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Subsidy Strategies of Ride-Hailing Platforms Considering Taxi Street-Hailing during Order Overflow

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ABSTRACT

The emergence of ride-hailing services has revolutionized the transportation industry for passengers, prompting taxi services to evolve from the conventional method of street-hailing to a combined "online-offline" operational approach. In this new model, taxis combine on-street pickups with platform-based orders. When market supply and demand are imbalanced, leading to excess orders, taxis prioritize street-hailing for faster customer acquisition. Meanwhile, ride-hailing platforms address surging passenger demand by offering subsidies to attract more vehicles to participate in online dispatching. This study focuses on the strategic choices of ride-hailing platforms and taxis during order overflow scenarios. An evolutionary game model is constructed to simulate taxi street-hailing behavior under such conditions. Simulations are conducted to generate interpolation-based probability curves, including the probability of taxis accepting offline orders and the probability of regional orders being served. These findings offer recommendations for ride-hailing platforms on designing subsidy strategies in response to changes in regional order density. Additionally, the study examines how factors such as order distance, passenger-seeking costs, and platform commission rates influence taxis' order acceptance strategies.

Keywords: Ride-Hailing Platforms, Taxis, Platform Subsidies, Order Overflow, Evolutionary Game Theory

1. Introduction

The development and transformation of the internet industry have diversified application scenarios. The integration of mobile internet and the transportation sector has given rise to new travel modes such as ride-hailing and carpooling [1]. These innovations have brought convenience to passengers and reshaped travel habits [2]. According to the 53rd Statistical Report on China's Internet Development, the number of ride-hailing users in China reached 528 million by December 2023.

Simultaneously, the impact of ride-hailing services on the traditional taxi market [3] has driven

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conventional taxis to adapt. While retaining their characteristic street-hailing function, many have partnered with ride-hailing platforms to accept online orders. In cities like Beijing and Shenzhen, all taxis have now been integrated into online platforms. Notably, the "Haode Taxi" service by Amap Taxi has supported over one million drivers. In 2024, the China Smart Street-Online Integration Alliance was established, and the drafting of the White Paper on the Integrated Development of Taxi Online-Offline Operations commenced.

During peak travel periods, factors such as congestion and adverse environmental conditions often reduce drivers' willingness to operate, leading to a significant overflow in passenger demand. This challenge has undergone notable changes with the rise of ride-hailing platforms. On one hand, platforms utilize intelligent dispatch and route planning to enhance order response efficiency. For example, Amap Taxi's "Libra System" has increased ride-hailing success rates by nearly 10% during peak hours and boosted drivers' income by 41%. On the other hand, ride-hailing platforms adjust vehicle supply during peak times through subsidies. For instance, Didi introduced 20% revenue acceleration cards and commission-free cards during the Mid-Autumn Festival and National Day holidays in 2023. Similarly, in February 2024, during rainy and snowy weather, Amap Taxi implemented a "per-order reward" initiative in Wuhan to incentivize drivers to accept orders during critical time periods.

The concentrated nature of orders during peak travel periods reduces passenger-seeking costs. Compared to regular times, when taxis rely on platform-based route planning to pick up passengers, taxis during peak periods can more easily find waiting passengers along the roadside through street-hailing. Offline street-hailing may yield higher earnings, leading some taxis to prioritize routes between high-demand areas such as tourist attractions and airports. Meanwhile, ride-hailing platforms face significant pressure during peak times, as surging passenger demand makes dispatch efficiency a critical factor in passenger satisfaction. Platforms require more vehicles to alleviate the strain on their dispatch systems and often use subsidies to retain a sufficient number of taxis, thereby improving the response rate for online orders. A key question is how varying degrees of order density influence the strategic choices of taxis and ride-hailing platforms. Additionally, identifying measures that platforms can take to incentivize taxis to participate in online dispatch warrants further investigation. Addressing these issues could provide valuable insights into subsidy strategies for ride-hailing platforms during peak periods.

The rapid growth of the ride-hailing market has attracted significant academic attention. Scholars domestically and internationally have explored key issues such as platform pricing [4], government regulation [5], and passenger satisfaction through game-theoretic approaches. Yang and Wei [6] examined the competitive dynamics between traditional taxis and ride-hailing platforms under passenger subsidies provided by platforms. Their findings suggest that traditional taxis will continue to hold a place in the transportation market. Yang and Zhong [7], considering drivers' sensitivity to income, proposed pricing recommendations based on several wage strategies currently adopted by ride-hailing platforms. Wang et al. [8] used a tripartite evolutionary game and system dynamics to model the interactions and dynamic processes among governments, ride-hailing platforms, and drivers, providing theoretical guidance for government regulation. Zhong et al. [9], focusing on regulatory strategies, applied differential pricing under various regulatory models and found that governments should encourage competition between taxis and ride-hailing services under both pricing strategies. Huang et al. [10] analyzed the competition between taxis and ride-hailing services, constructing a game model from the perspectives of taxi drivers and passengers at airports. Bernstein et al. [11] explored platform competition, investigating equilibrium pricing strategies for drivers operating on a single ride-hailing platform versus multiple platforms.

Discussions on peak-period ride-hailing markets have partially focused on the perspectives of market participants. For example, Morris and Hirsch [12] examined the impact of peak hours on driver emotions and found that the effect was not significant. Ben-Elia and Ettema [13] discovered that offering incentives to commuters could alleviate traffic pressure during peak times. Han et al. analyzed the equilibrium of public transportation systems during morning peak hours, considering single-origin-multi-destination scenarios [14] and multi-origin-multi-destination scenarios [15].

Research on ride-hailing operations during peak periods has mainly concentrated on whether these strategies improve travel efficiency. Zhong et al. [16], based on passengers' differentiated sensitivity to congestion, found that meeting higher passenger demand does not necessarily lead to increased profits. They proposed service strategies tailored to different market conditions. Henao and Marshall [17], using data from Uber and Lyft, argued that idle rides reduce travel efficiency and negatively impact urban congestion. Agarwal et al. [18], analyzing three major Indian cities, found that ride-hailing operations exceeded socially optimal levels and that suspending services reduced travel times. Jiang et al. [19] developed a simulation model considering the anisotropy of congestion near regional boundaries and concluded that fleet expansion by ride-hailing platforms could exacerbate congestion.

The impact of peak-period pricing and subsidies on the ride-hailing market, as well as the formulation of effective subsidy strategies, has garnered significant academic attention. Liu et al. [20] examined optimal peak-period subsidy strategies in the context of ride-hailing platforms offering subsidies to drivers during demand surges. They analyzed three subsidy approaches from the perspectives of platforms and passengers. Guda and Subramanian [21] investigated the effect of peak-period pricing on driver mobility, suggesting that price increases during peak times negatively impact demand, potentially causing drivers to leave high-demand areas. Wong and Szeto [22] explored how peak-period surcharges influence passengers' travel decisions. Chen et al. [23], considering peak pricing, passenger incentives, and driver incentives, proposed strategies to maximize platform revenue and optimize social welfare from both platform and government perspectives. Cachon et al. [24] focused on the impact of dynamic pricing on platform profitability, consumer welfare, and wages paid to providers. They investigated five different contract designs, and found that when the platform can choose different types of contracts, implementing surge pricing is beneficial for all stakeholders.

Existing studies have explored peak-period subsidy strategies for ride-hailing platforms, focusing on horizontal comparisons of various subsidy approaches and the revenue implications of peak-period pricing for platforms. However, they have not examined the correlation between varying levels of order overflow and the strategic adjustments of stakeholders within the road network. Additionally, the interaction between taxi behavior and ride-hailing platform subsidy decisions during peak-period order overflow remains underexplored, particularly in the context of the hybrid online-offline operating model widely adopted by taxis in China. Therefore, this study constructs an evolutionary game model to analyze the strategic choices of taxis and ride-hailing platforms. Simulations are conducted to examine scenarios involving offline taxi orders, focusing on the relationship between order density and the probability of taxis accepting offline orders. Sensitivity analyses are then performed to evaluate the impact of factors such as order density on taxis' online and offline order acceptance strategies. Finally, the study provides recommendations for ride-hailing platforms on adjusting subsidy strategies under varying levels of order overflow.

2. Model

2.1. Problem

Factors such as peak hours, adverse weather, and holiday travel often lead to a surge in passenger demand for taxis. Under limited vehicle supply, passengers frequently face difficulties hailing rides, and ride-hailing platforms experience operational strain, leaving some orders unfulfilled. At the same time, concentrated ride demand is often accompanied by spatial clustering of orders. Locations such as airports, train stations, large shopping centers, and business districts commonly witness large groups of passengers waiting for rides.

Taxis, equipped with the ability to accept offline street-hailing orders, can leverage this characteristic during periods of high demand. By operating traditional offline pickups, they incur lower search costs while avoiding platform commission fees. Consequently, taxi drivers may be less inclined to join ride-hailing platforms for order fulfillment during these periods. To enhance system dispatch efficiency and improve passenger satisfaction, ride-hailing platforms are often willing to offer subsidies as an incentive to retain taxi drivers and encourage them to accept orders through the platform.

2.2. Assumptions

In scenarios of order overflow, taxi drivers and ride-hailing platforms adjust their strategies in response to external environmental changes. Their decision-making is guided by their respective utility maximization objectives. Based on this behavioral logic, the following assumptions are proposed:

Assumption 1: Limited rationality of participants. Taxi drivers and ride-hailing platforms exhibit bounded rationality. They continuously learn and interact dynamically within the ride-hailing market. Through iterative adjustments during their strategic interactions, both parties aim to maximize their utility.

Assumption 2: Strategy space and benefits of participants. The strategy set S_D for taxi drivers is {online-only orders, combined online-offline orders}, where the proportion of taxi drivers choosing offline-only orders is $X\left(X\in[0,1]\right)$, and the proportion choosing combined online-offline orders is $1-X$. The strategy set S_P for ride-hailing platforms is {per-order subsidies, distance-based subsidies}, where the proportion of platforms choosing per-order subsidies is $Y\left(Y\in[0,1]\right)$, and the proportion choosing distance-based subsidies is $1-Y$.

Assumption 3: Cost and benefit parameters for taxi drivers. The fare per kilometer for taxis is R_T (in units of CNY/km), which is regulated by the government. Regardless of whether taxi orders are accepted online or offline, the fare charged to passengers remains consistent. When taxi drivers choose online-only orders, their baseline revenue is $R_T L(1-\tau)$, where τ represents the platform commission rate per order, and L is the travel distance associated with the order. Under the per-order subsidy strategy, drivers receive an additional income of u_1 per completed order. Under the distance-based subsidy strategy, platforms provide a subsidy of u_2 per kilometer. If drivers choose combined online-offline orders, they accept offline orders at a proportion $P_U\left(P_U\in[0,1]\right)$. In this case, their income is derived from both online and offline orders, but the offline passenger-seeking process incurs a cost a.

Assumption 4: Cost and benefit parameters for ride-hailing platforms. During order overflow, not all passenger orders can be fulfilled. The probability of order fulfillment is P_O. Unfulfilled orders result in a psychological dissatisfaction loss H_1 for passengers, negatively impacting the platform. Additionally, when taxis engage in offline street-hailing, passengers may be served by these taxis first, which undermines the platform's dispatch efficiency and causes a trust loss H_2 for the platform.

Assumption 5: Relationship between order density, offline taxi orders, and order fulfillment probability. Order density, denoted by ρ, represents the number of orders per square kilometer. The proportion of taxis engaging in offline street-hailing P_U is positively correlated with order density ρ. Conversely, the probability of passenger orders being fulfilled P_O is negatively correlated with ρ.

2.3. Model Formulation

All parameter symbols and their definitions used in this study are presented in Table 1.

Table 1. Parameters and Their Definitions

Parameters	Meaning of the parameters
R_T	Taxi unit price

L	Order travel distance
τ	Platform commission rate
ρ	Order density (The number of orders per square kilometer)
P_U	The percentage of offline street-hailing orders when taxis combine online and offline operations
P_O	The probability of passenger orders being fulfilled by vehicles
u_1	Per-order subsidy amount
u_2	Distance-based subsidy amount
H_1	The psychological loss experienced by passengers due to unfulfilled orders
H_2	The loss of trust in the platform when passengers are first served by street-hailing taxis
a	The cost incurred by taxi drivers when searching for passengers through street-hailing

Based on the above assumptions and parameter settings, the evolutionary game model for taxis and ride-hailing platforms is constructed, as shown in Table 2.

Table 2. Payoff Matrix of the Evolutionary Game Between Taxis and Ride-Hailing Platforms

		Taxi Order Acceptance Strategy	
		Accept Online-Only Orders X	Hybrid Online-Offline Operation $1-X$
Ride-Hailing Platform Subsidy Strategy	Per-Order Subsidy Y	$(R_T L\tau - u_1)P_O - H_1(1-P_O)$	$(R_T L\tau - u_1)P_O(1-P_U) - H_1(1-P_O) - H_2 P_O P_U$
		$R_T L(1-\tau)+u_1$	$[R_T L(1-\tau)+u_1](1-P_U) + R_T L P_U - a$
	Distance-Based Subsidy $1-Y$	$(R_T - u_2)L\tau P_O - H_1(1-P_O)$	$(R_T - u_2)L\tau P_O(1-P_U) - H_1(1-P_O) - H_2 P_O P_U$
		$(R_T + u_2)L(1-\tau)$	$(R_T + u_2)L(1-\tau)(1-P_U) + R_T L P_U - a$

Expected revenue for taxis choosing online-only orders:

$$U_T^X = Y\left[R_T L(1-\tau)+u_1\right] + (1-Y)\left[(R_T - u_2)L(1-\tau)\right] \tag{1}$$

Expected revenue for taxis operating under a hybrid online-offline model:

$$U_T^w = Y\left\{\left[R_T L(1-\tau)+u_1\right](1-P_U) + R_T L P_U - a\right\} + (1-Y)\left\{(R_T + u_2)L(1-\tau)(1-P_U) + R_T L P_U - a\right\} \tag{2}$$

Average revenue for taxis:

$$\overline{U_T} = XU_T^X + (1-X)U_T^w \tag{3}$$

Replicator dynamic equation for taxi strategy adoption:

$$\begin{aligned} f(X) &= \frac{dX}{dt} = X\left(U_T^X - \overline{U_T}\right) = X(1-X)\left(U_T^X - U_T^w\right) \\ &= X(1-X)\left\{YP_U\left[u_1 - u_2 L(1-\tau)\right] + P_U L u_2 - P_U R_T L\tau - P_U L u_2 \tau + a\right\} \end{aligned} \tag{4}$$

Expected revenue for ride-hailing platforms adopting per-order subsidies:

$$U_P^O = X\left[\left(R_T L\tau - u_1\right)P_O - H_1\left(1-P_O\right)\right] + \left(1-X\right)\left[\left(R_T L\tau - u_1\right)P_O\left(1-P_U\right) - H_1\left(1-P_O\right) - H_2 P_O P_U\right]$$

(5)

Expected revenue for ride-hailing platforms adopting distance-based subsidies:

$$U_P^D = X\left[\left(R_T - u_2\right)L\tau P_O - H_1\left(1-P_O\right)\right] + \left(1-X\right)\left[\left(R_T - u_2\right)L\tau P_O\left(1-P_U\right) - H_1\left(1-P_O\right) - H_2 P_O P\right]$$

(6)

Average revenue for ride-hailing platforms:

$$\overline{U_P} = YU_P^O + \left(1-Y\right)U_P^D \tag{7}$$

Replicator dynamic equation for ride-hailing platform strategy adoption:

$$g\left(Y\right) = \frac{dY}{dt} = Y\left(U_P^O - \overline{U_P}\right) = Y\left(1-Y\right)\left(U_P^O - U_P^D\right) = Y\left(1-Y\right)\left(XP_U - P_U + 1\right)\left(u_2 L\tau - u_1\right)P_O \tag{8}$$

3. Evolutionarily Stable Strategy Analysis

3.1. Equilibrium Point Analysis

To ensure that the game between the ride-hailing platform and taxi drivers has evolutionarily stable strategies, the replicator dynamic equations must satisfy $\frac{dX}{dt}=0$ and $\frac{dY}{dt}=0$. The evolutionary game yields five equilibrium points: $E_1\left(0,0\right)$, $E_2\left(0,1\right)$, $E_3\left(1,0\right)$, $E_4\left(1,1\right)$, $E_5\left(m^*,n^*\right)$, where: $m^* = \frac{1-P_U}{P_U}$, $n^* = \frac{-P_U L u_2 + P_U R_T L\tau + P_U L u_2 \tau - a}{P_U\left[u_1 - u_2 L\left(1-\tau\right)\right]}$. For simplicity, the following notations are introduced: $\pi_1 = P_U\left[u_1 - u_2 L\left(1-\tau\right)\right]$, $\pi_2 = P_U L u_2 - P_U R_T L\tau - P_U L u_2 \tau + a$, $\pi_3 = \left(u_2 L\tau - u_1\right)P_O$.

The Jacobian matrix is expressed as:

$$J = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \\ \frac{\partial g}{\partial x} & \frac{\partial g}{\partial y} \end{bmatrix} = \begin{bmatrix} \left(1-2X\right)\left(Y\pi_1 + \pi_2\right) & X\left(1-X\right)\pi_1 \\ Y\left(1-Y\right)\pi_3 P_U & \left(1-2Y\right)\left(XP_U - P_U + 1\right)\pi_3 \end{bmatrix} \tag{9}$$

The determinant and trace of the Jacobian matrix are as follows:

$$Det\left(J\right) = \left(1-2X\right)\left(Y\pi_1 + \pi_2\right)\left(1-2Y\right)\left(XP_U - P_U + 1\right)\pi_3 - X\left(1-X\right)\pi_1 Y\left(1-Y\right)\pi_3 P_U \tag{10}$$

$$Tr\left(J\right) = \left(1-2X\right)\left(Y\pi_1 + \pi_2\right) + \left(1-2Y\right)\left(XP_U - P_U + 1\right)\pi_3 \tag{11}$$

The expressions for the determinant $Det\left(J\right)$ and trace $Tr\left(J\right)$ of the Jacobian matrix at each equilibrium point are shown in Table 3.

Table 3. Determinant and Trace of the Jacobian Matrix at Each Equilibrium Point

Point	$Det\left(J\right)$	$Tr\left(J\right)$
$\left(0,0\right)$	$\left(1-P_U\right)\pi_2\pi_3$	$\pi_2 + \left(1-P_U\right)\pi_3$
$\left(0,1\right)$	$-\left(\pi_1+\pi_2\right)\left(1-P_U\right)\pi_3$	$\pi_1 + \pi_2 - \left(1-P_U\right)\pi_3$
$\left(1,0\right)$	$-\pi_2\pi_3$	$-\pi_2 + \pi_3$
$\left(1,1\right)$	$\left(\pi_1+\pi_2\right)\pi_3$	$-\left(\pi_1+\pi_2\right) - \pi_3$

(m^*, n^*)	$\frac{(1-P_U)(2P_U-1)(\pi_1+\pi_2)\pi_2\pi_3}{P_U\pi_1}$	0

3.2. Evolutionary Path Analysis

Proposition 1: When $\pi_2 < 0$, $\pi_3 < 0$, i.e., $P_U L u_2 (1-\tau) + a < P_U R_T L\tau$, $Lu_2\tau - u_1 < 0$, the equilibrium point $E_1(0,0)$ is the ESS. In this case, taxis adopt a hybrid online-offline strategy, and the ride-hailing platform implements a distance-based subsidy strategy.

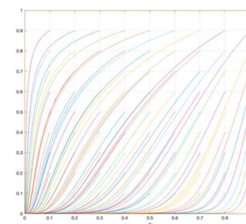
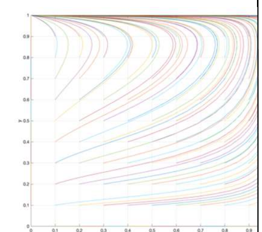
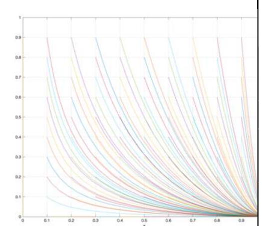
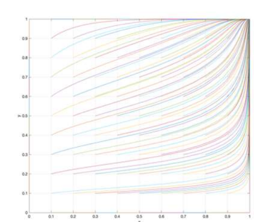
Proposition 2: When $\pi_1 + \pi_2 < 0$, $\pi_3 > 0$, i.e., $a < P_U (R_T L\tau - u_1)$, $Lu_2\tau - u_1 > 0$, the equilibrium point $E_2(0,1)$ is the ESS. Here, taxis adopt a hybrid online-offline strategy, and the ride-hailing platform chooses a per-order subsidy strategy.

Proposition 3: When $\pi_2 > 0$ $\pi_3 < 0$, i.e., $P_U L u_2 (1-\tau) + a > P_U R_T L\tau$, $Lu_2\tau - u_1 < 0$, the equilibrium point $E_3(1,0)$ is the ESS. In this scenario, taxis choose the online-only strategy, and the ride-hailing platform adopts a distance-based subsidy strategy.

Proposition 4: When $\pi_1 + \pi_2 > 0$, $\pi_3 > 0$, i.e., $a > P_U (R_T L\tau - u_1)$, $Lu_2\tau - u_1 > 0$, the equilibrium point $E_4(1,1)$ is the ESS. Here, taxis opt for the online-only strategy, and the ride-hailing platform implements a per-order subsidy strategy.

See Table 4, for taxis, the hybrid online-offline strategy will always be preferred as long as the cost of street-hailing is lower than the difference between the platform commission on online orders $P_U R_T L\tau$ and the subsidy income under the platform's current subsidy strategy. In this case, offline street-hailing allows taxis to avoid platform commissions. Drivers are willing to incur certain street-hailing costs in exchange for higher returns. For ride-hailing platforms, the choice between per-order subsidies u_1 and distance-based subsidies $u_2 L\tau$ depends on a cost comparison. The platform will adopt the subsidy strategy with the lower cost.

Table 4. Summarizes the local stability and evolutionary paths of the equilibrium points

	Point	$\pi_1+\pi_2<0$			$\pi_1+\pi_2>0$			Evolutionary Path Diagram
		$Det(J)$	$Tr(J)$	Results	$Det(J)$	$Tr(J)$	Results	
①	(0,0)	+	-	ESS	+	-	ESS	
	(0,1)	-	uncertain	Saddle point	+	+	Unstable	
	(1,0)	-	uncertain	Saddle point	-	uncertain	Saddle point	
	(1,1)	+	+	Unstable	-	uncertain	Saddle point	
	(m^*,n^*)		0			0		
	Point	$\pi_2<0$			$\pi_2>0$			Evolutionary Path Diagram
		$Det(J)$	$Tr(J)$	Results	$Det(J)$	$Tr(J)$	Results	
②	(0,0)	-	uncertain	Saddle point	+	+	Unstable	
	(0,1)	+	-	ESS	+	-	ESS	
	(1,0)	+	+	Unstable	-	uncertain	Saddle point	
	(1,1)	-	uncertain	Saddle point	-	uncertain	Saddle point	
	(m^*,n^*)		0			0		
	Point	$\pi_1+\pi_2<0$			$\pi_1+\pi_2>0$			Evolutionary Path Diagram
		$Det(J)$	$Tr(J)$	Results	$Det(J)$	$Tr(J)$	Results	
③	(0,0)	-	uncertain	Saddle point	-	uncertain	Saddle point	
	(0,1)	-	uncertain	Saddle point	+	+	Unstable	
	(1,0)	+	-	ESS	+	-	ESS	
	(1,1)	+	+	Unstable	-	uncertain	Saddle point	
	(m^*,n^*)		0			0		
	Point	$\pi_2<0$			$\pi_2>0$			Evolutionary Path Diagram
		$Det(J)$	$Tr(J)$	Results	$Det(J)$	$Tr(J)$	Results	
④	(0,0)	-	uncertain	Saddle point	+	+	Unstable	
	(0,1)	-	uncertain	Saddle point	-	uncertain	Saddle point	
	(1,0)	+	+	Unstable	-	uncertain	Saddle point	
	(1,1)	+	-	ESS	+	-	ESS	
	(m^*,n^*)		0			0		

4. Simulation Analysis

4.1. Simulation Analysis of Taxi Offline Order Acceptance Probability

This section simulates the offline order acceptance behavior of taxis. It examines the relationship between order density, the probability of taxis accepting offline orders, and the probability of regional orders being fulfilled.

In real-world scenarios, if taxi drivers see passengers waiting on the roadside within their line of sight, they are likely to accept offline orders to maximize their revenue. Conversely, if no waiting passengers are visible, drivers will prioritize platform-dispatched orders to minimize cruising costs. In this context, it is stipulated that when the distance between a passenger's location and an available taxi is no more than 0.05 kilometers, the taxi will opt to pick up the passenger directly offline.

Additionally, taking into account the pause caused by passenger boarding and disembarking, an extra 0.04 hours is added to the operational time for each order when calculating the vehicle's running time. If multiple passengers are visible within 0.05 km, drivers are assumed to randomly select one passenger to complete the order, ignoring road complexity.

Using publicly available data from the Wuxi Municipal Transport Bureau, the simulation considers 750 taxis and 4,250 ride-hailing vehicles operating within a 100 km2 area. The average vehicle speed is set at 28 km/h, representing the peak-period road network speed in Wuxi. To account for queuing when all vehicles are occupied, simulations begin with an order density of 5,000 orders per 100 km2.

Table 5. Example of Changes in Order Density and Proportion of Taxi Offline Order Acceptance

Order Volume	5000	10000	15000	20000	25000	30000	35000	40000	45000	50000
Total Completed Orders	24537	24755	24865	24976	24980	25026	24940	25008	25054	25026
Orders Completed by Taxis	3674	3748	3725	3745	3745	3726	3747	3717	3754	3730
Completed Offline Orders	891	1330	1628	1772	2027	2333	2404	2591	2746	2881
Proportion of Offline Orders Accepted by Taxis	24.25%	35.49%	43.70%	47.32%	54.13%	62.61%	64.16%	69.71%	73.15%	77.24%
Order Fulfillment Probability	83.07%	71.23%	62.37%	55.53%	49.98%	45.48%	41.61%	38.47%	35.76%	33.36%

Considering an increase in order density from 5,000 to 50,000 as a complete experiment, the results are presented in Table 5. The experimental data illustrates the number of offline orders accepted by taxis, the number of orders completed by taxis, and the total number of completed orders at different order densities. From these data, the proportion of offline orders accepted by taxis and the probability of regional orders being fulfilled can be calculated.

In this section, seven tests were conducted to calculate the proportion of offline orders accepted by taxis and the probability of regional order fulfillment. The results showed that the averages stabilized over time. The probability of taxis accepting offline orders P_U and regional order fulfillment probability P_O corresponding to different order densities are shown in Table 6. Using cubic spline interpolation, the relationships between order density and P_U as well as P_O were visualized in Figure 1 and Figure 2 respectively. Based on the interpolation results, approximate values for P_U and P_O can be obtained for any given order density ρ. For ride-hailing platforms with access to regional order information, these findings provide valuable references for subsequent decision-making.

As the number of orders increases, corresponding to a rise in order density ρ, the probability of taxi cruisers encountering passenger demand rises, leading to the proportion of offline orders accepted by taxis gradually increases. Meanwhile, due to the limited number of vehicles, the probability of passenger orders being responded to decreases with increasing regional order density. This aligns with real-world scenarios and significantly impacts the order processing speed of ride-hailing platforms. However, the growth in the proportion of offline orders slows over time. This is due to the random nature of order pickup and drop-off locations. Even at high order densities, it is unlikely that a waiting passenger will always be nearby when a driver searches for one. This phenomenon becomes particularly evident at higher order densities.

Table 6. Probability of Taxis Accepting Offline Orders and Order Fulfillment Probability Under Different Order Densities

Order Volume	Probability	①	②	③	④	⑤	⑥	⑦
5000	P_U	24.25 %	24.03 %	24.00 %	24.04 %	24.01 %	23.69 %	23.66 %
	P_O	83.07 %	83.09 %	83.11 %	83.09 %	83.09 %	83.08 %	83.08 %
10000	P_U	35.49 %	34.68 %	34.75 %	34.88 %	34.85 %	35.01 %	34.83 %
	P_O	71.23 %	71.24 %	71.23 %	71.23 %	71.25 %	75.39 %	74.80 %
15000	P_U	43.70 %	42.67 %	42.03 %	42.17 %	42.17 %	42.17 %	42.06 %
	P_O	62.37 %	62.40 %	62.41 %	62.40 %	62.39 %	62.39 %	62.39 %
20000	P_U	47.32 %	48.23 %	48.67 %	48.84 %	48.63 %	48.64 %	48.65 %
	P_O	55.53 %	55.44 %	55.44 %	55.44 %	55.48 %	55.46 %	55.47 %
25000	P_U	54.13 %	53.83 %	54.71 %	55.06 %	54.76 %	54.85 %	55.03 %
	P_O	49.98 %	49.98 %	49.99 %	49.94 %	49.92 %	49.91 %	49.92 %
30000	P_U	62.61 %	60.44 %	60.46 %	60.37 %	60.42 %	60.34 %	60.41 %
	P_O	45.48 %	45.47 %	45.47 %	45.44 %	45.43 %	45.43 %	45.44 %
35000	P_U	64.16 %	64.77 %	64.81 %	65.16 %	65.01 %	65.14 %	65.26 %
	P_O	41.61 %	41.67 %	41.70 %	41.66 %	41.68 %	41.66 %	41.66 %
40000	P_U	69.71 %	68.92 %	69.29 %	68.92 %	69.22 %	69.14 %	69.28 %
	P_O	38.47 %	38.46 %	38.45 %	38.46 %	38.48 %	38.48 %	38.47 %
45000	P_U	73.15 %	73.25 %	72.77 %	73.10 %	73.12 %	73.13 %	72.98 %
	P_O	35.76 %	35.74 %	35.76 %	35.77 %	35.74 %	35.73 %	35.74 %
50000	P_U	77.24 %	76.30 %	77.26 %	77.04 %	76.99 %	76.95 %	76.99 %
	P_O	33.36 %	33.38 %	33.33 %	33.34 %	33.34 %	33.35 %	33.35 %

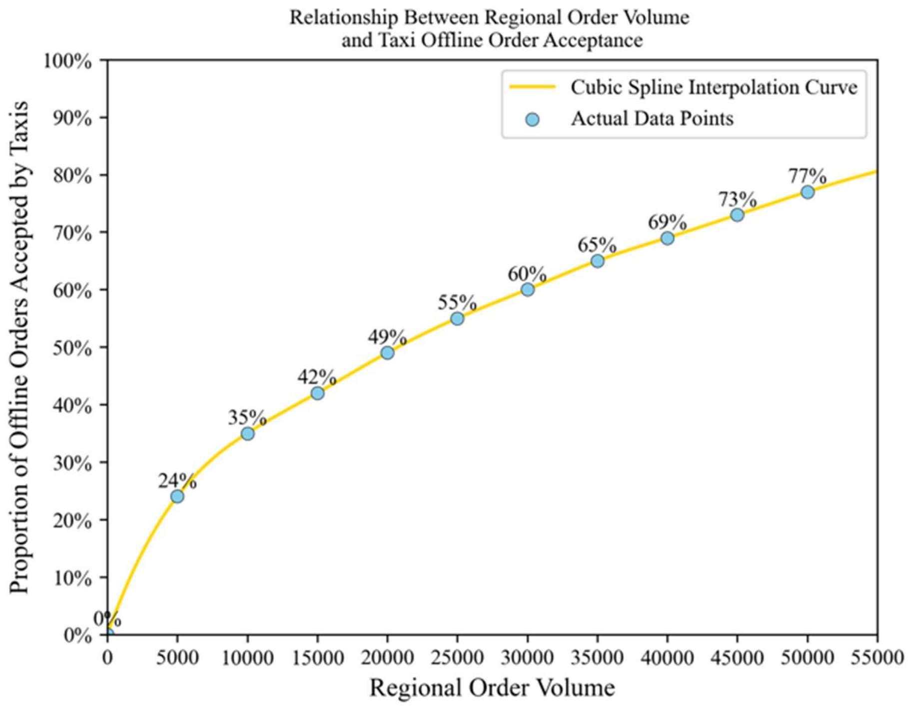


Fig. 1. Taxi Offline Order Acceptance Probability Under Different Order Densities

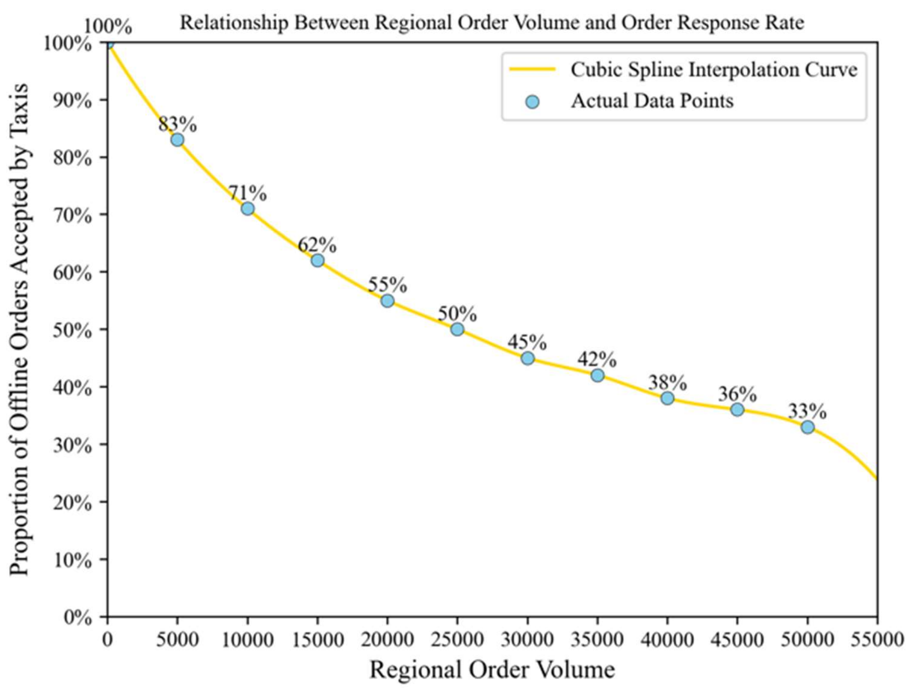


Fig. 2. Order Response Probability Under Different Order Densities

4.2. Sensitivity Analysis

To more intuitively explore the impact of key factors on the evolutionary process and outcomes, this section simulates the evolutionary trajectories of the game participants. Using transportation data from Wuxi as an example, the initial parameter values are set as follows: taxi unit price $R_T = 2.5$, order travel distance $L=6$, platform commission rate $\tau=0.25$, per-order subsidy amount $u_1=2$, distance-based subsidy amount $u_2=0.4$, offline order proportion in hybrid operation $P_U=0.5$, order fulfillment probability $P_O=0.54$, and passenger-seeking cost in hybrid operation $a=2$.

4.2.1. Impact of Order Density on Evolutionary Outcomes. As indicated by the simulation results in the previous section, order density significantly affects the probability of taxis accepting offline orders and the probability of passenger orders being fulfilled in an overflow state. Using the interpolation results from Section 4.1, the offline order acceptance probability and order fulfillment probability can be calculated for a given order density. Additionally, Section 4.1 shows that order density is negatively correlated with the passenger-seeking cost of taxis. Based on this analysis, the changes in evolutionary outcomes under different order densities are examined. The results are illustrated in Figure 3.

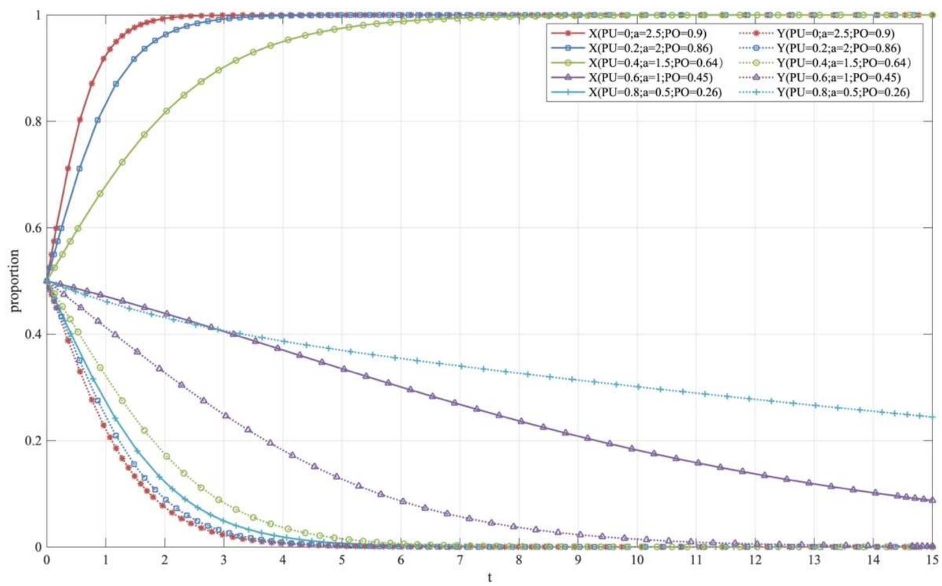


Fig. 3. Impact of Order Density Changes on Evolutionary Outcomes

When there is an order overflow and the order density is relatively low, due to the difficulty and high cost of offline customer acquisition, taxis will still choose to accept orders through the ride-hailing platform to ensure their earnings. As the order density continues to increase, the strategy gradually shifts to a combination of online and offline order acceptance. As shown in Figure 3, when the proportion of offline orders accepted by taxis $P_U>0.6$, the strategy changes. At this point, the order density $\rho=30000$. For the ride-hailing platform, under the initial conditions, it will always choose the distance subsidy strategy.

4.2.2. Impact of Ride-Hailing Platform Subsidy Changes on Evolutionary Outcomes. As the subsidies offered by the platform are influenced by the number of vehicles available for allocation, Figure 4 to Figure 7 analyze the effects of changes in the one-time subsidy u_1 and distance subsidy u_2 under two different order densities. Specifically, Figure 4 and Figure 5 represent the medium-order density scenario with $P_U=0.5$, $P_O=0.54$, $a=2$, while Figure 6 and Figure 7 represent the high-order density scenario with $P_U=0.7$, $P_O=0.37$, $a=1$.

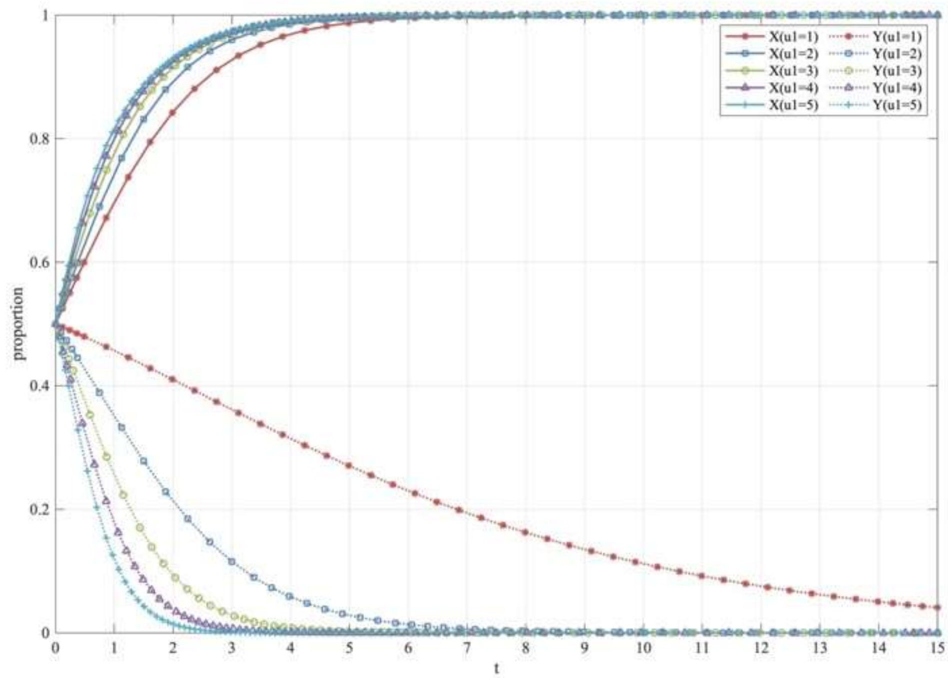


Fig. 4. Impact of One-Time Subsidy u_1 Changes on Evolutionary Outcomes ($P_U = 0.5$)

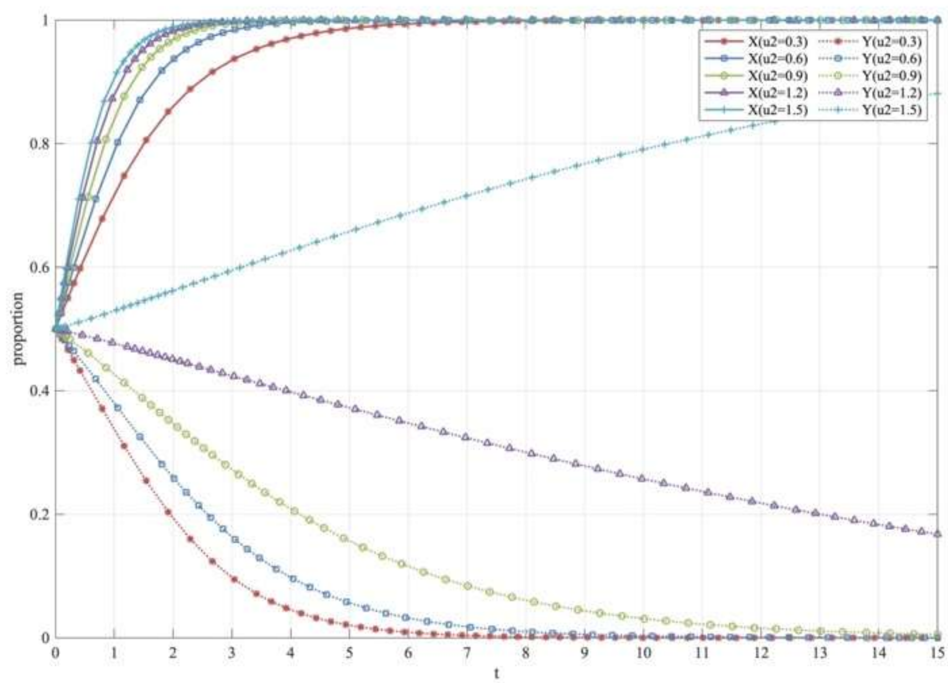


Fig. 5. Impact of Distance Subsidy u_2 Changes on Evolutionary Outcomes ($P_U = 0.5$)

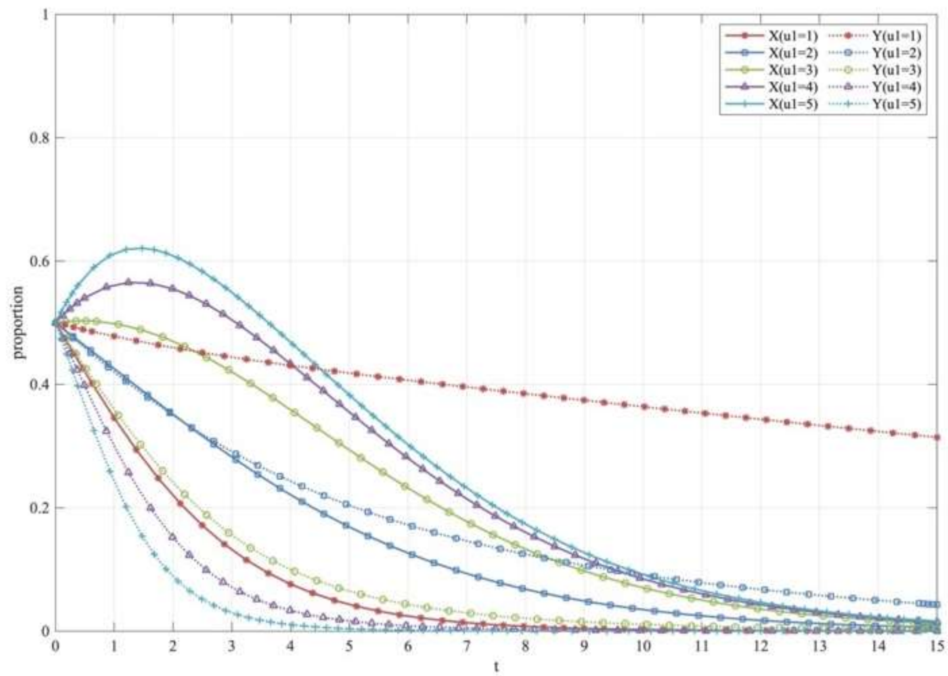


Fig. 6. Impact of One-Time Subsidy u_1 Changes on Evolutionary Outcomes ($P_U = 0.7$)

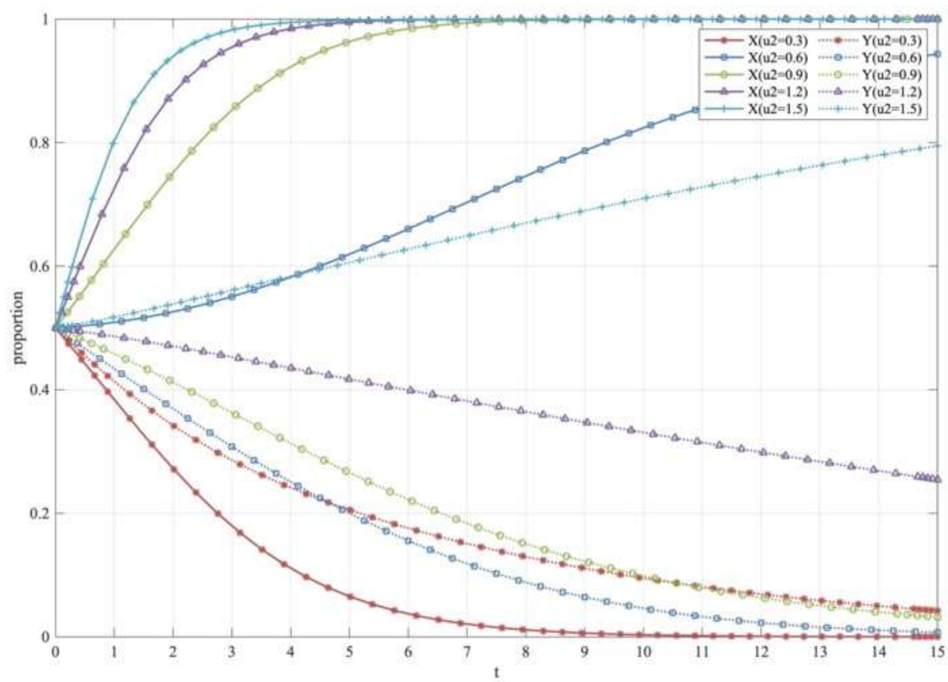


Fig. 7. Impact of Distance Subsidy u_2 Changes on Evolutionary Outcomes ($P_U = 0.7$)

From a horizontal comparison, within the same order density scenario, changes in the distance subsidy u_2 have a more pronounced impact on evolutionary outcomes compared to changes in the one-time subsidy u_1. From a vertical comparison, increasing order density reduces the willingness of taxis to accept platform subsidies alone, leading them to adopt a hybrid online-offline strategy. Growth in u_2 is more appealing to taxis than growth in u_1. When $u_2 \geq 0.6$, taxis ultimately revert to accepting platform-dispatched orders.

For ride-hailing platforms, adjusting the distance subsidy amount has a more significant effect on controlling the number of taxis participating in online dispatch. However, when $u_2 \geq 0.6$, the higher costs make this approach unsuitable as a long-term strategy.

4.2.3. Impact of Order Distance, Passenger-Seeking Cost, and Platform Commission Rate on Evolutionary Outcomes. Figure 8 to Figure 10 analyze the effects of changes in order distance L, passenger-seeking cost a, and platform commission rate τ on evolutionary outcomes. These factors significantly influence taxi strategy selection. Longer distances and lower passenger-seeking costs make offline orders more attractive to taxis. Orders with distances exceeding 12 km strongly incentivize offline acceptance. Conversely, when the passenger-seeking cost exceeds 1, taxis tend to abandon the hybrid strategy and shift to accepting orders only through the platform. This explains why drivers often prefer locations such as airports, train stations, and tourist attractions for direct customer acquisition.

Additionally, unfamiliar roads or nighttime driving, which increase passenger-seeking costs, encourage drivers to rely on ride-hailing platforms. When the platform commission rate exceeds 40%, taxi drivers are unwilling to collaborate with the platform. This aligns with real-world reports criticizing ride-hailing platforms for excessively high commission rates.

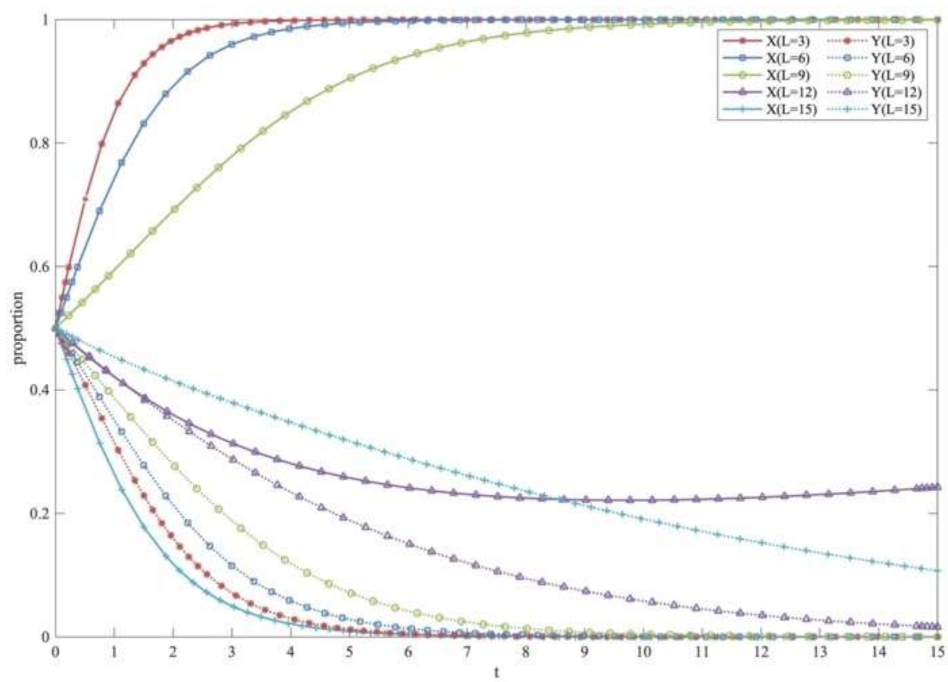


Fig. 8. Impact of Order Distance L on Evolutionary Outcomes

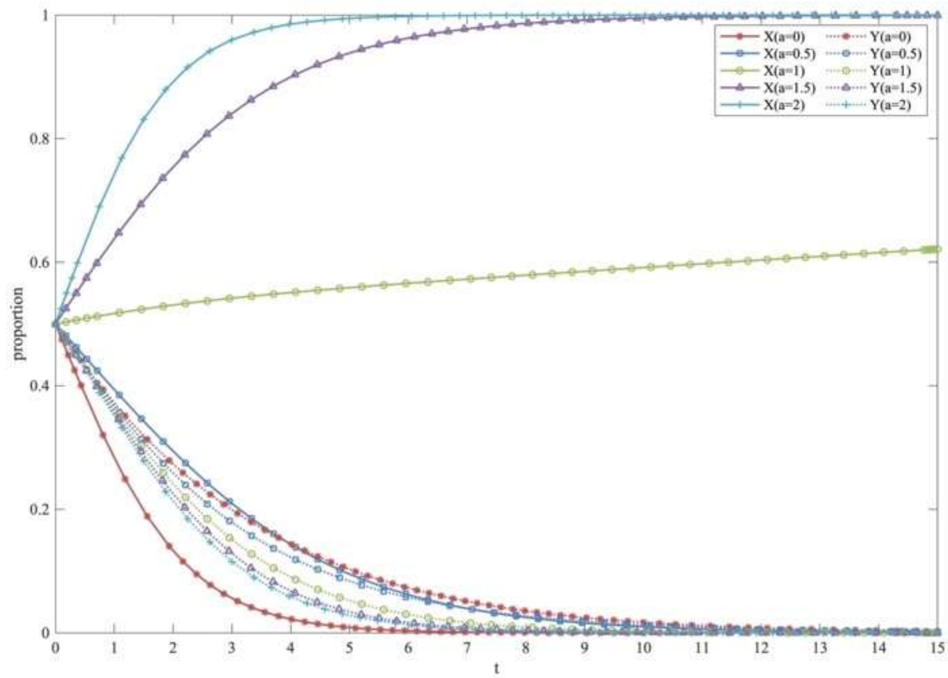


Fig. 9. Impact of Passenger-Seeking Cost a on Evolutionary Outcomes

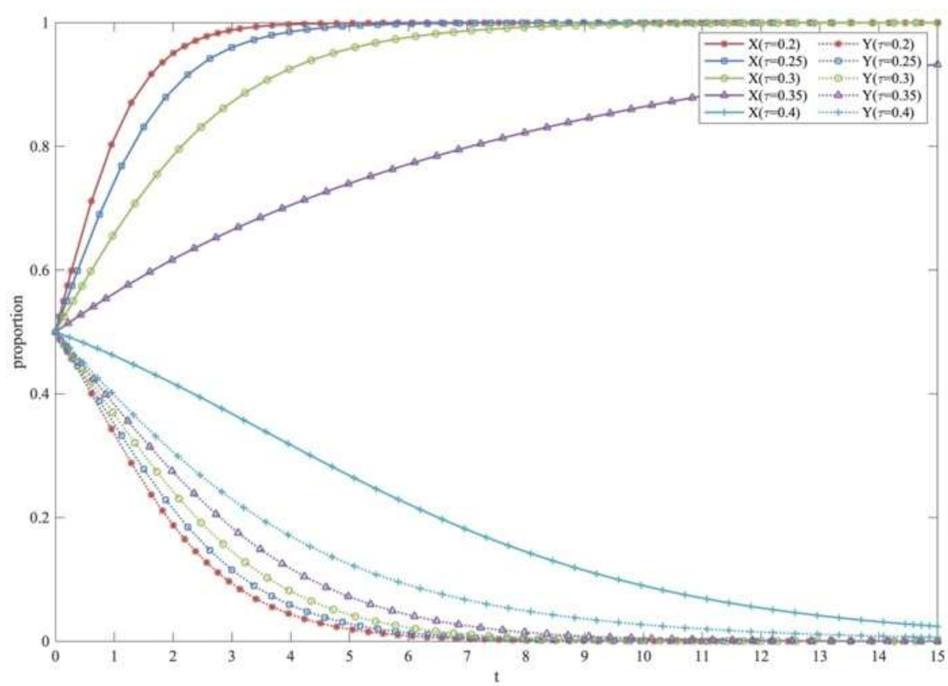


Fig. 10. Impact of Platform Commission Rate τ on Evolutionary Outcomes

5. Conclusions

This study examines the subsidy strategies of ride-hailing platforms and the online-offline order acceptance strategies of taxis during order overflow scenarios, considering taxi street-hailing behavior.

An evolutionary game model was constructed to simulate the ride-hailing market under order overflow conditions. The study analyzes taxis' strategies under varying order densities and conducts sensitivity analyses to explore the impact of relevant factors on the decision-making of taxis and ride-hailing platforms.

The main conclusions and managerial implications are as follows:

1) Ride-hailing platforms can adopt different subsidy strategies based on regional order density. Platforms have access to extensive real-time data on regional orders. By dynamically adjusting subsidy strategies according to passenger demand and the number of available vehicles, platforms can share a portion of their profits to effectively attract taxis to accept orders through the platform.

2) Distance-based subsidies are more effective for regulation. At moderate order densities, platforms can use lower distance-based subsidies to maintain profitability. However, at higher order densities, increasing the per-order subsidy amount loses its appeal to taxi drivers. To incentivize taxis to abandon offline street-hailing, the distance-based subsidy must be maintained at a higher level.

3) Ride-hailing platforms can allocate orders to taxis based on order attributes. Taxi order acceptance strategies are influenced by factors such as order attributes, taxi operating costs, and platform commission rates. Taxis tend to prioritize offline orders for long-distance trips or those with low passenger-seeking costs. When platform commission rates are high, taxis are more likely to leave the platform. Therefore, platforms can prioritize assigning long-distance orders to taxis, indirectly encouraging them to remain on the platform and accept orders.

This study does not consider the heterogeneity of taxi drivers regarding their order acceptance preferences or sensitivity to subsidies. In practice, individual differences among drivers lead to varied decisions when choosing between online and offline orders or responding to platform subsidies. Future research should explore this issue in greater depth.

Declaration of competing interest

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

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