riders from other provinces being more dispersed.

4. Key Characteristics Analysis of Delivery Riders

In this section, we will use data analysis to identify the key characteristics of rider performance. Based on riders' basic information and behavioral data, we will explore how personal factors such as age, work experience, and birthplace influence their delivery performance.

Specifically, this study will use daily average utilization rate and daily average score to analyze the delivery performance of riders with different characteristics. Additionally, we will further analyze how different weather conditions and public holidays affect the work performance of riders with varying

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characteristics.

We define the calculation method for utilization rate as follows:

$$\mathrm{AUR}_{\mathrm{it}} = \frac{\mathrm{AR}_{\mathrm{it}}}{\mathrm{TNR}_{\mathrm{it}}}, (\mathrm{i}, \mathrm{t} \in 1,2,3)$$

In this case, AUR represents the Average Utilization Rate; AR represents the actual number of riders working (Actual number of Riders); TNR represents the total number of riders (Total Number of Riders); i represents different rider characteristics, including age, work experience, and birthplace. t represents different conditions such as favorable weather, average weather conditions, poor weather conditions, and public holidays. The calculation method for average performance is as follows:

$$\mathrm{BP}_{\mathrm{it}} = \frac{\mathrm{TNR}_{\mathrm{it}}}{\mathrm{AR}_{\mathrm{it}}}, (\mathrm{i}, \mathrm{t} \in 1,2,3)$$

RP represents Rider Performance, calculated as the completed order quantity multiplied by the punctuality rate. TRP represents Total Rider Performance; AR represents the total number of riders (Actual number of Riders); i represents different rider characteristics, including age, work experience, and birthplace. t represents various conditions such as favorable weather, average weather, poor weather, public holidays, as well as behavioral characteristics such as working hours and delivery frequency, and how these factors affect the rider's delivery efficiency and user experience.

Additionally, we will analyze the performance differences between different types of riders (full-time vs. part-time) and identify the key factors influencing rider performance, providing a foundation for further analysis.

Table 3 Age Group Performance

Age Group	18-25	26-30	31-35	36-40	41-50	50+
Overall Work Rate	39.85%	53.96%	62.93%	64.64%	66.73%	71.45%
Holiday Daily Work Rate	38.72%	52.95%	62.37%	83%	65.86%	70.49%
Workday Daily Work Rate	40.38%	54.11%	63.19%	64.5%	67.14%	71.88%
Poor Weather Work Rate	38.46%	53.96%	62.36%	64.05%	66.67%	72.09%

Table 4 Registration Duration Performance

Registration Duration	5+ years	4 years	3 years	2 years	1 year	Less than 1 year
Holiday Daily Work Rate	56.9%	58.53%	46.57%	54.92%	70.06%	48.18%
Workday Daily Work Rate	57%	57%	52.24%	54.87%	71.39%	49.11%
Poor Weather Work Rate	56.86%	56.25%	49.29%	54.63%	70.39%	48.25%

Table 5 Performance Based on Birthplace

Birthplace	Hebei	Heilongjiang	Jilin	Liaoning	Nei Menggu	Henan
Holiday Daily Work Rate	53.71%	64.89%	59.14%	57.32%	60.78%	56.51%
Workday Daily Work Rate	54.9%	65.51%	58.17%	58.26%	62.27%	57.36%
Poor Weather Work Rate	53.74%	65.71%	59.8%	57.5%	61.32%	54.65%

As shown in Table 3,4,5, we can draw the following conclusions:

• There is a significant difference in the utilization rates across different age groups. Specifically, older riders tend to have higher utilization rates.

• Riders' workday utilization rates are generally slightly higher than their holiday utilization rates,

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and poor weather conditions did not reduce the utilization rates of riders in any age group.

• Riders with 1-2 years of registration have the highest utilization rates, while those with less than a year of registration have the lowest.

• Holidays have the greatest impact on riders with 3-4 years of registration, with their utilization rate during holidays being 6% lower than on workdays.

• Whether during holidays or in poor weather, riders from Heilongjiang have higher utilization rates than riders from other provinces.

Table 6 Age Group Performance

Age Group	18-25	26-30	31-35	36-40	41-50	50+
Holiday Average Score	10.6879	16.76532	17.7086	18.0647	16.9411	15.5702
Workday Average Score	11.0956	18.0963	18.6042	19.1177	17.478	16.1849
Poor Weather Average Score	10.9439	18.3654	18.7141	18.9654	17.5962	15.9779

Table 7 Registration Duration Performance

Registration Duration	5+ years	4 years	3 years	2 years	1 year	Less than 1 year
Holiday Average Score	13.945	10.954	11.331	13.812	20.471	13.132
Workday Average Score	14.474	10.663	11.458	15.705	21.347	13.8619
Poor Weather Average Score	14.26	10.137	12.036	15.683	21.398	13.9471

Table 8 Performance Based on Birthplace

Birthplace	Hebei	Heilongjiang	Jilin	Liaoning	Nei Menggu	Henan
Holiday Average Score	15.80	18.8684	16.35	13.057	15.678	15.18
Workday Average Score	16.59	19.6806	17.42	13.527	16.001	17.22
Poor Weather Average Score	16.71	19.6032	17.14	13.620	16.3184	16.595

As shown in Table 6,7,8, we can draw the following conclusions:

• Riders aged 18-25 have lower work performance compared to other age groups.

• Riders aged 36-40 have the best average performance.

• Riders with 1-2 years of registration have the best work performance.

• Riders from Heilongjiang perform better than riders from other regions, whether on holidays or in poor weather conditions.

• Riders from Henan are most affected by holidays in terms of work performance.

5. Analysis of Rider Punctual Delivery Rates in Different Scenarios

Punctuality is crucial for the operation of food delivery platforms. One of the core goals of the platform is to ensure that customers receive their orders on time, thereby improving customer satisfaction and loyalty. The rider's punctuality directly affects the achievement of this goal. High punctuality not only enhances user experience but also reduces order complaints and the occurrence of negative platform reviews. In a highly competitive market environment, punctual delivery has become a key competitive indicator, influencing the platform's reputation and market share. Punctuality reflects the rider's work efficiency and the effectiveness of the platform's scheduling system. High punctuality generally means that the rider can complete delivery tasks efficiently, which helps the platform optimize resource allocation and ensure stable service during peak periods and special scenarios. Additionally, punctuality

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is closely related to the rider's workload, traffic conditions, and weather conditions. Therefore, by analyzing these factors, the platform can develop more accurate scheduling strategies, reasonably allocate rider resources, and ensure high delivery efficiency across different scenarios.

Moreover, improving punctuality can directly enhance the platform's brand value. In the era where customer experience is paramount, punctual delivery is not only part of the service commitment but also a reflection of the customer's trust in the platform. Riders with high punctuality usually receive higher user ratings and platform rewards, while low punctuality may lead to user dissatisfaction and churn. Therefore, platforms should focus on improving punctuality.

At the same time, through literature research, we found that rider fatigue significantly affects work performance, especially in high-intensity working environments. Long working hours and continuous delivery tasks can lead to rider fatigue, which in turn affects their delivery efficiency and service quality. Fatigued riders often experience problems such as lack of focus and slow reactions, which not only increase the risk of mistakes during delivery but also may lead to traffic accidents, further impacting the platform's delivery efficiency and customer satisfaction. Therefore, this study measures rider fatigue based on the number of completed deliveries and rest days, and the specific calculation method is as follows:

$$RF_{it} = ln\frac{CDO_{it}}{1 + RD_{it}}, (i, t \in 1,2,3)$$

In this case, RF represents Rider Fatigue; CDO represents Consecutive Delivery Orders; RD represents the number of rest days before the rider starts working.

Table 9 Regression Analysis

VARIABLES	Punctuality Rate
Fatigue	-0.188***
	(0.0684)
Maximum Perceived Temperature	0.0987***
	(0.0308)
Maximum Air Humidity	-0.0151*
	(0.00796)
Maximum Wind Strength	-0.266***
	(0.0594)
Is It a Holiday	-0.955***
	(0.157)
Constant	60.23***
	(0.931)
Individual Fixed Effects	YES
Time Fixed Effects	YES
Observations	57,081
R-squared	0.002

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To reduce estimation bias, this study uses a fixed-effects model for regression analysis. According to the regression results, riders with higher fatigue levels tend to have lower punctuality rates, and their service quality declines. Through data analysis, the platform can prioritize scheduling riders in better condition, reduce the workload of fatigued riders, and thus improve overall delivery efficiency while ensuring the stability of customer experience.

Table 9 examines the effects of rider fatigue, weather conditions, and holidays on the on-time delivery rate. The regression results show that a one-unit increase in fatigue is associated with a 0.188 percentage-point decline in punctuality ($p < 0.01$); each 1 °C rise in maximum perceived temperature raises punctuality by 0.0987 percentage points ($p < 0.01$), while a 1 % increase in maximum air humidity lowers it by 0.0151 points ($p < 0.1$); and each one-level increase in maximum wind strength reduces punctuality by 0.266 points ($p < 0.01$). Moreover, the holiday effect is significant: the on-time rate on a holiday is 0.955 percentage points lower than on a regular day ($p < 0.01$). These findings further confirm that rider fatigue and adverse weather substantially impair delivery efficiency, whereas moderate winter warming slightly improves punctuality, and holiday delivery pressure leads to a marked drop in on-time performance.

Therefore, managing rider fatigue is a key factor in improving the service quality of food delivery platforms. The sample data considered is from December, with relatively cold and dry weather. In this context, under constant conditions, each 1°C increase in the maximum perceived temperature results in a 0.098% increase in punctuality; each 1% increase in the maximum air humidity leads to a 0.015% decrease in punctuality; each 1-level increase in the maximum wind strength results in a 0.266% decrease in punctuality. Additionally, on public holidays, the rider's delivery accuracy tends to decrease by 0.95% compared to regular days.

6. Conclusion

With the rapid development of the food delivery industry, rider performance has become a key indicator for evaluating platform service quality, improving customer satisfaction, and enhancing market competitiveness. This study provides an in-depth exploration of the key factors influencing food delivery rider performance, particularly focusing on the impact of different contexts such as weather, public holidays, and peak work periods. By analyzing riders' personal characteristics (such as age, work experience, and birthplace) and external environmental factors (such as weather and holidays), the study identifies performance differences among various rider groups in different contexts and offers strategies for optimizing rider resource allocation and improving delivery efficiency.

Firstly, the study finds that riders with 1-2 years of registration experience generally perform better than those with different registration durations. Riders from Heilongjiang consistently exhibit higher work efficiency across all scenarios. By comparing the performance of these rider groups, the study recommends strengthening rider training and optimizing the rider structure to further improve overall performance.

Then, rider fatigue has a significant impact on timely delivery rates, which is one of the key findings of this study. Fatigued riders tend to have lower punctuality rates and reduced service quality. Therefore, platforms should focus on managing rider fatigue by implementing reasonable scheduling, providing rest days, and offering psychological support to reduce riders' workload. This will help improve rider efficiency and ensure stable customer experience. During high-pressure periods, particularly during holidays and peak work times, platforms should adopt dynamic scheduling systems to balance rider work and rest, preventing fatigue from affecting delivery performance.

Moreover, the study reveals that weather conditions significantly influence rider performance. Extreme weather conditions such as heavy rain, high temperatures, or strong winds greatly reduce riders' work efficiency and punctuality. In response, platforms should adopt flexible scheduling strategies during adverse weather conditions, adjust delivery volume, and allocate resources wisely to ensure smooth deliveries. Additionally, platforms should consider weather factors, issue early warnings, and adjust delivery routes to manage potential delays. Public holidays also play a significant role. During major promotions and holidays, the surge in demand leads to increased pressure on riders, which typically results in lower work efficiency. The study suggests that during such periods, platforms should increase the number of riders, optimize delivery routes, and introduce incentive measures to effectively alleviate peak pressure and ensure service quality.

In conclusion, this research not only provides a scientific foundation for the operational management

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of food delivery platforms but also offers theoretical support and practical guidance for optimizing delivery services using data analysis. As the industry continues to evolve, food delivery platforms should continuously leverage new technologies and methodologies to optimize resource allocation and rider management, adapting to the changing market demands and consumer expectations, and laying a solid foundation for long-term sustainable development.

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