

The Centralized Meal Service Delivery Mode

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Abstract: Meal delivery with high delivery timeliness requirements in demand-intensive areas often leads to several issues such as chaotic terminal management and low efficiency during peak times, reducing consumer satisfaction and increasing complaints. This study constructs a dynamic model of meal delivery systems to analyse the operational models and centralized dispatching modes in Guangzhou University City, and applies an evolutionary game model to explore the decisions from the perspectives of government, meal suppliers, riders, and consumers. The study analyses how centralized dispatching mode affects the performance of delivery systems and its impact on the willingness of government, merchants, and riders to participate. The results indicate that demand-intensive areas, centralized dispatching modes have sustainable advantages in terms of cost and efficiency. The effectiveness is closely related to the intensity of government intervention (supervision and support), but weakly related to the timing of intervention. Consumer preferences, shaped by consumer type and perceived value, affect the benefits of participating in a centralized dispatch mode, but not the willingness of meal suppliers to participate. The evolutionary framework in this study provides valuable references for the quantitative evaluation of the meal delivery system, theoretical support for the decision-making of the participants of the meal delivery system, and a research framework for the relevant decision-making scenarios, so as to optimize the allocation of meal resources and promote the sustainable development of meal delivery.

Keywords: Meal delivery, Centralized delivery mode, System dynamics, Evolutionary game theory, Consumer preference.

1. Introduction

The O2O meal delivery industry in China is growing steadily. By 2022, the number of online meal delivery users in China reaches 521 million, with a market size of 11 trillion yuan. With the continuous expansion of the meal delivery market, incidents of meal delivery timeouts, wrong orders and missed orders have become increasingly common. Especially in densely populated areas with high volumes of meal orders, unclear delivery routes, limited public spaces and asymmetric and asymmetric information between drivers and merchants often result in slow delivery speeds. In addition, during peak meal times in densely populated areas, the delivery pressure often forces meal delivery drivers to violate traffic rules in order to deliver on time, leading to public transport safety risks and even incorrect deliveries. These issues not only affect the efficiency of meal delivery, but also consumer satisfaction with the meal delivery market. Therefore, optimizing the allocation of meal delivery resources in densely populated areas, reducing delivery times and improving delivery efficiency have become key concerns.

The majority of research on meal delivery systems employs qualitative analysis methods, lacking specific quantitative indicators to analyse trends. System dynamics (SD), which combines qualitative and quantitative methods, has advantages in studying resource allocation issues in nonlinear complex systems. Guangzhou University City represents the largest campus meal delivery market in the country, with issues related to meal delivery particularly prominent. The high population density results in a significant overlap in time between peak meal delivery periods and students' class schedules, as well as a characteristic of extensive crisscrossing paths, which often leads to on-campus traffic congestion and disorderly conditions at meal delivery endpoints (drop-off locations). Therefore, this study uses

Guangzhou University City, a densely populated area with a good demonstration, as an example to illustrate the application of system dynamics to construct a meal delivery system. The analysis results of the system dynamics model indicate that an evolutionary game is an appropriate tool for exploring the game trends of the participants in the distribution system, thereby providing a more effective means of guiding their decision-making. Furthermore, consumers represent the sole demand side of the market, and the factors influencing their demand have received considerable attention (1). As consumers' knowledge and preferences for services evolve, they are willing to pay a premium to satisfy their preferences (2, 3). How consumer preference affects market development is of great research value. This study uses system dynamics and evolutionary games to explore the development of centralized scheduling systems and decision-making processes that consider consumer preferences, with the aim of providing suggestions for the development of a meal delivery market according to local conditions.

The remainder of this paper is organized as follows. In section 2, a comprehensive literature review is conducted. In section 3, a dynamic model of the meal delivery system is constructed in the context of Guangzhou University City, with the objective of analysing the impact of centralized dispatching on system performance. In section 4, an evolutionary game model of the meal delivery system is constructed, considering the participation of the game stakeholders in the centralized dispatch mode and consumer preferences. Section 5 presents a solution to the game model. Section 6 presents the main results and their managerial implications. The study concludes with a summary and recommendations for future research.

2. Literature Review

The article primarily concerns the field of meal delivery,

which has been widely researched. A number of scholars have provided recommendations to address challenges in peak-hour catering delivery from various perspectives, including order processing ([4]), path optimization ([5]), and collaborative delivery ([6]). Firstly, in terms of order processing before meal delivery, Wang et al. ([7]) developed a real-time response method for instant delivery orders based on a diversified scheme pool to address the real-time response issue of delivery orders. Wang et al. ([8]) investigated the issue of delivery delays resulting from the lack of information regarding orders in the catering delivery process. Luo et al. ([9]) subsequently delineated the various zones of meal delivery based on the high frequency and large volume of consumer orders and the distribution of customer demands. Chen et al. ([10]) and their colleagues explored the potential strategies for meal delivery crowdsourcing, with a focus on optimizing the waiting time for customers and the earnings of riders.

In the field of meal delivery route optimization, Yu et al. ([11]) conducted route optimization for on-demand meal delivery with hard time windows, taking into account the high dynamics of fresh meal delivery orders and the high efficiency of delivery services. Wu et al. ([12]) addressed the real-time delivery route optimization problem in asymmetric urban traffic networks. Differing from the traditional many-to-many delivery model, Tang et al. ([13]) proposed a one-to-many model, effectively reducing the working time and delivery distance for riders in meal delivery while enhancing the intelligence level of meal delivery. Teng et al. ([14]) further optimized meal delivery routes by considering the joint satisfaction of both meal suppliers and customers. Zhang et al. ([15]) optimized meal delivery routes by leveraging consumer historical habitual data in response to the increasing number of pickup and service points. Additionally, Wang et al. ([16]) and Fan et al. ([17]) addressed the traffic risks and delivery time constraints in meal delivery by analysing the platform's established compensation mechanism for delays and the corporate social responsibility performance of the platform, respectively. The research discussed above proposes improvements to various aspects of meal delivery, including the implementation of unified management and combined delivery for orders within a specific area. So, whether the "centralized dispatching model is suitable for meal delivery in densely populated areas" is raised, and this paper attempts to analyse and answer this question from a systemic perspective.

Additionally, another research area relevant to this article

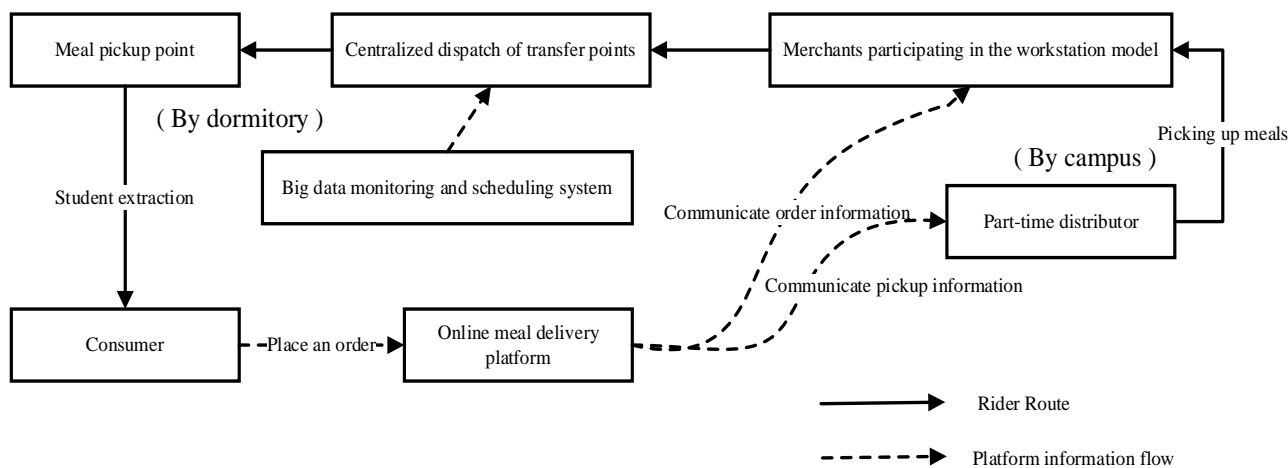


Figure 1. Structure of the centralized scheduling model for meal delivery

is system dynamics, which has been widely applied in fields such as social economics ([18], [19], [20], [21]), public affairs ([22], [23], [24]), and engineering management ([25], [26], [27]). System dynamics methodology has been less frequently utilized in the realm of meal delivery services. Instead, many scholars have opted to apply system dynamics methods to analyze and research food safety issues within the O2O meal delivery sector ([28], [29], [30]). Therefore, we try to construct a model of meal delivery, including a centralized scheduling mode and other mainstream modes, by using system dynamics.

In addition to this, our article also deals with the aspect of consumer preference in terms of its impact on meal delivery. Zhong et al. ([31]) introduced the perceived promotional value factor, studying consumer preferences for different meal prices and promotional strategies by constructing a structural equation model. Cheng et al. ([32]) researched consumer preferences for food freshness in catering delivery. Zhang et al. ([33]) and Yu et al. ([34]) considered consumer satisfaction in meal delivery. It can be observed that there is a lack of literature on the evolution of meal delivery systems considering consumer preferences at the current stage. Therefore, this study aims to comprehensively utilize the methods of system dynamics and evolutionary game theory to explore the relevant decisions of centralized scheduling systems when considering consumer preferences.

3. The Dynamics of the Meal Delivery System

3.1. System Scoping and Modelling

Taking the University City as a typical densely populated area, we utilize system dynamics to construct a meal delivery system incorporating a centralized dispatching model.

Meal delivery includes several steps, such as merchants preparing meals and riders picking up and delivering meals. Currently, there are three main delivery modes: merchant self-owned delivery, platform delivery, and crowd-sourced logistics delivery ([35]).

A centralized dispatch model for meal delivery was constructed through practical research. As shown in Figure 1, riders are responsible for transporting meals centrally to a transfer point near the school dormitory, and the staff at the transfer point assigns the meals to the point to be picked up according to the building. The staff in this model are standing staff, which is an inherent system cost.

This study established a flow diagram of the meal delivery multi-modal delivery system containing a centralized scheduling mode through the Vensim PLE (personal learning environment). As shown in Figure 2, the system of equations is embedded, based on which validity and authenticity tests are conducted. Distinguishing from the method of constructing a game model and then presenting it with a system flow diagram in the literature ([36], [37], [38]), this article further builds an evolutionary model by presenting the meal delivery system.

Ordering meal delivery mainly to save time or money ([39]); therefore, this study takes “system delivery cost accumulation” and “system delivery efficiency” as the main observation variables. The former refers to the costs paid in specific scenarios, including regional inherent costs (the costs of capacity and resource inputs that cannot be easily relocated) and mobility costs (the marginal costs incurred by the flow of orders into each mode); the latter refers to the delivery volume per unit of time of each mode. Based on the fieldwork in the University City, the key equations in Figure 2 and the data sources used are explained below:

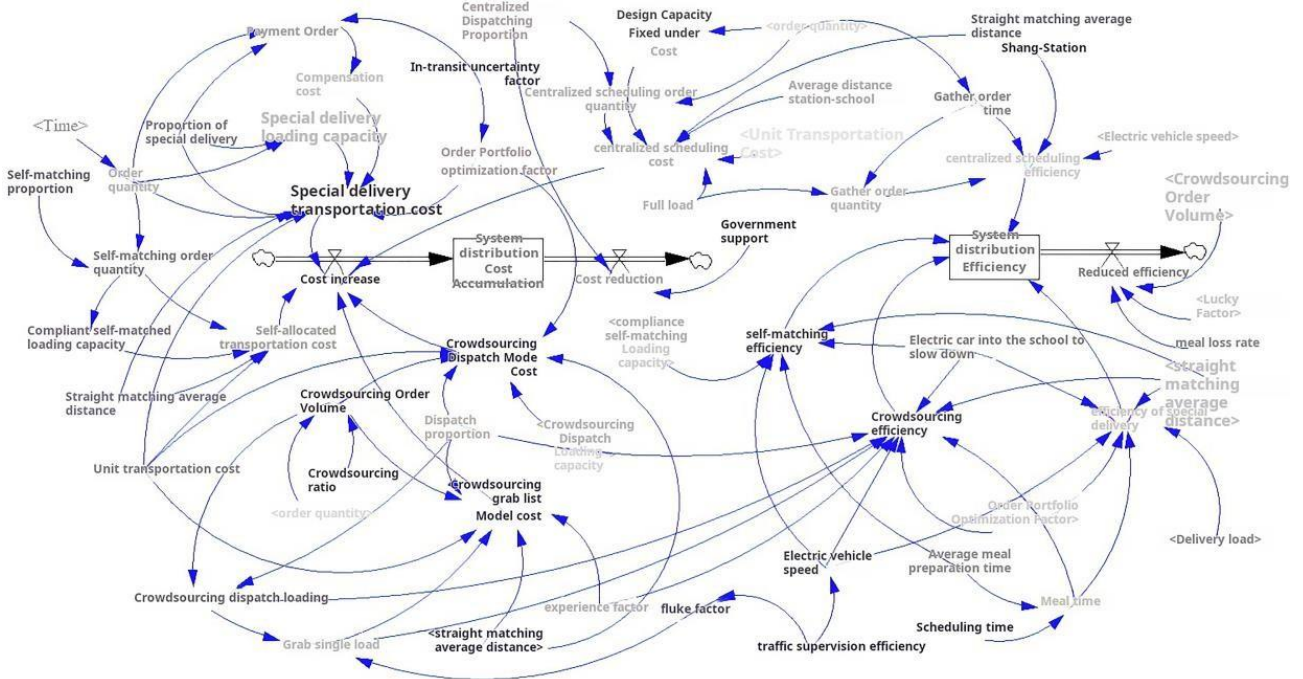


Figure 2. Flow diagram of multi-mode delivery system (including centralized scheduling mode)

(1) Initial time: INITIAL TIME=0; simulation period: FINAL TIME=1440; time unit: minutes (*min*).

(2) According to publicly available transaction data from the 2019 Meituan meal delivery market, the average daily number of orders in university cities is approximately 80,000, and the ordering time is mainly concentrated during the lunch

(11:00-13:00) and dinner (17:00-19:00) periods. As shown in Table 1, the lunch and dinner distribution hours are highly consistent with the annual reports of Meituan. Assuming that the ordering demands are independent, the orders in each period are processed according to a normal distribution and then superimposed to obtain the order quantity data used for system simulation.

Table 1. Distribution of online meal delivery users' ordering time slots, 2017

Ordering period (time)	Proportion of users ordering food	Order ratio	Average order size
Breakfast (7-9 a.m.)	24.9%	11.1%	8880
Lunch (11-13 a.m.)	75.5%	33.6%	26880
Afternoon tea (15-16 p.m.)	27.1%	12.0%	9600
Dinner (17-19 p.m.)	61.6%	27.4%	21920
Late-night snack (21-22 p.m.)	35.8%	15.9%	12720

Note: The order percentage is converted according to the user percentage

Based on the law of two or eight, assume that the main ordering time $[T_{min}^i, T_{max}^i]$ for each ordering period I concentrates 80% of the “average order volume” and that the order volume of each period O obeys the normal distribution $N(\mu_i, \sigma_i^2)$ and is symmetric to the median of the ordering times, which is obtained by substituting $p(80\%)$:

$$\sigma_i \approx \begin{cases} 46.7, & \text{if } T_{max}^i - T_{min}^i = 2h \\ 23.3, & \text{if } T_{max}^i - T_{min}^i = 1h \end{cases} \quad (1)$$

Calculate the distribution of order volumes over the time dimension *Time*:

$$order\ volume = \sum_{i=1}^5 average\ order\ volume \times \frac{e^{-\frac{(Time-\mu_i)^2}{2\sigma_i^2}}}{\sigma_i\sqrt{2\pi}} \quad (2)$$

Where i is taken as 1, 2...5, corresponding to the five ordering periods in Table 1. The total simulated order volume is shown in Figure 3.

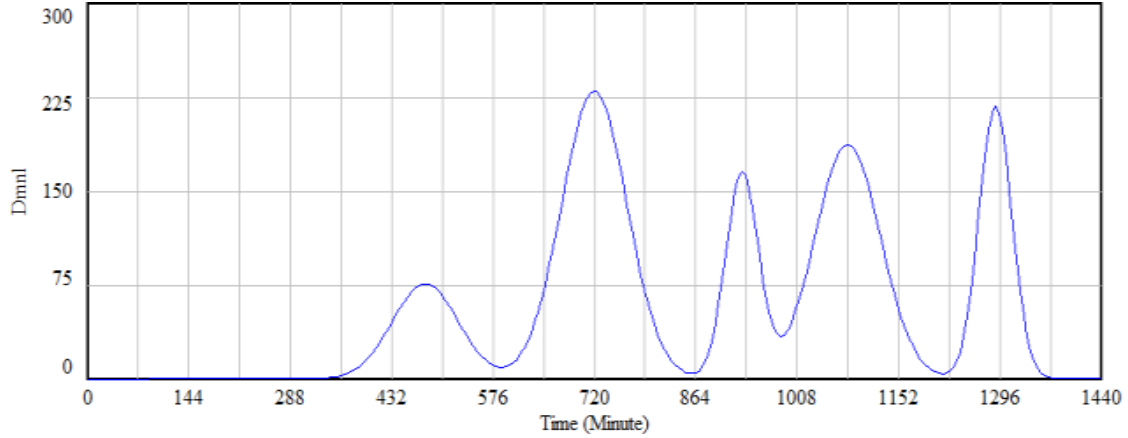


Figure 3. Order volume real-time analog data

The average distance d_{jk} of the system's direct matching represents the overall supply and demand distance of the system. It is obtained based on the distance data in Table 2 without considering the order quantity (weighting):

$$Average\ Distance\ of\ Direct\ Matching = \frac{1}{JK} \sum_{j=1}^J \sum_{k=1}^K d_{jk} = 2.7km \quad (3)$$

Table 2. Distance of Guangzhou University City campuses from villages on the island (km)

Workstation k (point of need)	Supply point j			
	Beiting Village	Nanting village	Soi Shek Tsuen	Pui Kong Village
Guangzhou University (Central West Road)	1.6	1.6	4.8	4.1
Guangzhou Academy of Fine Arts (Archives Road)	0.67	1.8	4.9	3.0
Guangdong University of Technology West Living Quarter (West Guomao Road)	1.5	1.1	4.2	2.7
Guangdong University of Technology East Living Quarter (Guang Gong Er Road)	2.5	1.2	3.1	2.6
South China Normal University/Star Ocean Conservatory of Music (Huashi 2nd Road)	1.6	2.8	4.4	2.0
Sun Yat-sen University (Pui Kong Tsuen Street)	3.4	3.4	3.2	0.16
Guangdong Pharmaceutical University/Guangzhou University of Traditional Chinese Medicine (Huagong North Road)	4.3	3.5	1.4	2.0
South China University of Technology North Campus (Huagong North Road)	4.3	3.5	1.4	2.0
Guangdong University of Foreign Studies (2 Benan Road)	3.7	3.7	3.4	0.11

Note: The above data were collected through Baidu map.

Based on the 2018 mandatory standard “Safety Technical Code for Electric Bicycles” ([40]), the upper-speed limit of electric bicycles is $25\ km/h$, the upper load limit is 15 kg; and the efficiency of traffic regulation is set at 0.95.

System dynamics emphasize the overall logic among system factors, which weakens the dependence on parameter values to a certain extent ([41]). In this study, auxiliary variables are used to summarize the end-end characteristics that are difficult to quantify, including the “on-the-way uncertainty factor”, “rider experience factor” and “order combination optimization factor”. The “in-transit uncertainty factor” is the degree to which the platform is aware of the real delivery environment. If the platform has a probability of 0.8 of accurately predicting the order fulfillment time, the uncertainty factor is 0.2. The “rider experience factor” is the degree to which the rider has advantages and disadvantages in choosing delivery combinations and routes, and the experience factor is the degree to which the rider has experience choosing delivery combinations and routes. The

“rider experience factor” is the rider’s experience in choosing delivery combinations and paths of the degree of superiority or inferiority. The experience was time-tested, which was slightly greater than the value of the information provided by the system; thus, it was set to 0.85. The “order combination optimization factor” is the dispatching system (algorithm) used to match the location of the rider and the order information on the optimization of the path degree. Assuming that the optimization effect of the dispatch algorithm has a greater probability of not being significantly better than experience, that is, that the order combination optimization factor is not less than half of the experience factor, the order combination optimization factor is 0.5.

3.2. Comparison of System Performance with Different Centralized Dispatch Ratios

This study focuses on analyzing the performance of meal delivery systems with different centralized scheduling ratios. Referring to the reported centralized scheduling scale, the range of centralized scheduling ratios is set between 0% and

60%.

It is assumed that the proportion of delivery modes in the system is the proportion of orders flowing into each delivery mode, and the proportion of orders flowing in depends on consumer preferences and the performance of these modes. In specific scenarios, consumer preferences, as well as the performance of the distribution modes, are uncertain, and the proportion of each distribution mode in different regions varies significantly. Compared to centralized dispatching, decentralized distribution has constant returns to scale. For simplicity, it is assumed that the proportions of the other three distribution modes are equal. Based on the system simulation results, the following conclusions can be drawn:

3.2.1. Higher starting input costs for centralized dispatching

A simulation of the above ratios yields the cumulative trend line of the system's distribution costs, as shown in Figure 4. When the centralized dispatch proportion of the system

increases, the initial fixed cost of the system increases, including the salary of employees at the centralized dispatch site and the rental cost of the site. For a specific region, the cost of operating centralized dispatch cannot be spread to other regional operations, raising the average cost of regional orders in the previous period.

3.2.2. The higher the order volume is, the greater the advantage of centralized scheduling

The trend line in Figure 4 shows that systems with a high proportion of centralized dispatch services have lower marginal costs and exhibit a trend toward decreasing average distribution costs as the order volume increases. The centralized scheduling mode has a higher load capacity, and during peak order periods, multiple distribution modes complement each other; however, the less the system with a higher proportion of centralized scheduling relies on the complement of other modes, the more moderate the overall cumulative cost growth trend of the system is.

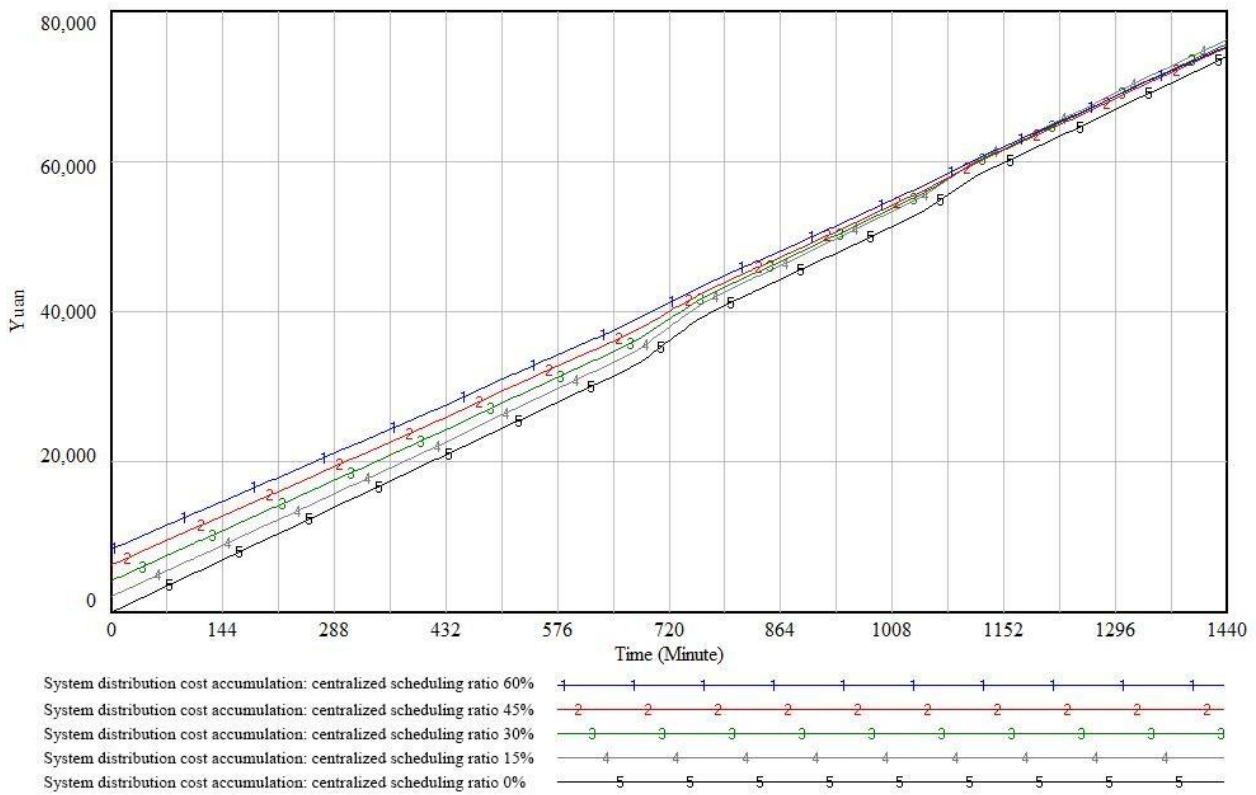


Figure 4. Cumulative Comparison of System Distribution Costs

3.2.3. More stable efficiency of the centralized dispatch system

As shown in the system distribution efficiency curve in Figure 5, when the order volume increases, other modes will flexibly supplement the capacity so that the overall efficiency of the system increases. The higher the proportion of centralized dispatching is, the lower the volatility of the distribution efficiency of the system is, and the more stable the system is; the smaller the proportion of centralized dispatching is, the more flexible the system is, but this

flexibility is built on the platform's capacity scheduling, and the transfer of the capacity to a certain extent increases the marginal cost. Peak comparison results for the same period show that the overall distribution efficiency of the system with a low centralized scheduling ratio is slightly lower, mainly because during the peak order period, there is competition for transportation resources at the end of the riders, and non-centralized scheduling of distribution lowers the overall efficiency to a certain extent.

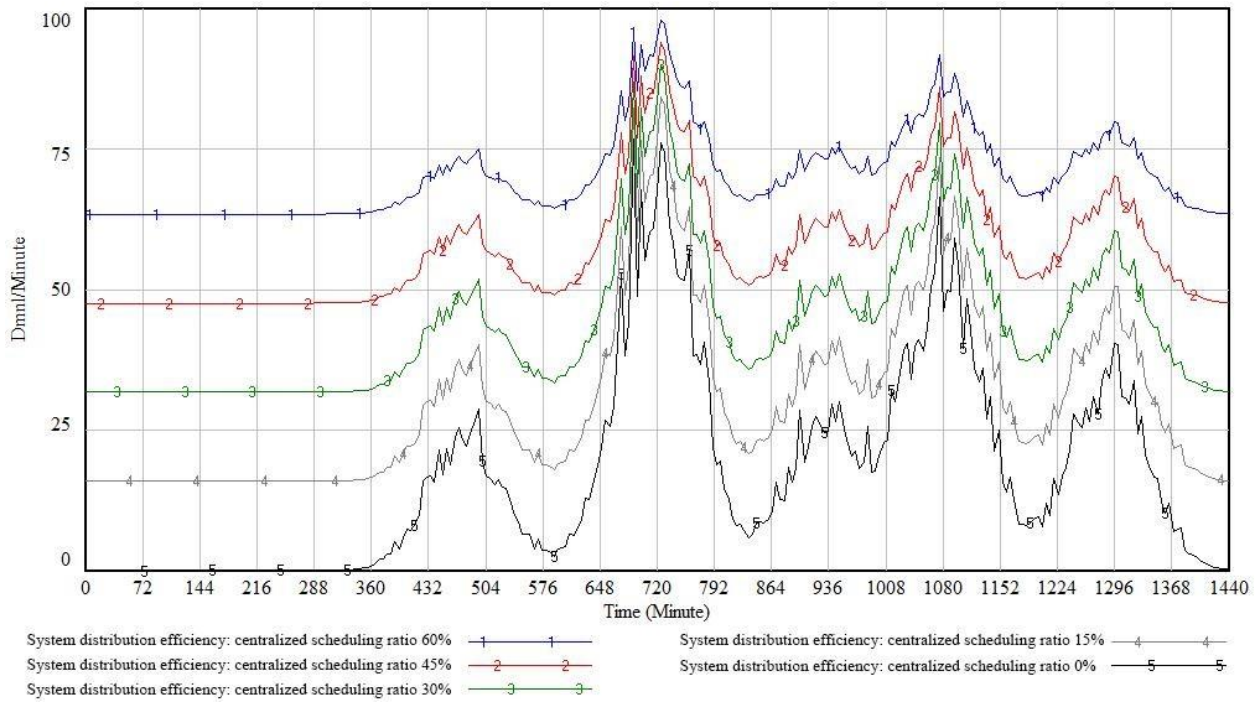


Figure 5. Comparison of system distribution efficiency

The causal loop of the system flow diagram is derived from the literature and experience and, to some extent, reflects objective cognition. The above visualizes the effect of the centralized scheduling mode ratio on system performance through system dynamics modelling and semi-quantitative analysis combined with simulation data, which strongly supports the view that the centralized scheduling mode has marginal cost advantages and more stable system efficiency in the case of higher-order volumes.

4. Problem Description and Assumptions

Implementing the centralized dispatch model faces the problem of attracting the participation of consumers, riders, and merchants. Many studies have pointed out ([42], [43]) that the government must regulate and intervene in the market's unhealthy behaviour and environment, so the government has been introduced into the game model. To address these issues, this study explores the evolution of the willingness of the government, merchants, and riders to participate in implementing the centralized dispatch model, taking into account consumer preferences.

The stakeholders in the meal delivery system encompass the service providers and recipients, regulatory bodies, and service intermediaries. The entities engaging in the centralized dispatch model include government-led social organizations and platforms. Merchants and riders will choose to participate in the centralized dispatch model when they have higher expected returns from participating in the model, setting the strategy space for merchants as (enter, not enter) and for riders as (participate, not participate). The government intervenes in the centralized dispatch model by utilizing regulation in addition to regulating fiscal policy. Under continuous regulation, the government's intervention in the system depends more on whether or not it is supported, setting the government's strategy space as (support, no support).

On the docking side, it is assumed that a third-party organization implements the centralized dispatch model. If

there is no government lead, the third-party organization will decide whether to implement the centralized dispatch model based on whether the supply side participates in the decision-making of the centralized dispatch model; if the government leads and supports the model, the third-party organization will make efforts to implement the model, except for the case where neither the merchants nor the riders participate in the model. The study considers only cases where a third-party organization can implement a centralized dispatch model.

Based on the conclusion of section 3.2, the following assumptions are made assuming that the order quantity K is higher.

Assumption 1: The three-game subjects are finite rational; the probability that the government supports centralized dispatch is $x(0 \leq x \leq 1)$ and the probability that it does not support it is $1-x$. The probability that merchants move into centralized dispatch is $y(0 \leq y \leq 1)$, the probability that they do not support centralized dispatch is $1-y$, the probability that a rider participates in the centralized dispatch model is $z(0 \leq z \leq 1)$ and the probability that he does not participate is $1-z$.

Assumption 2: The centralized dispatching model can better manage the quality of meals at the delivery end. The government performs the essential regulatory function to regulate the behaviors that cause meal delivery safety problems and affect the cityscape, such as placing meals on the road at the end of delivery, with a regulatory efficiency of $\alpha(0 \leq \alpha \leq 1)$, and imposes penalties on riders who violate the rules in the process of regulation P_1 . When the government does not support the centralized dispatch model, regulatory costs C_1 occur, and the government obtains a reputation for its performance R_{base} ($R_{base} > C_1$); when the government supports the centralized dispatch model, it invests in financial subsidies and policy incentives C_2 . If both merchants and riders choose to join the centralized dispatching model, the government gains the reputation of regional management R_1 , and if either merchants or riders tend to join the centralized dispatching model, which can

optimize the performance of the delivery system or the management of end-user meals, the government gains the reputation of performance R_2 ($R_2 < R_1$); a similar assumption is made in the study of Hui et al. ([44]).

Assumption 3: Merchants will enter multiple delivery modes at the same time. The basic revenue per order of meal delivery is set to R_0 , the delivery cost of self-distribution or crowd-sourcing is set to C_3 , and the cost per order of merchants after entering into the centralized dispatch mode is set to C_4 , and when the government supports the centralized dispatch, the merchants will be able to enjoy preferential benefits for each centralized delivery order R_3 . The delivery fee of the dedicated delivery mode is also paid to the platform, and the size of the fee does not affect the merchants' revenue. As mentioned above, the platform has no incentive to implement the centralized dispatch mode, and the amount of its profit does not affect the overall performance of the meal delivery system; therefore, the cost of merchants' participation in the dedicated delivery portion of the platform is not considered.

Assumption 4: The main factor that encourages riders to change their behavior in meal delivery is the incentive gain ([45]). Riders can only be in one mode at the same time. In the centralized dispatch mode, the rider has less risk of uncertainty in the transportation path and time, when the expected revenue per order is R_4 ; when the government supports the centralized dispatch mode and the rider increases the revenue per order ($C_2/K - R_3$). When the rider is in the other delivery mode the revenue is R_5 , due to the assumption of all the links in the delivery, when $R_5 > R_4$ and $R_5 < P_1$ in order to make the discipline can work ([46]). When the order volume K is at a high level, the other modes will face a greater risk of uncertainty, which in turn will increase the pressure on the rider's delivery, and then the probability that the rider has a chance to break the existing constraints (overloading,

travelling in violation of the law) is β ($0 \leq \beta \leq 1$). If the rider violates the rules, there is a γ ($0 \leq \gamma \leq 1$) probability that the delivery will be wrong or untimely, for which there will be a cost payout P_2 . Information platforms often limit feedback channels, allowing consumers to evaluate riders and merchants one-sidedly, and if merchants are not part of a centralized dispatch, they lose the externality of collective responsibility and suffer from word-of-mouth losses P_3 .

Assumption 5: Satisfaction is a significant factor influencing consumers' loyalty to meal delivery platforms and depends mainly on price and delivery efficiency ([47]). In this study, consumers are divided into two categories: price-sensitive consumers account for τ ($0 \leq \tau \leq 1$); efficiency-sensitive consumers account for $1 - \tau$. According to Section 3.2, the centralized scheduling model improves the efficiency of the system from an overall perspective, but the delivery efficiency of specific orders under the centralized scheduling model is not the highest during non-peak order periods. Under the assumed order volume level K , it is assumed that orders from price-sensitive consumers will flow into the centralized dispatch mode and that orders from efficiency-sensitive consumers will not flow into the centralized dispatch mode. The consumer group in the region behaves more price-sensitively at $\tau > 0.5$. Conversely, the consumer group behaves more efficiency-sensitively at $\tau < 0.5$. When the meal delivery system is stabilized, the scale of each delivery mode matches the demand, so it is assumed that the proportion of each mode is consistent with the frequency with which the orders flow into each mode.

The above assumptions are summarized in Table 3, which shows the strategy combinations and benefit matrices of the three-party game among the government, merchants, and riders.

Table 3. Tripartite Evolutionary Game Benefits Matrix for the Government, Merchants, and Riders

Gaming Party		Local Government	
		Support (x)	Not supported (1-x)
Merchants (y)	Riders participate (z)	$R_{base} + R_1 - C_1 - C_2$ $(1 - \tau)(R_0 - C_3) + \tau(R_0 - C_4 + R_3)$ $R_4 + C_2 / K - R_3$	$R_{base} - C_1$ $(1 - \tau)(R_0 - C_3) + \tau(R_0 - C_4) R_4$
	Riders do not participate (1-z)	$R_{base} + R_2 - C_1 - C_2 + \beta\alpha P_1$ $(1 - \tau)(R_0 - C_3) + \tau(R_0 - C_4 + R_3)$ $R_5 - \beta\alpha P_1 - \gamma P_2$	$R_{base} - C_1 + \beta\alpha P_1$ $(1 - \tau)(R_0 - C_3) + \tau(R_0 - C_4)$ $R_5 - \beta\alpha P_1 - \gamma P_2$
Merchants do not move in (1-y)	Riders participate (z)	$R_{base} + R_2 - C_1 - C_2$ $R_0 - C_3$ $R_4 + C_2 / K - R_3$	$R_{base} - C_1$ $R_0 - C_3$ R_4
	Riders do not participate (1-z)	$R_{base} - C_1 - C_2 + \beta\alpha P_1$ $R_0 - C_3 - \gamma P_3$ $R_5 - \beta\alpha P_1 - \gamma P_2$	$R_{base} - C_1 + \beta\alpha P_1$ $R_0 - C_3 - \gamma P_3$ $R_5 - \beta\alpha P_1 - \gamma P_2$

5. Model Solution

The expected returns E_z^1 , E_z^2 and average returns $\overline{E_z}$ of

the government's choice of supportive and non-supportive strategies are as follows:

$$\begin{aligned}
E_z^1 &= yz(R_{base} + R_1 - C_1 - C_2) + y(1-z)(R_{base} + R_2 - C_1 - C_2 + \beta\alpha P_1) + (1-y)z(R_{base} + R_2 - C_1 - C_2) \\
&\quad + (1-y)(1-z)(R_{base} - C_1 - C_2 + \beta\alpha P_1) \\
&= -C_1 - C_2 + R_{base} + (1-z)\beta\alpha P_1 + R_1 yz + R_2(y+z-2yz)
\end{aligned} \tag{4}$$

$$\begin{aligned}
E_z^1 &= yz(R_{base} + R_1 - C_1 - C_2) + y(1-z)(R_{base} + R_2 - C_1 - C_2 + \beta\alpha P_1) + (1-y)z(R_{base} + R_2 - C_1 - C_2) \\
&\quad + (1-y)(1-z)(R_{base} - C_1 - C_2 + \beta\alpha P_1) \\
&= -C_1 - C_2 + R_{base} + (1-z)\beta\alpha P_1 + R_1 yz + R_2(y+z-2yz)
\end{aligned} \tag{5}$$

$$\overline{E}_z = xE_z^1 + (1-x)E_z^2 \tag{6}$$

growth rate of the probability of government support x is equal to $E_z^1 - \overline{E}_z$, which yields the replication dynamic equation

According to Malthusian dynamic theory ([48]), the

$$F(x) = \frac{dx}{dt} = x(E_z^1 - \overline{E}_z) = x(x-1)[C_2 - R_1 yz + R_2(2yz - y - z)] \tag{7}$$

The expected revenues E_s^1 , E_s^2 and average revenue \overline{E}_s of merchants opting in and out are as follows:

$$\begin{aligned}
E_s^1 &= x[(1-\tau)(R_0 - C_3) + \tau(R_0 - C_4 + R_3)](1-x)[(1-\tau)(R_0 - C_3) + \tau(R_0 - C_4)] \\
&= (1-\tau)(R_0 - C_3) + \tau(R_0 - C_4) + x\tau R_3
\end{aligned} \tag{8}$$

$$\begin{aligned}
E_s^2 &= z(R_0 - C_3) + (1-z)(R_0 - C_3 - \gamma P_3) \\
&= R_0 - C_3 - (z-1)\gamma P_3
\end{aligned} \tag{9}$$

$$\begin{aligned}
\overline{E}_s &= yE_s^1 + (1-y)E_s^2 \\
&= (1-y)[R_0 - C_3 - (z-1)\gamma P_3] + y[(1-\tau)(R_0 - C_3) + \tau(R_0 - C_4) + x\tau R_3]
\end{aligned} \tag{10}$$

Replicated dynamic equations for the probability of merchant on-boarding:

$$G(y) = \frac{dy}{dt} = y(E_s^1 - \overline{E}_s) = -y(y-1)[\tau C_3 - \tau C_4 + x\tau R_3 + (z-1)\gamma P_3] \tag{11}$$

Similarly, the expected returns E_q^1 , E_q^2 and average returns \overline{E}_q for riders choosing to participate and not choosing to participate are as follows:

$$E_q^1 = x(R_4 + C_2 / K - R_3) + (1-x)R_4 = x(C_2 / K - R_3) + R_4 \tag{12}$$

$$E_q^2 = R_5 - \beta\alpha P_1 - \gamma P_2 \tag{13}$$

Replicated dynamic equations for rider participation probabilities:

$$\overline{E}_q = zE_q^1 + (1-z)E_q^2 \tag{14}$$

$$H(z) = \frac{dz}{dt} = z(E_q^1 - \overline{E}_q) = z(z-1)(R_5 - R_4 - \beta\alpha P_1 - C_2 x / K + R_3 x - \gamma P_2) \tag{15}$$

The following system of equations is obtained by associating the replicated dynamic equations:

$$\begin{cases}
F(x) = x(E_z^1 - \overline{E}_z) = x(x-1)[C_2 - R_1 yz + R_2(2yz - y - z)] \\
G(y) = y(E_s^1 - \overline{E}_s) = -y(y-1)[\tau C_3 - \tau C_4 + x\tau R_3 + (z-1)\gamma P_3] \\
H(z) = z(E_q^1 - \overline{E}_q) = z(z-1)(R_5 - R_4 - \beta\alpha P_1 - C_2 x / K + R_3 x - \gamma P_2)
\end{cases} \tag{16}$$

If the combination of strategies makes the system to reach the equilibrium point when $F(x)=0$, $G(y)=0$, $H(z)=0$, it is easy to obtain 9 local equilibrium points: A (0, 0, 0), B (0, 0, 1), C (0, 1, 0), D (0, 1, 1), E (1, 0, 0), F (1, 0, 1), G (1, 1, 0), H (1, 1, 1), and I (x^* , y^* , z^*). In practice, the game player will

choose one strategy, so the equilibrium point I in the sense of mixed strategy is not considered for the time being.

The equilibrium point that still evolves to a stable state in the face of perturbation is the stable point; with reference to

the Lyapunov stability theory ([49]), the equilibrium point is stable when and only when the rate of change in the decision probability of the subjects involved in the game at the point is negative, and the equilibrium point can be analyzed through the eigenvalue symbols of the Jacobi matrix (denoted as J).

$$J = \begin{bmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} & \frac{\partial F(x)}{\partial z} \\ \frac{\partial G(y)}{\partial x} & \frac{\partial G(y)}{\partial y} & \frac{\partial G(y)}{\partial z} \\ \frac{\partial H(z)}{\partial x} & \frac{\partial H(z)}{\partial y} & \frac{\partial H(z)}{\partial z} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad (17)$$

The values of the elements in Eq. (14) are respectively:

$$a_{11} = (2x - 1)[C_2 - R_1 y z + R_2(2yz - y - z)]$$

$$a_{12} = x(x - 1)[R_2(2z - 1) - R_1 z]$$

$$a_{13} = x(x - 1)[R_2(2y - 1) - R_1 y]$$

$$a_{21} = -y(y - 1)\tau R_3$$

$$a_{22} = -(2y - 1)[\tau C_3 - \tau C_4 + x\tau R_3 + (z - 1)\gamma P_3] \quad (18)$$

$$a_{23} = -y(y - 1)\gamma P_3$$

$$a_{31} = z(z - 1)(R_3 - C_2 / K)$$

$$a_{32} = 0$$

$$a_{33} = (2z - 1)(R_5 - R_4 - \beta\alpha P_1 - C_2 x / K + R_3 x - \gamma P_2)$$

Substituting each equilibrium point into the Jacobi matrix (14) yields its corresponding Jacobi matrix eigenvalues as shown in Table 4.

Table 4. Eigenvalues of the Jacobi matrix at each equilibrium point

Balance Point	Eigenvalue (math.) λ_1	Eigenvalue (math.) λ_2	Eigenvalue (math.) λ_3
A (0, 0, 0)	$-C_2$	$\tau C_3 - \tau C_4 - \gamma P_3$	$-(R_5 - R_4 - \beta\alpha P_1 - \gamma P_2)$
B (0, 0, 1)	$-C_2 + R_2$	$\tau C_3 - \tau C_4$	$(R_5 - R_4 - \beta\alpha P_1 - \gamma P_2)$
C (0, 1, 0)	$-C_2 + R_2$	$-\tau C_3 + \tau C_4 + \gamma P_3$	$-(R_5 - R_4 - \beta\alpha P_1 - \gamma P_2)$
D (0, 1, 1)	$-C_2 + R_1$	$-\tau C_3 + \tau C_4$	$(R_5 - R_4 - \beta\alpha P_1 - \gamma P_2)$
E (1, 0, 0)	C_2	$\tau C_3 - \tau C_4 + \tau R_3 - \gamma P_3$	$-(R_5 - R_4 - \beta\alpha P_1 - C_2 / K + R_3 - \gamma P_2)$
F (1, 0, 1)	$C_2 - R_2$	$\tau C_3 - \tau C_4 + \tau R_3$	$(R_5 - R_4 - \beta\alpha P_1 - C_2 / K + R_3 - \gamma P_2)$
G (1, 1, 0)	$C_2 - R_2$	$-\tau C_3 + \tau C_4 - \tau R_3 + \gamma P_3$	$-(R_5 - R_4 - \beta\alpha P_1 - C_2 / K + R_3 - \gamma P_2)$
H (1, 1, 1)	$C_2 - R_1$	$-\tau C_3 + \tau C_4 - \tau R_3$	$(R_5 - R_4 - \beta\alpha P_1 - C_2 / K + R_3 - \gamma P_2)$

When the order volume K is at a higher level, it is suitable to implement the centralized scheduling mode. It is necessary to guide the merchants and riders in the system to participate, as the stable points at which the third-party organization can continue to promote the centralized scheduling mode are point D (0, 1, 1) and point H (1, 1, 1), thus the stable conditions of D and H can be used as a basis for decision-making. The specific analysis is as follows.

6. Results and Discussion

6.1. If D (0, 1, 1) is a Stable Point

The corresponding evolution strategy is as follows: (unsupported, inbound, participate) and $R_5 - \beta\alpha p_1 - \gamma p_2 < R_4$, $R_1 < C_2$ and $C_4 < C_3$. The government's performance gain from supporting the centralized dispatch model is less than the invested capital (R_1

$< C_2$), the government adopts the strategy of not supporting; according to the conclusion of section 2.4, when the volume of meal delivery orders reaches a certain density, the marginal delivery cost of orders under the centralized dispatch model is lower than that of the other modes ($C_4 < C_3$); under the premise of keeping the efficiency constant, when the basic traffic regulation efficiency and punishment are greater, the riders do not participate in the centralized dispatch. The expected return to the model is less ($R_5 - \beta\alpha p_1 - \gamma p_2 < R_4$). Therefore, the managerial implication of D is that merchants and riders will spontaneously form a centralized scheduling pattern for a certain density of order volume. For this spontaneous and standardized evolution of merchants and riders, the government can continue to perform basic regulatory actions to ensure that the market develops in an orderly manner without intervention.

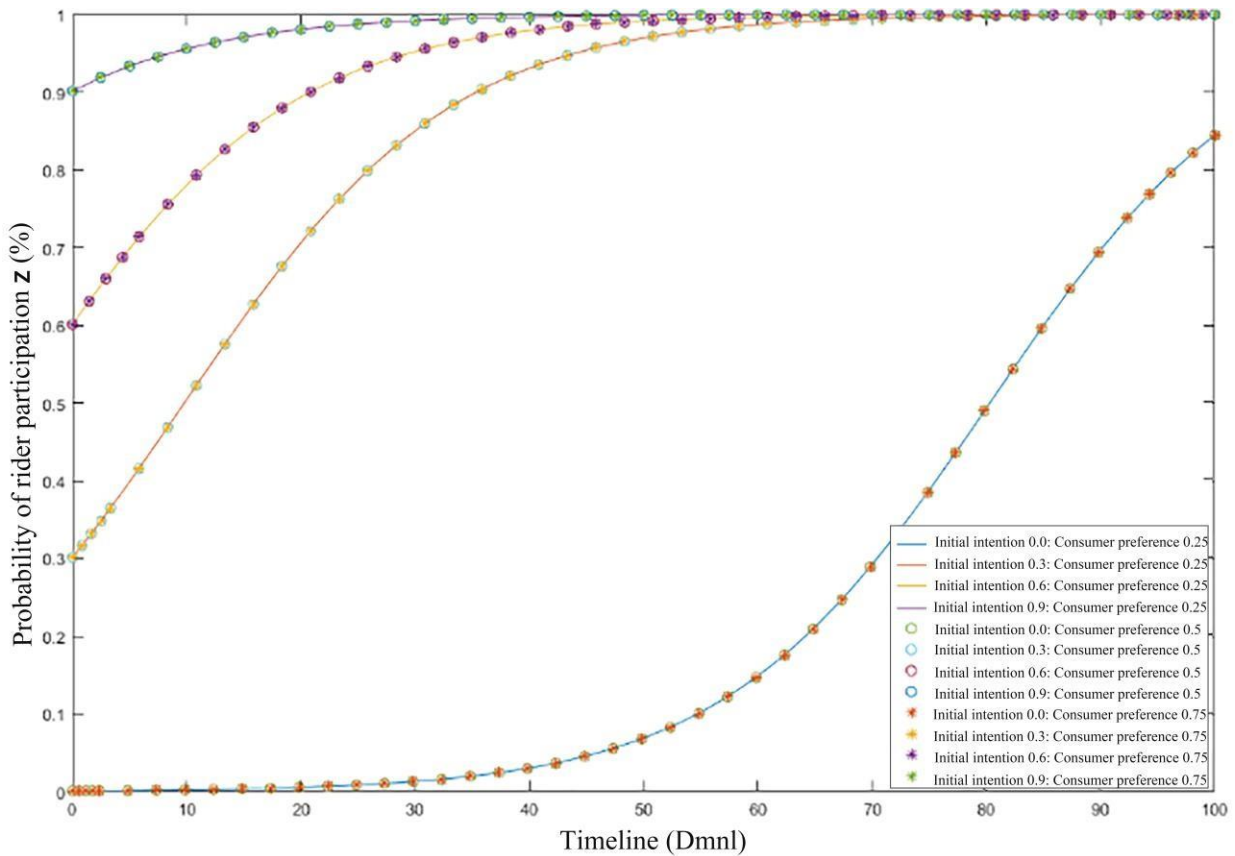


Figure 6. Trends in riders' willingness to participate in stabilization condition (D)

The trend of riders' willingness to participate when D serves as a stabilization point is reflected in Figure 6, which shows that the time required for a rider to evolve to a stable state will be substantially longer when his or her initial willingness to

participate is too low. Since riders' earnings are affected by merchants' and governments' penalties and not by consumers' choices, the trend does not differ across the three notches of consumers' willingness to participate (0.25, 0.50, and 0.75).

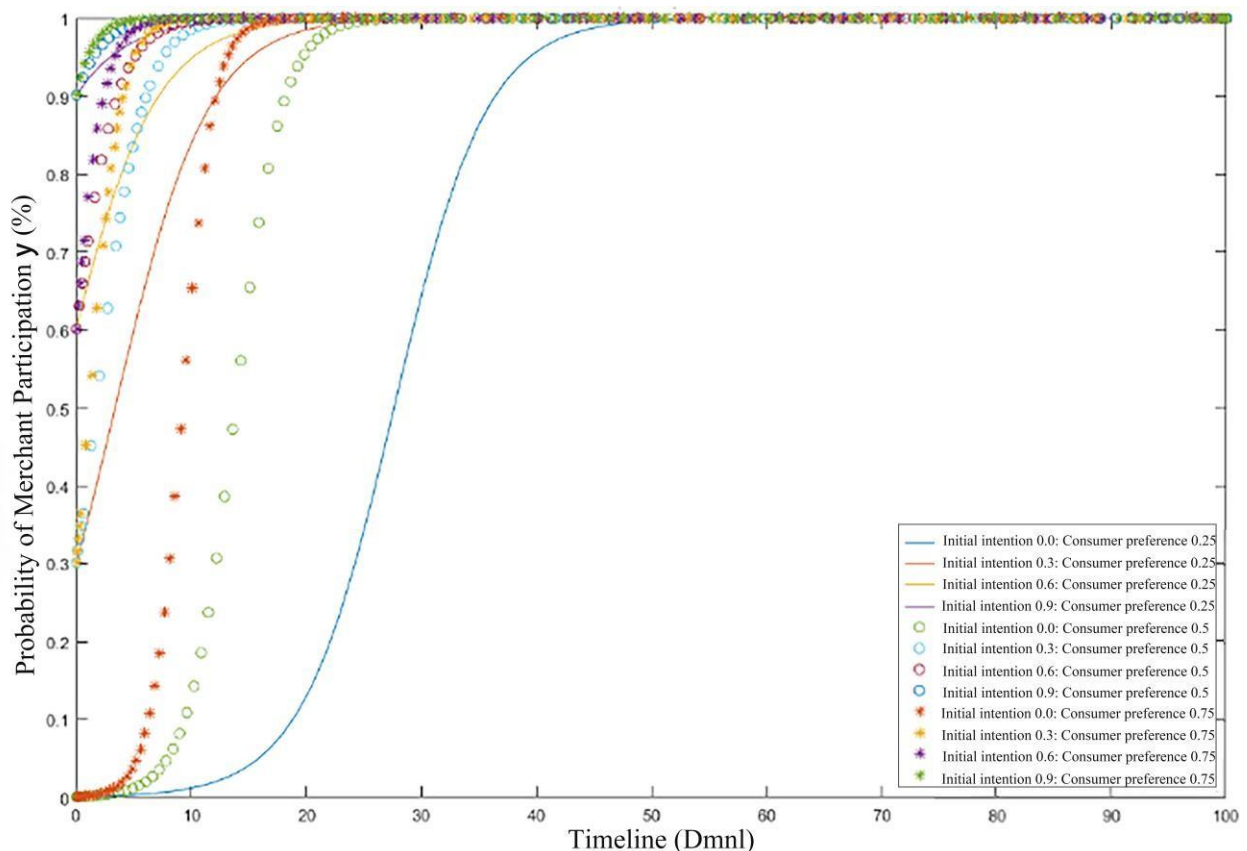


Figure 7. Trends in merchants' willingness to participate under stabilization condition (D)

When D serves as the stabilization point, the trend of merchants' willingness to participate is reflected in Figure 7,

which shows that a merchant's initial willingness to participate does not affect the rate at which it evolves to a stable state. In addition, consumers' willingness to participate in centralized scheduling dramatically influences the change in merchants' participation probability; the more consumers intend to participate, the faster merchants move into the centralized scheduling model.

Conclusion 1: With the goal that the government does not support but merchants and riders are willing to participate in the centralized dispatch model, the government and third-party agencies are required to focus on how to guide the merchants and riders to recognize the advantages of the centralized dispatch model so as to increase their willingness to participate. Then when the order density is large enough, merchants and riders will spontaneously participate in the centralized dispatch mode to maximize their own interests, thus optimizing the distribution system to a certain extent. At the same time, the government should increase the efficiency

and strength of the investigation and punishment of riders, especially when the willingness of riders to participate in the centralized scheduling is low, so as to promote the orderly development of the market.

6.2. If $H(1, 1, 1)$ is a Stable Point

The corresponding evolutionary strategies are (support, on-boarding, and participation). At this point, the performance gains harvested from government intervention are greater than those from financial investment ($C_2 < R_1$); the average cost per order for merchants participating in the centralized dispatch model is reduced under all conditions with policy support ($C_4 - R_3 < C_3$); the expected gains from rider participation in centralized dispatches are satisfied ($R_5 - \beta\alpha p_1 - \gamma p_2 < R_4 + (C_2 / K - R_3)$), indicating a greater gain than when participating in other scheduling modes.

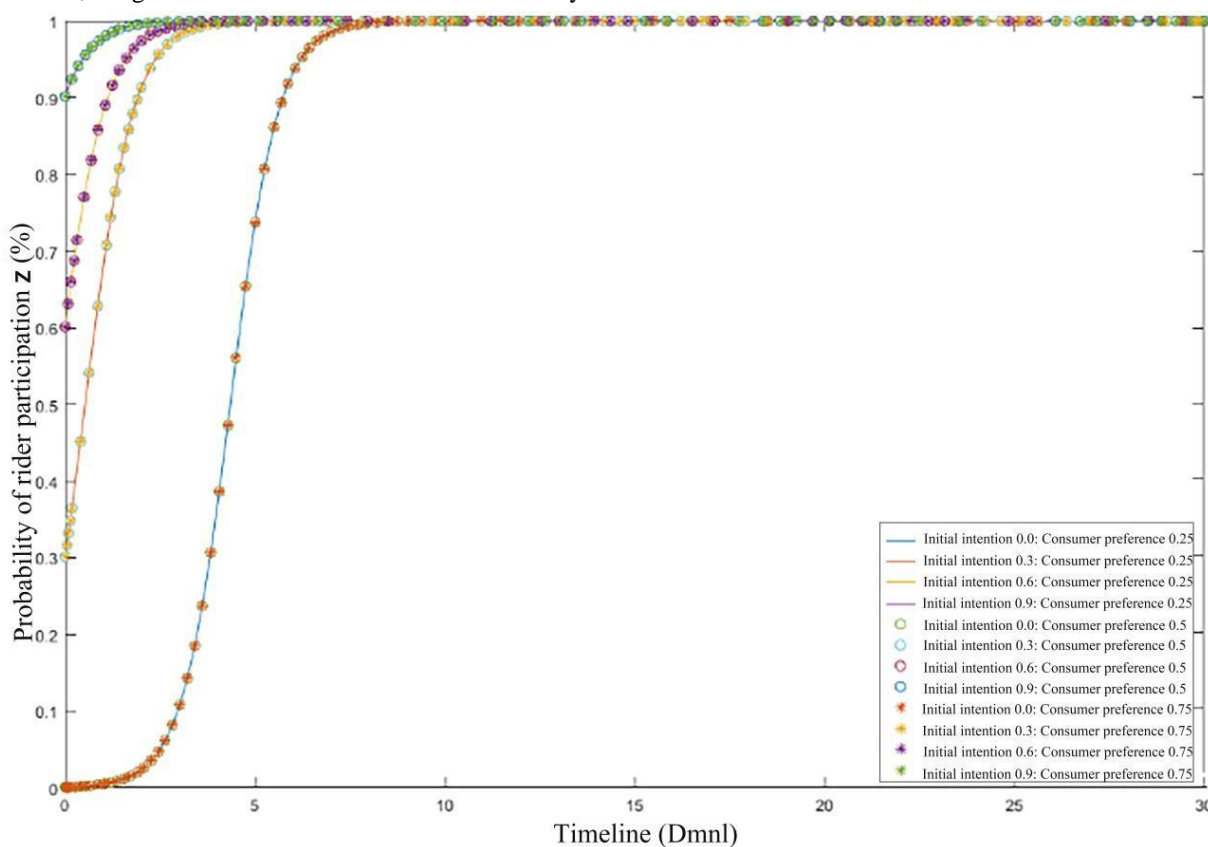


Figure 8. Trends in riders' willingness to participate under stabilization conditions (H)

When H serves as a stabilization point, the trend of riders' willingness to participate in Figure 8 compared to Figure 6 reflects that the willingness of riders to participate in centralized dispatching evolves dramatically when the government adopts financial support, even though the initial

willingness to participate is 0. After receiving financial incentives, the model evolves to a stable state after approximately 8 units of simulation time. Similarly, riders are insensitive to consumer choice.

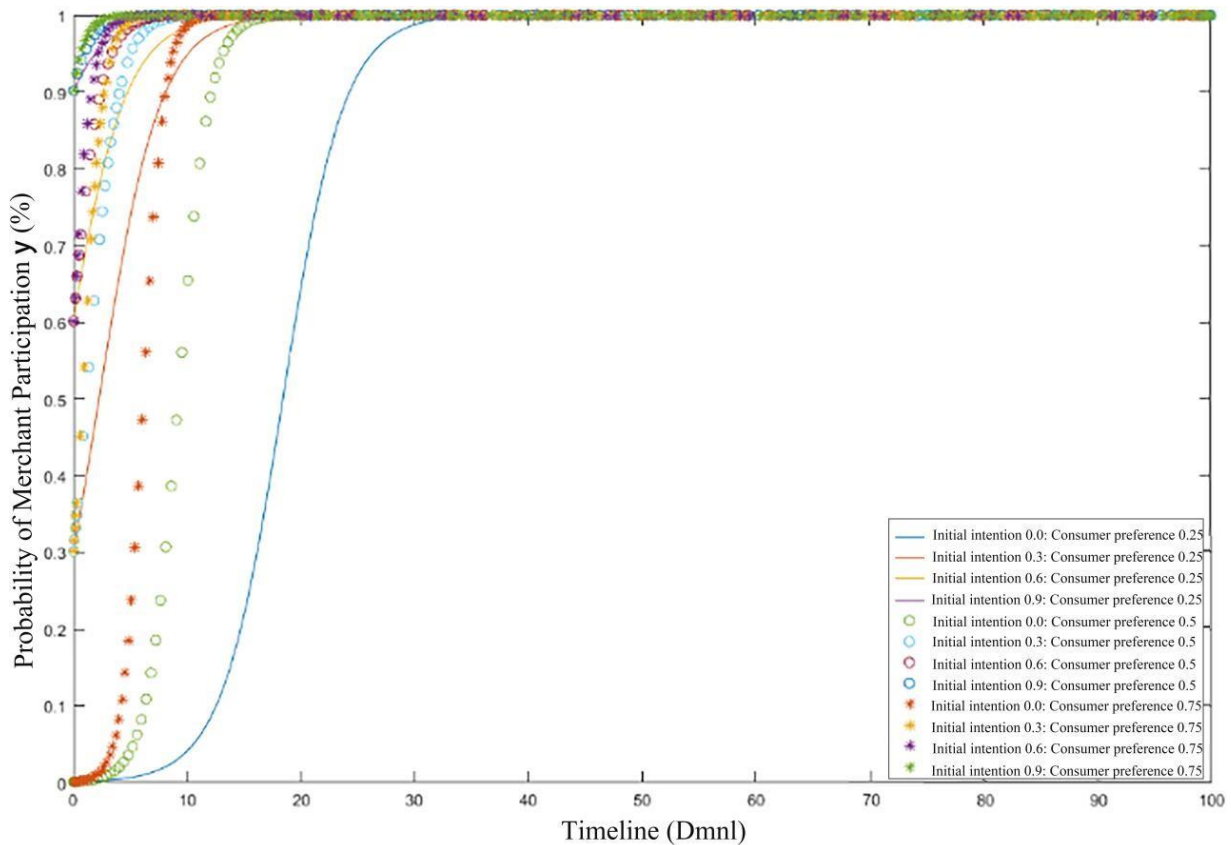


Figure 9. Trends in merchants' willingness to participate under stabilization conditions (H)

As shown in Figure 9, when H serves as a stabilization point, at which point the evolution of merchants' willingness to participate accelerates with the government's financial support, there is a strong positive correlation between consumers' willingness to participate in centralized scheduling and merchants' attitudes toward participation.

Conclusion 2: According to Figures 8 and 9, it is evident that, under government financial support, even when the initial willingness of merchants and riders to participate is zero, they can quickly engage in the centralized dispatching model due to financial subsidies. In other words, in comparison to a centralized dispatching model led by a third-party organization, government financial support plays a positive role in encouraging merchants' and riders' participation in the centralized dispatching model. By comparing Figures 6 and 8, it is observed that if the initial willingness of riders to participate in centralized dispatching is low, maintaining the centralized dispatching model solely relying on the third-party organization becomes challenging. In such cases, the government must take the lead and employ positive intervention means. The primary reason for the difficulty in establishing a unified centralized dispatching model in these regions is the tendency of the market to develop in a disorderly and unstable manner. In practice, decentralized competition among carriers leads to a lack of a dominant carrier with a strong voice, making it challenging to ensure the orderly development of takeaway delivery. However, after the government intervenes positively, the system evolves towards a stable target state at a faster pace. A comprehensive analysis of Figures 6 to 9 reveals that different initial willingness to participate, i.e., the point in time of government intervention, does not affect the final evolution results. Therefore, the government can focus more on regions with a more chaotic market order, adopting a strategy of continuous observation for other regions with more favorable

development.

Conclusion 3: In Table 3 of the revenue matrix, the regional consumer type share τ directly affects the merchants' expected revenues under the condition that the revenues of each model are not equal. In Table 4, for the eigenvalues, except for strategy combinations A, C, E, and G, the stabilization conditions for all strategy combinations are independent of τ . This result is attributed to the fact that merchants can be stationed in multiple modes and that there is no additional cost associated with the stationing process. As long as centralized scheduling has a greater expected return, merchants will choose to be stationed. In this case, regional consumer preference affects the revenue of the centralized dispatch model and does not affect the merchant's decision to join the centralized dispatch model.

7. Conclusion and Future Recommendations

In this article, we first constructed a meal delivery system model incorporating a centralized dispatching mode using system dynamics. The cumulative delivery cost and delivery efficiency were chosen as the main observation variables of the system. Through simulation, we compared the performance of the system under different centralized dispatching ratios, using the population-dense area of Guangzhou University City as a backdrop. The results show that the greater the proportion of centralized scheduling mode used for meal delivery is, the greater the fixed cost of the system, and the advantage of centralized scheduling mode will be revealed only when the total number of orders increases within a certain range. Moreover, a higher proportion of centralized scheduling will enable the meal delivery system to have a higher delivery capacity so that the system will be able to maintain a more stable delivery

efficiency when facing sudden increase in the number of order demands.

Second, to take advantage of centralized dispatching in areas where meal delivery orders are concentrated (e.g., University City), we analyse the willingness of the government, merchants, and riders to participate in the centralized dispatching model by using an evolutionary game, taking into account consumer preferences. The government does not intervene in the market when the meal delivery environment in order-concentrated areas is healthy. Consumer preferences for the centralized dispatch model affect merchants' expected returns, and if the marginal returns of the centralized dispatch model are greater than the returns of other models, merchants' willingness to enter the model is independent of the percentage of consumer types τ . As market competition intensifies and participants pursue cost reduction and efficiency, the market will tend to form a centralized dispatch model. When disordered behaviors such as illegal driving by meal delivery riders and unregulated placement of end meals in areas where orders are gathered are frequent, the local government will be inclined to intervene--increasing the efficiency of supervision and punishment of illegal operations and supporting the centralized dispatch model.

In summary, this study innovatively applies system dynamics to explore the field of meal delivery centralized dispatching mode in densely populated areas. Ultimately, through simulation comparisons, it identifies the advantages of the centralized dispatching mode in areas with concentrated meal orders. Considering consumer preferences as a basis, game theory is utilized to provide theoretical support for decision-making by participants in the meal delivery system, offering a research framework for relevant decision scenarios. In addition to meal delivery scenarios in densely populated areas and manually operated centralized dispatching modes, meal lockers, meal kiosks, and other solutions demonstrate the flexible application of centralized dispatching mode. Further considerations involve exploring the impact of different transfer devices and transfer station setups on the delivery system. Additionally, investigating whether the benefits to all parties involved in the game theory vary dynamically with different order volumes is crucial. Under such dynamic benefits, understanding the system's evolutionary characteristics becomes essential. These questions await further in-depth exploration in future research.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

LM: Conceptualization, Investigation, Validation, Writing - review & editing. WT: Investigation, Validation, Writing - review & editing. CZ: Validation, Writing - review & editing. LS: Conceptualization, Methodology, Model setup and analysis, Writing - Original Draft, Writing - review & editing. ML: Supervision, Validation, Writing - review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

- [1] Zhao X, Zhang WJ, He Wj. Research on the Influence of Logistics Information Technology Adoption on Customer Purchase Intention in the Online Take-out Platform. *Mathematics in Practice and Theory*. (2020) 50:44-55.
- [2] Gong BG, Tang JJ, Cheng JS. Decision-making and Coordination of Dual-channel Supply Chain with Consumers' Preference under Capacity Restraint. *Chinese Journal of Management Science*. (2019) 27:79-90.
- [3] Ni X, Cheng HF, Liu C. Hybrid Sales Channel Decision Model Considering Consumer Preference. *Chinese Journal of Management*. (2020) 17:1544-1553.
- [4] Zhang YK, Huang MF, and Hu XP. Integrated optimization approach to order allocation and delivery problem of online supermarket. *Journal of Systems Engineering*. (2015) 30:251-258.
- [5] Chen P, Li H. Optimization Model and Algorithm based on Time Satisfaction for O2O Food Delivery. *Chinese Journal of Management Science*. (2016) 24:170-176.
- [6] Wang Z, Sheu J B. Vehicle routing problem with drones", *Transportation Research Part B: Methodological*. (2019) 122:350-364. doi: 10.1016/j.trb.2019.03.005
- [7] Wang Z, Li TY, Hou XY. A Real-time Response Method to Instant Delivery Orders Based on a Pool of Various Solutions. *Journal of Management Science*. (2018) 31:2-103.
- [8] Wang XP, Zhang J, Yi CY. Joint scheduling model and algorithm for online food ordering production and delivery. *Journal of Systems and Management*. (2020) 17:159-167.
- [9] Luo J, Tang JF, Yu QY, Wu ZQ. Discovery of O2O takeaway shopping area segmentation and customer demand distribution pattern. *Chinese Journal of Management Science*. (2023) 31:58-68.
- [10] Chen XG, LI XY, CHENG LQ. Research on Optimization strategy of takeaway crowdsourcing considering order preference. *Chinese Journal of Management Science*. (2022) 1-13. doi: 10.16381/j.cnki.issn1003-207x.2021.1262
- [11] Yu HY, TANG WQ, Wu TY. Vehicle Routing Problem with Hard Time Windows for Instant Delivery of O2O Fresh Takeout Orders. *Journal of Systems and Management*. (2021) 30:584-591.
- [12] Wu TY, ZHANG JL, YU HY. Optimization of online pick-up and delivery paths in asymmetric networks. *Chinese Journal of Management Science*. (2023)31:214-221. doi:10.16381/j.cnki.issn1003-207x.2021.0183.
- [13] Tang C, Liu, C, Li C. Research on delivery problem based on two-stage multi-objective optimization for takeout riders. *Journal of Industrial and Management Optimization*. (2023) 19:7881-7919. doi: 10.3934/jimo.2023025

- [14] Teng R, Hong-bo X, Kang-ning J, Tian-yu L, Ling W, Li-ning X. Optimisation of takeaway delivery routes considering the mutual satisfactions of merchants and customers. *Computers & Industrial Engineering*. (2021) 162:107728. doi: 10.1016/j.cie.2021.107728
- [15] Zhang MX, Wu JY, Wu X, Zheng YJ. Hybrid evolutionary optimization for takeaway order selection and delivery path planning utilizing habit data. *Complex & Intelligent Systems*. (2022) 8:4425-4440. doi: 10.1007/s40747-021-00410-0
- [16] Wang Y, Li XH, LUO XG. Three-Party Evolutionary Game Analysis of New Retail Platform, Deliverymen, and Consumer Considering Delivery Traffic Risk. *Journal of Systems and Management*. (2024)33:46-58.
- [17] Fan B, Lv L, Han G. Online platform's corporate social responsibility for mitigating traffic risk: Dynamic games and governmental regulations in O2O food delivery industry. *Computers & Industrial Engineering*. (2022) 169:108188. doi: 10.1016/j.cie.2022.108188
- [18] Qiu Y, Shi X. A System Dynamics Modeling Framework for Urban Logistics Demand System With a View to Society, Economy and Environment. *LISS 2014: Springer, Berlin, Heidelberg*. (2014) 299-303. doi: 10.1007/978-3-662-43871-8_45
- [19] Lai XF, Wang X, Chen CC. System Dynamic-Based Risk Analysis of Transportation Disruption in Transnational Supply Chain in Different Multimodal Transportation Modes: A Case Study of FMCG Food Supply Chain. *Journal of Systems and Management*. (2022) 05:825-839.
- [20] Chen XH, Yu W, Li XH. Research on green technology transformation strategy of inter-regional enterprises under environmental regulation based on evolutionary game theory. *Systems Engineering Theory and Practice*. (2021) 41:1732-1749.
- [21] Li Y, Liang C, Ye F, Zhao X. Designing government subsidy schemes to promote the electric vehicle industry: A system dynamics model perspective. *Transportation Research Part A: Policy and Practice*. (2023) 167:103558. doi:10.1016/j.tra.2022.11.018
- [22] Qi YQ, Li JM, Yao YX. Dynamic simulation of emergency medical material reserve system from the perspective of government enterprise alliance. *Systems Engineering*. (2023) 1-17.
- [23] Quan J, Chu YQ, Wang XJ. Public goods game under voluntary participation mechanism and the evolution of cooperation. *Journal of Systems Engineering*. (2020) 35:188-200.
- [24] Shi WQ, Kong ZJ, Wang MY, He J. System Dynamics Analysis of Emergency Materials Mobilization Chain Resilience under the Coupling of Multiple Disruptions. *Chinese Journal of Management Science*. (2023)1-18.
- [25] Huang W, Lu C, Fang D. City and infrastructure engineering and management. *Frontiers of Engineering Management*. (2021) 8:1-14. doi: 10.1007/s42524-020-0150-0
- [26] Zhang Y, Wang SX, Yao JT, Tong RP. The impact of behavior safety management system on coal mine work safety: A system dynamics model of quadripartite evolutionary game. *Resources Policy*, (2023) 82:103497. doi:10.1016/j.resourpol.2023.103497
- [27] Lu LL, Wang ZF. Co-Evolution Simulation Analysis of Transaction Behavior Supervision for Major Construction Projects under Digital Construction Situation. *Journal of Systems and Management*. (2022) 440-452.
- [28] Wu T, Pei Y, Li D, Su P. Modeling the Formation Mechanism of Food Safety Risk in Catering O2O Distribution Link. *Discrete Dynamics in Nature and Society*. (2021) 1-9. doi:10.1155/2021/2778209
- [29] Li TZ, Li MX, Tang P, Liu JX, Aikebaier S. Analysis and Countermeasures of Safety Influencing Factors of Take-out Catering Based on SD-GA. *Journal of Wuhan University of Technology (Information and Management Engineering)*. (2022) 44:166-172.
- [30] Zhang Y, and Zhu H. Stochastic Evolutionary Game in Food Takeaway Management with Improved Replication Dynamic Equations in Postepidemic Era. *Mathematical Problems in Engineering*. (2022). doi: 10.1155/2022/9058007
- [31] Zhong Q, Qu GQ, Tang JF. Research on the Influence of O2O Take-out Promotion Strategy on Consumers' Purchase Intention. *Chinese Journal of Management Science*. (2024) 32:254-264.
- [32] Cheng C, Jiang HW. Optimization of delivery path of fitness nutrition meal considering food freshness. *Journal of Beijing Information Science and Technology University (Natural Science Edition)*. (2021) 36:68-75.
- [33] Zhang LY, Zhang J, Xiao B. Multi-objective O2O Take-Out Instant Delivery Routing Optimization Considering Customer Priority *Industrial Engineering and Management*. (2021) 26:196-204.
- [34] Yu JJ, Cheng WQ, Wu YZ. Path Planning of Fresh Takeout Considering Customer Satisfaction. (2021) 26:158-167.
- [35] Xing P, He TR. Optimal Quality Effort Strategy in O2O Food Delivery Service Supply Chain Based on Three Operation Models. *Chinese Journal of Management Science*. (2020) 28:115-126.
- [36] Zhang CJ, Yu XL, Tu JW. Evolutionary Game of Technology Innovation Input of Supply Chain Enterprises. *Statistics & Decision*. (2020) 36:163-167.
- [37] Hu H, Guo XJ, Liang YR. Epidemic Based on Prospect Theory Game Analysis of the Three-Way Evolution of Network Rumor Control under the Major. *Information Science*. (2021) 39:45-53.
- [38] Du ZP, Fu SS, Mu D. Multi-party Behavior Game Research of Cross-border E-commerce Logistics Alliance Based on 4PL. *Chinese Journal of Management Science*. (2020) 28:104-113.
- [39] Zhu W. Meal delivery APP spawns university 'house era'. (2015) available at: <https://china.huanqiu.com/article/9CaKrnJpA6.2015>.
- [40] Xu Q. Interpretation of GB 17761-2018 'Safety Technical Code for Electric Bicycles'. *China Quality Supervision*. (2019) 61-63.
- [41] Wang DD. (2016) The analysis of the distribution mode of the chain supermarkets' vegetable of Beijing considering carbon emissions [dissertation/master's thesis]. Beijing: Beijing Jiaotong University.
- [42] Huang T, Guo K. Research on State-owned Zombie Firm's Exit Mechanism Based on Evolutionary Game Theory. *Business and Management Journal*. (2019) 41:5-20.
- [43] Andr e F, Gonz lez P, Porteiro N. Strategic quality competition and the Porter Hypothesis. *Journal of Environmental Economics and Management*. (2009) 57:182-194.
- [44] Hui Y, Yang H, Yang GH. Evolutionary Game Analysis on the Safety of Meal delivery. *Journal of Quantitative Economics*. (2019) 36:41-45.
- [45] Bell DR, Gallino S, Moreno A. Inventory Showrooms and Customer Migration in Omni-Channel Retail: The Effect of Product Information. *SSRN Electronic Journal*. (2013) 2370535: 1-33.

- [46] Zhu LL, Rong JM, Zhang SY. Three-party Evolutionary Game and Simulation Analysis of Drug Quality Supervision under the Government Reward and Punishment Mechanism Chinese Journal of Management Science. (2021) 29:56-57.
- [47] Chen HT, Li TQ, Song SS. Molding and Empirical Study of User's Repeat Purchase Intention of Online Meal delivery Platform. Soft Science. (2015) 29:79-82.
- [48] Huang MM. Evolutionary Game Analysis of Cooperation Mechanism for Collaborative Product Development in Supply Chain. Chinese Journal of Management Science. (2010) 18:155-162.
- [49] Kalman R, Bertram J. Control system analysis and design via the "second method" of Lyapunov: (I) continuous-time systems (II) discrete time systems. I-RE Transactions on Automatic Control. (1959) 4:112.