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Food-delivery behavior under crowd sourcing mobility services

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HIGHLIGHTS

- This review promotes the development of urban traffic safety management.
- The decision-making behaviors of delivery drivers are discussed.
- The stakeholder decision-making behaviors involving traffic safety within the food-delivery industry are concluded.
- Recommendations for future development are provided.

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ABSTRACT

The rapid development of the online food-delivery industry, has led to not only increases in the number of the crowd-sourced shared food-delivery service drivers on our roads, but also growing urban traffic safety management concerns. This study investigates the decision-making behaviors that exist between delivery drivers, their food-delivery platform and their potential impact on traffic safety. Using the evolutionary game theory, stakeholder decision-making behaviors involving traffic safety within the food-delivery industry were analyzed. From our analysis, several behavioral influencers were identified, including penalties for traffic violations, the opportunity cost of delivery drivers complying with traffic rules, the costs associated with risk and strict management approaches, reputation incentives, costs related to the delivery platform being punished, the probability of compliance with traffic rules, and the probability of adopting a strict management approach by the delivery platform. Our study demonstrates that stabilization strategies used by the food service industry differ when the types of government control measures also differ. When the government takes a more aggressive approach to regulation and control, compliance with the traffic rules and the adoption of strict enforcement measures by management are the only evolutionary stability strategies available to food-delivery platforms. As part of a strict management strategy, appropriate compensation or incentive measures should be provided by the distribution platform. Furthermore, the fines given for

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traffic violations should be increased to create a safer road environment that has fewer traffic accidents involving food-delivery drivers.

1. Introduction

As the “internet + services” and “intelligence + logistics” models continue to rapidly develop in responses to today's increasingly fast-paced world, online delivery platforms have emerged as the most popular means of ordering food among China's urban population. By the end of 2019, China's food-delivery platforms were used by some 460 million customers (53.9% of the total urban residents in China), and employed nearly 10 million people across the country (Ii Media Research, 2019). As reported by Meituan Foresight Industry Research Institute, the number of online food orders has increased from 2.74 billion in 2015 to 18.28 billion orders in 2019, with an average annual compound growth rate of 60.71% (MFIRI, 2020). While an increasing number of consumers have sought to place online food-delivery orders, it is crucial that enough drivers are available to carry out the required deliveries (Howe, 2006; Sampaio et al., 2017, 2019). Crowd-sourced delivery, or alternatively crowd-shipping, constitutes a major class of crowd-logistics (Hong et al., 2018; Liu et al., 2020; Rey et al., 2018; Yildiz, 2021). Shared crowd-sourced and mobility services present a potential means of relieving the supply and demand pressures facing the food-delivery marketplace (Paloheimo et al., 2016; Perboli and Rosano, 2019; Reuters, 2016). However, a growing problem has emerged in which the drivers (the term we will use throughout the paper to refer to a crowd-sourced shared food-delivery e-bike rider) of these food-delivery services ignore traffic rules by speeding, running red lights, and retrograding their vehicles in an effort to meet the demands of the industry's “just in time” management process (Wang et al., 2021a; Zhang et al., 2021). As a result, the number of traffic accidents caused by these drivers have also been increasing year on year, greatly impacting the safety of urban public transportation systems. Exacerbating the problem, are requirements by the food-delivery platform in cities like Beijing, that orders made within a 2 km proximity of the restaurant must be delivered in 30 min (CCTV, 2020). For drivers that fail to complete their delivery within this specified time limit are fined and/or see their number of orders reduced. In terms of delivery time limits and large order volumes, Meituan (2018) found that 45% of delivery staff receive more than 20 orders per day, and the concentration of orders around specific times have created a series of traffic safety risks that are difficult to manage. The food-delivery ordering time of consumers is basically coincides with the peak traffic hours on urban roads. According to news investigations that have been conducted, a driver was found to have violated 6 different traffic regulations across a 50-minute period in Beijing (CCTV, 2020). Clearly, these growing trends of illegal driving behavior can have a negative impact on traffic flows and road safety, which can in turn, endanger the lives of other motorists and nearby pedestrians. In order to reduce the likelihood of illegal driving behavior, several policies have been implemented by various local government transportation administration departments (TADs). However, the effect of these policies has been limited, as they are not able to completely manage the safety risks associated with a driver's traffic violations. Therefore, it is of great practical significance to clarify the internal mechanisms associated with these increasingly frequent traffic violations and to explore the traffic safety control measures that have been implemented to address the driving behaviors of drivers.

In order to manage the traffic safety risks of food-delivery, it is imperative that the key stakeholders (drivers, delivery platforms, and TADs) within the food-delivery market work together to address all key concerns. However, differences in opinion on how policy should be developed and implemented exist across each of the stakeholders (Kafle et al., 2017; Kurisu and Bortoleto, 2011; Yau, 2010). The main concern of TADs are the social benefits enjoyed by the local communities they serve, such as a safe road environment. Food-delivery platforms tend to be more interested in developing a strong brand reputation and an economically viable and profitable business model. While achieving a good reliable income is at the center of the drivers concerns. Based on how the Chinese Government's overall policy environment has developed, the strategies of the food-delivery platform and the drivers directly influence each other. In particular, the food-delivery platform considers the behavioral influences of the drivers when making operational decisions that seek to maximize profits, while ensuring relevant service quality targets are met. While on the other hand, the drivers seek to implement their own strategic plans according to the policies implemented by the delivery platform. One key characteristic of the crowd-sourced food-delivery environment is the self-scheduling delivery capacity (Rai et al., 2017; Wang et al., 2020b; Yildiz and Savelsbergh, 2019), i.e., drivers independently adjusting the order and route of delivery according to the actual situations they face. Therefore, the decision-making processes are highly dynamic and can greatly influence the road safety environment of the food-delivery industry.

Evolutionary game theory is a common tool for modeling decision-making research (Cardell et al., 1997; Wang et al., 2020a). In addition, when compared with traditional classic game theory, evolutionary game theory considers the bounded rationality of decision makers, making the results of this contemporary game more realistic (Leyton-Brown and Shoham, 2008). Meanwhile, evolutionary game theory pays attention to the dynamics of strategy changes (Smith and Price, 1973), which helps to analyze decision-making behavior in multiplayer situations. From a transport management perspective, such an approach can provide important mathematical solutions to areas of both conflict and potential cooperation in the food-delivery industry. Therefore, evolutionary game theory can be used to explain the decision-making behavior of stakeholders involved in the development and implementation of traffic safety risk management strategies in the food-delivery industry. Game theory is applied to explore how each player selects the most reasonable strategy in an intricate and interactive situation, thereby studying the interactions of both players from the perspective of strategy selection (Ji and Levinson, 2020; Shao et al., 2018). In evolutionary game theory, player populations with bounded rationality are taken as study objects, and various factors affecting the behavior of the players are incorporated into the model, with the strategy selection process of each player being analyzed (Leyton-Brown and Shoham, 2008). Evolutionary game theory is an effective method for studying long-term dynamic games. It overcomes the shortcomings of traditional game theory by analyzing bounded rational players and the dynamic process of games (Liu et al., 2015). Moreover, evolutionary game theory is suitable for studying the evolutionary process of the two parties' strategic choices. In fact, the TADs of food-delivery represent an asymmetric game with two bounded rational populations. In this instance, both parties of the game constantly change their strategies by observing and comparing their respective returns. This is a typical long-term dynamic game.

The remainder of the study is as follows. In Section 2, the relevant literature is reviewed. In Section 3, the research model is constructed, with the equilibrium point and stability of evolutionary games analyzed. In Section 4, we substitute specific numerical values and provide relevant analysis and discussion. Finally, in Section 5 the key results are documented, with a range a of important risk management initiatives also proposed, which seek to enhance the level of road safety across the food-delivery industry.

2. Literature review

In China, food-delivery is mainly realized through non-motorized vehicles (e-bikes or motorcycles). In recent times, researchers have increasingly sought to address road safety concerns for bicycles and e-bikes involved in the food-delivery industry (Lu et al., 2015; Kocatepe et al., 2019; Waard et al., 2011; Zhang et al., 2018). Eboli et al. (2017) divided the risk of traffic accidents into three grades (low, medium and high risk), and identified the accident risk level of drivers by combining subjective and objective parameters. Yu et al. (2019) used association rules to identify the factors affecting road collision patterns and found that fatal road traffic accidents can be effectively reduced by regulating risky driving behaviors. In an examination of non-motorized road users (i.e., e-bike riders), Yao and Wu (2012) showed that risk perception, and attitudes towards safety and responsibility are associated with risky riding behavior. Stelling-Konczak et al. (2015) proposed that the characteristics of cyclists and the traffic environment in general are also important aspects of bicycle safety. The lower the risk perception, the more likely a traffic accident will be caused (Li et al., 2020). While listening to music and talking on the phone was found to impair cyclists' perceptions of relevant traffic sounds, such as the sound of a bicycle bell (Waard et al., 2011). Utilizing the theory of planned behavior (TPB), Satiennam et al. (2018) found that rider attitudes influence their intention to obey traffic signals, particularly when they feel that they have a lack of control over work performance. Research into driving behavior, by Wu et al. (2012), examined three signalized intersections in Beijing by analyzing the red-light behaviors of cyclists using real-time video. Their study showed that 56% of non-motorized vehicles violate traffic rules, with the most common traffic violation being people driving through red lights at intersections. Yang et al. (2016) showed that drivers riding electric bicycles violated red light traffic laws far more frequently than conventional cyclists. Electric bikes were also more likely to be involved in risk-taking behaviors, such as riding into vehicle lanes, violating traffic laws, and running red-lights at intersections (Du et al., 2013; Shao et al., 2018). Other studies used both a control and an experimental group to study the behavior and traffic accidents of Chinese e-bike riders (Qian et al., 2020). Moreover, Zhang et al. (2019) sought to predict cyclist behavior of Chinese employees by integrating the perceived physical environment and social cognitive factors. While Sheu (2013) developed onlooker traffic models that examine the key causes of traffic accidents. A severe lack of safety knowledge is strongly related to dangerous driving behaviors and a failure of Chinese e-bike riders to adhere to traffic rule (Wang et al., 2018). Moreover, the incidence of running a red light was more prevalent when the waiting time was longer (Wu et al., 2012). In addition, a courier driver's income is paid by the platform itself. There are two aspects to a delivery driver's salary structure that need to be considered. The first is the income obtained from completing the order on time (+), the other is the penalty/fine received for failing to complete the delivery on time (−), which includes the cost of traffic violations. In order to complete their deliveries in a timely manner, the personnel involved in the food-delivery service industry are more likely going to commit driving offences than the usual everyday e-bike rider. Moreover, driving a bike while on the phone, speeding, and needing to cross the road, all impact one's ability to deliver these food orders safely.

In summary, the food-delivery service has a significant impact on urban road traffic safety management. Although a large number of studies have examined traffic safety, most of them have analyzed the factors that influence traffic accidents. The ordering platform and delivery personnel are all key stakeholders of the online ordering market, and only a few of them are integrated into the model (Mourad et al., 2019; Yu et al., 2022). Although using compensation to manipulate capacity has been investigated in the expanding on-demand service platforms literature (Bimpikis et al., 2016; Cachon et al., 2017; Taylor, 2018), we are, to the best of our knowledge, the first to investigate the traffic safety risk management initiatives involving the crowd-sourced food-delivery service industry. Furthermore, even less is known about the evolutionary game behavior of the key players within the food-delivery market. For drivers, delivery efficiency and traffic safety are very important. In-depth research on how to clarify the relationship and promote the "perceived balance" between these two factors requires further examination. Therefore, this study will investigate the decision-making behaviors that exist between the delivery drivers, their food-delivery platform and their potential impact on traffic safety. Based on the evolutionary game theory, stakeholder decision-making behaviors involving traffic safety within the food-delivery industry were analyzed to provider greater insight into the governance of urban road traffic safety.

Since the evolutionary game was first introduced to the fields of management and social economics, it has been a popular tool for assessing a wide range of practical problems (Leyton-Brown and Shoham, 2008; Ozkan-Canbolat et al., 2016). However, from a TAD's perspective, it is important that whatever electric bicycle travel control measures are implemented, it is imperative that the issues of delivery efficiency and traffic safety are at the heart of the decision-making process. In particular, the issues regarding the kind of game that will occur between the food-delivery platform and their drivers and the factors that affect the stability of the equilibrium result need to be addressed. In order to assess these issues, our study utilizes the evolutionary game theory to examine the takeout distribution market. In doing so, we analyze the evolutionary relationship between food-delivery platforms and drivers, under the assumption that the government places strict traffic controls on how e-bikes can be used and driven. Our study provides an important empirical reference for governmental transportation institutions that are seeking to formulate safer and more effective food-delivery mechanisms.

The potential academic contributions of this paper are as follows. (1) This research focuses on the traffic safety risk management issues that impact the crowd-sourced shared food-delivery mobility service industry using an "internet +" new business model which differs from the traditional traffic safety issues. (2) Our study explores the potential differences that exist in decision-making behaviors between the drivers and their food-delivery platform, from a crowd-sourced food-delivery perspective. As these two groups represent the main actors involved in the assessment of road safety issues within the food-delivery industry, our evolutionary game approach forms a new methodological approach and research perspective. (3) This study analyzes the impact that scientific and technological progress has on the differences in psychological perception and road user behavior. Such a focus, provides a basis for discussing the relationship between emerging technologies and traffic safety.

3. Research model

Evolutionary game theory is a complex dynamic game process, in which a certain number of game groups continuously adjust their behavioral strategies according to the information that they acquire and their own experiences, under bounded rational conditions. The core connotation of this theory is evolutionary stability strategy and replication dynamics (Leyton-Brown and Shoham, 2008). Given these principles of evolutionary game theory, the modelling process is provided as follows.

3.1. *Establishment of game relationship*

Through the implementation of stricter e-bike travel rules by the relevant governmental traffic management departments, the food-delivery platform and food-delivery drivers have proposed the following requirements. On the one hand, the food-delivery platform is required to strictly manage drivers in accordance with the relevant governmental and organizational regulations, which can increase the operational costs of the platform. On the other hand, for food-delivery drivers, platform management's introduction of strict new rules that seek to improve the delivery process and in doing so help to reduce the frequency of traffic violations, has increased the time cost of their delivery.

In this research, the main players within the evolutionary game, are the food-delivery platform and the drivers. Given such a context, we assume that the food-delivery platform has two strategies to choose from, namely a strict or passive management strategy. A strict management strategy is one in which the food-delivery platform seeks to ensure that their drivers strictly comply with all the pertinent traffic regulations created by the central and local government transportation bodies. Under such a regime, drivers that fail to adhere to these regulations and have repeated traffic violations will have their employment contracts terminated. A passive management strategy is one in which the food-delivery platform does not review the driving history of its food-delivery drivers. A failure to do so, means that the platform is unable to assess whether their drivers are operating in accordance with the TAD regulations, which means staff that frequently violate traffic laws can continue working for the platform. Alternatively, food-delivery drivers also have two strategies available to them, in which they can choose to comply or not comply with the traffic laws. A compliance strategy is one in which the food-delivery drivers follow the new e-bike traffic laws and regulations. A non-compliance strategy refers to the food-delivery drivers who do not follow the relevant road rules. In specific terms, the pure strategic options available to the delivery platform are either strict or passive management approaches, while the strategies of the delivery drivers is one of either compliance or non-compliance with the relevant traffic laws.

3.2. *Model assumptions*

In order to meet the basic conditions of evolutionary games and facilitate quantitative research, the modelling process is given as follows.

Assumption 1. The fundamental premise of evolutionary game theory, is a dynamic and repetitive game in which each party operates under conditions of limited rationality. Therefore, in a traffic safety context, it is assumed that two players representing both the food-delivery platform and the drivers are bounded rational economic men with learning abilities. As such, and in an effort to maximize profits, both players will constantly adjust their decision-making behaviors through imitation and by learning the best strategic choice to make.

Assumption 2. It is assumed that the probability of the drivers to choose the strategy of "compliance with traffic rules" and "non-compliance with traffic rules" is x ($0 \le x \le 1$) and $1-x$ respectively, $x = 1$ means that the drivers have chosen to adopt a strategy of "compliance with traffic rules", while $x = 0$ means that the food-delivery staff have chosen to adopt a strategy of "non-compliance with traffic rules". Furthermore, the probability of the delivery platform to choose the strategy of "strict management" or "passive management" is y ($0 \le y \le 1$) and $1-y$ respectively, $y = 1$ means that the food-delivery platform has chosen to adopt a "strict management" strategy, while $y = 0$ means the food-delivery platform has chosen to adopt a "passive management" strategy.

Assumption 3. Here the costs and benefits of food-delivery drivers are examined. In this instance, when the drivers choose to adopt a strategy of "non-compliance with traffic rules", they incur a penalty cost of $C_{11} > 0$. For example, the TADs impose penalties, fines and etc. Alternatively, when the drivers choose the "compliance with traffic rules" strategy, the cost paid is $C_{12} > 0$ (to comply with the traffic rules, the cost of waiting for the red-light, the time cost associated with taking longer to deliver their order etc.). Since the TADs have implemented stricter regulatory requirements for e-bike driving, it is assumed that the cost of a food-delivery driver to comply with the traffic rules must be less than the cost of punishment for non-compliance with the traffic rules, that is $C_{12} < C_{11}$. Otherwise, the delivery staff have no incentive to choose the "compliance with traffic rules" strategy. In addition, it is assumed that the tangible income obtained by the drivers under the two strategic choices is equal, shown here as R_{11}, and $R_{11} > 0$.

Assumption 4. Here the costs and benefits of the delivery platform are examined. In this case, when the food-delivery platform chooses to embrace a "strict management" strategy, the time and material cost spent in its management process is $C_{21} > 0$. While at the same time, due to a strict management approach, the number of drivers is reduced, resulting in risks to the platform; here cost is $C_{22} > 0$. In a situation whereby management strictly follows the regulations implemented by the governmental traffic agency, the platform adopts strict management measures to give the platform a reputation incentive of $R_{21} > 0$. When the food-delivery platform adopts a passive management strategy, the punishment cost of the TADs is $C_{23} > 0$. For example, the government traffic division stops access to the food-delivery service because it has not been operating in a manner that adheres to their traffic regulations.

Assumption 5. When the delivery staff follow the traffic rules, they can actually help to reduce the frequency of consumers dining out, which in turn reduces the problem of urban traffic congestion, improves economic efficiencies, and then finally increases the welfare utility enjoyed by society as a whole. Assuming that the economic gains obtained by the delivery platform are $R_{22} > 0$, when the delivery person fails to drive in a manner which adheres to the traffic rules, their behavior can negatively impact traffic flow, which may even cause hidden dangers to the urban residents, resulting in a decline in the level of social welfare. The loss to the food-delivery platform due to the management of the drivers is $C_{24} > 0$.

Based on the above assumptions, the various parameters of traffic safety from a food-delivery perspective, are summarized in Table 1.

Table 1 – Parameters and meaning.

Parameter	Description
C_{11}	Infringement costs for traffic violations by drivers
C_{12}	Opportunity cost of delivery staff complying with traffic rules
R_{11}	Tangible income obtained by the delivery staff under the two strategic choices
C_{21}	Cost to food-delivery platforms using a strictly supervisory approach
C_{22}	Cost of strict management by food-delivery platforms that leads to reductions in driver numbers
R_{21}	Reputation incentives for food-delivery platforms that are strictly regulated
C_{23}	Penalty costs of negative management decisions by food-delivery platforms
R_{22}	Governance benefits of the platform, when the food-delivery market is operating normally
C_{24}	Control losses by the platform, when the food-delivery market is not operating normally

Table 2 – Payment matrix of the game between takeout delivery platform and drivers under strict management.

Food-delivery driver		Food-delivery platform	
		Strict management	Passive management
		y	$1-y$
Compliance with traffic rules	x	$R_{11}-C_{12}$; $R_{21}-C_{21}+R_{22}$	$R_{11}-C_{12}$; $R_{22}-C_{23}$
Non-compliance with traffic rules	$1-x$	$R_{11}-C_{11}$; $R_{21}-C_{21}-C_{22}-C_{24}$	R_{11}; $-C_{24}-C_{23}$

3.3. *Perceived benefits for each game player*

Based on the above assumptions, the payment matrix of the game between the food-delivery platform and the drivers can be constructed using the corresponding strategic combination. The results are shown in Table 2.

(1) For the delivery drivers, the respective perceived benefits of drivers "compliance with traffic rules" and "non-compliance with traffic rules" strategies and the average perceived benefit to the drivers are shown in Eqs. (1)–(3).

$$E_1 = y(R_{11} - C_{12}) + (1 - y)(R_{11} - C_{12}) = R_{11} - C_{12} \tag{1}$$

$$E_2 = y(R_{11} - C_{11}) + (1 - y)R_{11} = R_{11} - yC_{11} \tag{2}$$

$$E_{average1} = xE_1 + (1 - x)E_2 = R_{11} - xC_{12} - yC_{11} + xyC_{11} \tag{3}$$

where E_1 is the respective perceived benefit of drivers complying with traffic rules, E_2 represents the respective perceived benefit of drivers violating traffic rules, $E_{average1}$ indicates the average perceived benefit to the drivers, x represents the probability of the drivers to choose the strategy of "compliance with traffic rules", y represents the probability of the delivery platform to choose the strategy of "strict management".

(2) For the delivery platform, the respective perceived benefits of the delivery platform's "strict management" and "passive management" strategies and the average perceived benefit to the delivery platform are shown in Eqs. (4)–(6).

$$\begin{aligned} E_3 &= x(R_{21} - C_{21} + R_{22}) + (1 - x)(R_{21} - C_{21} - C_{22} - C_{24}) \\ &= xR_{22} + R_{21} - C_{21} - (1 - x)C_{22} - (1 - x)C_{24} \end{aligned} \tag{4}$$

$$E_4 = x(R_{22} - C_{23}) + (1 - x)(-C_{24} - C_{23}) = xR_{22} - (1 - x)C_{24} - C_{23} \tag{5}$$

$$\begin{aligned} E_{average2} = yE_3 + (1 - y)E_4 = &-y(1 - x)C_{22} - yC_{21} + yR_{21} \\ &- (1 - x)C_{24} + xR_{22} - (1 - y)C_{23} \end{aligned} \tag{6}$$

where E_3 is the respective perceived benefits of the delivery platform choosing the strategy of "strict management", E_4 is the respective perceived benefits of the delivery platform choosing the strategy of "passive management", and $E_{average2}$ is the average perceived benefit to the delivery platform.

In addition, according to the payment matrix, (observing traffic rules, strict management) is our ideal strategy combination. As documented above, the probability of delivery personnel choosing the strategy of "obeying traffic rules" is X ($0 \le x \le 1$), and the probability of a delivery platform choosing the strategy of "strict management" is Y ($0 \le y \le 1$). We set the probability that delivery personnel obey traffic rules and the delivery platform strictly manage as Z ($0 \le z \le 1$), $Z = XY$, and Z is the function equation of the ideal equilibrium strategy. The three-dimensional function curve of Z about X and Y is established, as shown in Fig. 1. Obviously, the maximum value

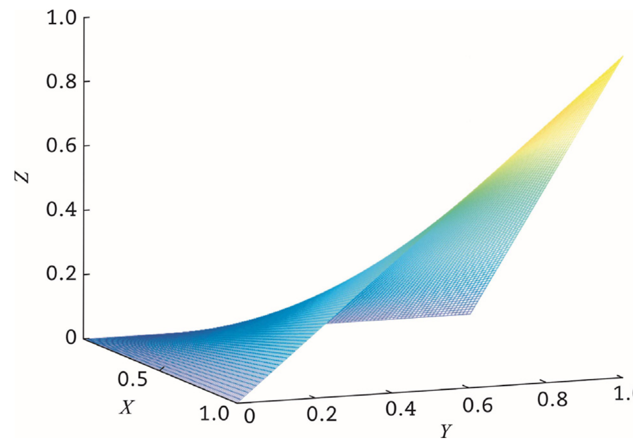

Fig. 1 – Probability of the ideal equilibrium strategy.

of z is 1, and the corresponding value of (x, y) is (1, 1). In this case, the delivery personnel will abide by the traffic rules, with the delivery platform adopting a strict management approach. In order to further analyze the strategy selection of each decision-making body (Fig. 1), the numerical values shown in Table 3 are used. From this anlysis we can deduce that when the values of x and y are large, the value of z will be large. Corresponding measures can be taken to adjust the probability of x and y to achieve the ideal equilibrium strategy.

3.4. *Replication dynamic equations of each game player*

According to the above perceived benefits for each game player, the replication dynamic equations of the drivers and food-delivery platform are provided, respectively.

(1) For the food-delivery drivers, the replication dynamics formula is as Eq. (7).

$$F(x) = \frac{dx}{dt} = x(E_1 - E_{average1}) = x(1 - x)(yC_{11} - C_{12}) \tag{7}$$

The second derivative of formula is as Eq. (8).

$$F'(x) = (1 - 2x)(yC_{11} - C_{12}) \tag{8}$$

For the food-delivery platform, the replication dynamics formula is as Eq. (9).

$$F(y) = \frac{dy}{dt} = y(E_3 - E_{average2}) = y(1 - y)[R_{21} - C_{21} - (1 - x)C_{22} + C_{23}] \tag{9}$$

The second derivative of formula is as Eq. (10).

Table 3 – Numerical values of the strategy combination.

Strategy combination	Corresponding data
(Violation of traffic rules, strict management)	(0, 1)
(Obey traffic rules, passive management)	(1, 0)
(Obey traffic rules, strict management)	(1, 1)
(Violation of traffic rules, passive management)	(0, 0)

$$F'(y) = (1-2y)[R_{21} - C_{21} - (1-x)C_{22} + C_{23}] \tag{10}$$

3.5. *Stability analysis of game strategy*

From a traffic safety perspective, an analysis of the player decision-making behaviors for food-delivery drivers centers around the choice of equilibrium strategies by the delivery staff and the delivery platform. According to the stability theorem and the dynamic game theory of replication, "k" is evolutionary stable strategy (ESS) point when the conditions of $F(k^*) = 0$ and $F'(k^*) < 0$ are satisfied. Based on the above assumption, the cost of "compliance with traffic rules" for delivery staff must be less than the cost of "non-compliance with traffic rules", so the stable state of the game can only be judged according to the relationship between the net income of "the positive management strategy" and "the negative management strategy" when the delivery platform implements different strategies. The different decision-making behaviors are discussed in detail below.

(1) Stability analysis of the game strategy when the net income of a "positive management" approach in the food-delivery platform is greater than the net income of "negative management" approach.

When the net income of an "active management" approach on the food-delivery platform is greater than a "negative management" approach (case 1), that is $R_{21} - C_{21} - C_{22} > -C_{23}$, $R_{21} - C_{21} - C_{22} + C_{23} > 0$. According to the replication dynamic equation of the delivery platform, $F(y) > 0$ is always established, so all the equilibrium points are located on the boundary, and as such there is no internal equilibrium point.

Combining the replication dynamic equation of the drivers and the food-delivery platform, that is, when $F(x) = F(y) = 0$, the equilibrium solution of the game can be obtained as: $A(0, 0)$, $B(0, 1)$, $C(1, 0)$, $D(1, 1)$. The Jacobian matrix formed by $F(x)$ and $F(y)$ is shown as Eq. (11).

$$J = \begin{bmatrix} (1-2x)(yC_{11} - C_{12}) & x(1-x)C_{11} \\ y(1-y)C_{22} & (1-2y)[R_{21} - C_{21} - (1-x)C_{22} + C_{23}] \end{bmatrix} \tag{11}$$

By calculating the determinant symbol and eigenvalue of the Jacobian matrix, the stability of the four equilibrium points is analyzed. The results are shown in Table 3. Among the four equilibrium points, only point $D(1, 1)$ has local stability, point $C(1, 0)$ is an unstable equilibrium point, and points $A(0, 0)$ and $B(0, 1)$ are saddle points. According to Table 4, the dynamic phase diagram of replication for the evolutionary game between the drivers and the food-delivery platform in this case is shown in Fig. 2.

Fig. 2 shows that when the net income of using a strict management approach on the food-delivery platform is greater than the net income of a passive management approach, the probability of the food-delivery platform using a strict management strategy gradually increases. However, the type of strategic choice used by food-delivery drivers will also change as this probability increases. When y is less than $\frac{C_{12}}{C_{11}}$, the probability of a strict management strategy being used by the food-delivery platform is small, while the probability of the drivers choosing a strategy of non-compliance with traffic rules increases; when y is greater than $\frac{C_{12}}{C_{11}}$, the probability of a strict management approach being used by the food-delivery platform is greater. In this instance, the strategy of the drivers gradually changes from one of non-compliance to compliance with traffic rules, with the probability of choosing compliance gradually increasing.

(2) Stability analysis of the game strategy when the net income of the "strictly managed" delivery platform is

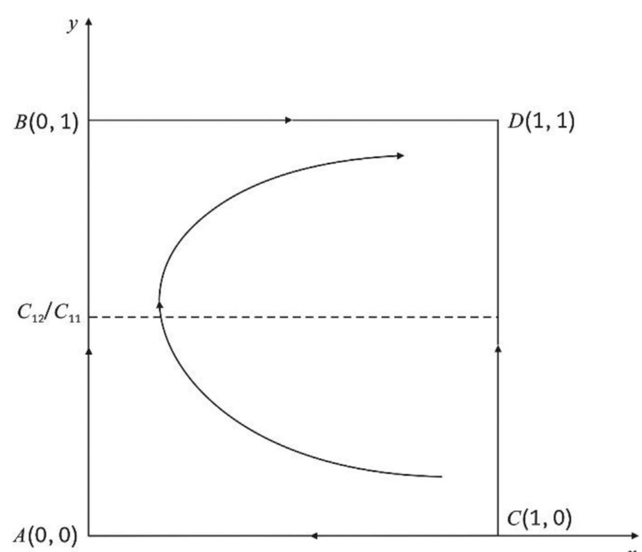

Fig. 2 – Copying dynamic phase diagram of evolutionary game between food-delivery platform and drivers (case 1).

Table 4 – Stability analysis of evolutionary game between food-delivery platform and drivers (case 1).

Equilibrium point	Determinant symbol	Eigenvalue	Eigenvalue symbol	Stability
A(0, 0)	−	$\lambda_1 = -C_{12}$ $\lambda_2 = R_{21} - C_{21} - C_{22} + C_{23}$	$\lambda_1 < 0$ $\lambda_2 > 0$	Saddle point
B(0, 1)	−	$\lambda_1 = C_{11} - C_{12}$ $\lambda_2 = C_{21} + C_{22} - C_{23} - R_{21}$	$\lambda_1 > 0$ $\lambda_2 < 0$	Saddle point
C(1, 0)	+	$\lambda_1 = C_{12}$ $\lambda_2 = R_{21} - C_{21} + C_{23}$	$\lambda_1 > 0$ $\lambda_2 > 0$	Unstable
D(1, 1)	+	$\lambda_1 = C_{12} - C_{11}$ $\lambda_2 = C_{21} - C_{23} - R_{21}$	$\lambda_1 < 0$ $\lambda_2 < 0$	Stable

less than the net income of a "negative management" approach.

When the net income of an "active management" approach by the food-delivery platform is less than a "negative management" approach, that is, $R_{21} - C_{21} - C_{22} < -C_{23}$, and $C_{21} - C_{23} - R_{21} > -C_{22}$ can be obtained.

1) When $C_{21} - C_{23} - R_{21} > 0$ (case 2), $F(y) < 0$ is always established, therefore all equilibrium points are located on the boundary, and there is no internal equilibrium point. Combining the replication dynamic equation of the food-delivery platform and drivers, that is, when $F(x) = F(y) = 0$, the equilibrium solution of the game can be obtained as: $A(0,\ 0)$, $B(0,\ 1)$, $C(1,\ 0)$, $D(1,\ 1)$.

By calculating the determinant symbol and eigenvalue of the Jacobian matrix, the stability of the four equilibrium points is analyzed. The results are shown in Table 4. From this, we are able to see that among the four equilibrium points, only point $A(0,\ 0)$ has local stability, point $B(0,\ 1)$ is an unstable equilibrium point, while points $C(1,\ 0)$ and $D(1,\ 1)$ are located at the saddle point. According to the analysis illustrated in Table 5, the dynamic phase diagram of replication of the evolutionary game between the drivers and the food-delivery platform is shown in Fig. 3.

As Fig. 3 shows, when the net income of the strictly managed food-delivery platform is greater than the passively managed net income, and $C_{21} - C_{23} - R_{21} > 0$ is satisfied, the cost of using an active management approach by the food-delivery platform is greater than the sum of the penalty cost inflicted on reputation value. Therefore, the food-delivery platform will choose a passive management strategy, that is, its probability of choosing passive management $1 - y$ gradually increases. Similarly, during the process of increasing the probability of negative management practices being used within the food-delivery platform, the strategy used by food-delivery drivers changed from one of obeying the traffic rules to one of non-compliance with the regulations. When y is greater than $\frac{C_{12}}{C_{11}}$, the probability of applying strict management processes within the food-delivery platform is greater. The probability that the drivers choose to comply with the with traffic rules gradually increases; when y is less than $\frac{C_{12}}{C_{11}}$, the probability of adopting a strict management approach within the delivery platform is low, and as such a more negative management strategy is used. At the same time, the probability of the drivers choosing to adopt a strategy of non-compliance with the traffic rules increases. In the end, the evolutionary game stabilization equilibrium strategy under this situation (non-compliance with traffic rules, passive management) is realized, which is the result that the TADs least want to see.

2) When $C_{12} - C_{23} - R_{21} < 0$ (case 3), and $\frac{R_{21} - C_{21} + C_{23}}{C_{22}} < 1$, combining the replication dynamic equation of the food-delivery platform and drivers, that is, when $F(x) = F(y) = 0$, the equilibrium solution of the game can be obtained as: $A(0,\ 0)$, $B(0,\ 1)$, $C(1,\ 0)$, $D(1,\ 1)$, $E\left(1 - \frac{R_{21} - C_{21} + C_{23}}{C_{22}},\ \frac{C_{12}}{C_{11}}\right)$, where point E is an internal equilibrium point.

By calculating the determinant symbol and eigenvalue of the Jacobian matrix, the stability of the five equilibrium points is analyzed. The results are shown in Table 6, where $A(0,\ 0)$ and $D(1,\ 1)$ both have local stability, $B(0,\ 1)$ and $C(1,\ 0)$ have an unstable equilibrium point, $E\left(1 - \frac{R_{21} - C_{21} + C_{23}}{C_{22}},\ \frac{C_{12}}{C_{11}}\right)$. The dynamic phase diagram of replication for the evolutionary

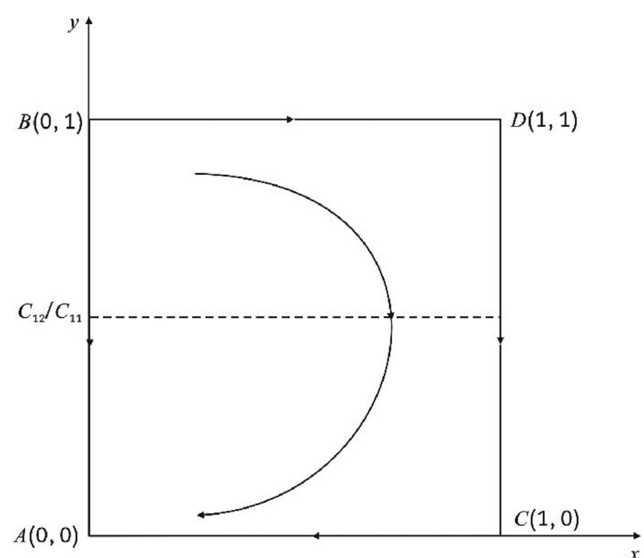

Fig. 3 – Copying dynamic phase diagram of evolutionary game between food-delivery platform and drivers (case 2).

Table 5 – Stability analysis of evolutionary game between food-delivery platform and the drivers (case 2).

Equilibrium point	Determinant symbol	Eigenvalue	Eigenvalue symbol	Stability
$A(0,\ 0)$	+	$\lambda_1 = -C_{12}$	$\lambda_1 < 0$	Stable
		$\lambda_2 = R_{21} - C_{21} - C_{22} + C_{23}$	$\lambda_2 < 0$	
$B(0,\ 1)$	+	$\lambda_1 = C_{11} - C_{12}$	$\lambda_1 > 0$	Unstable
		$\lambda_2 = C_{21} + C_{22} - C_{23} - R_{21}$	$\lambda_2 > 0$	
$C(1,\ 0)$	−	$\lambda_1 = C_{12}$	$\lambda_1 > 0$	Saddle point
		$\lambda_2 = R_{21} - C_{21} + C_{23}$	$\lambda_2 < 0$	
$D(1,\ 1)$	−	$\lambda_1 = C_{12} - C_{11}$	$\lambda_1 < 0$	Saddle point

Table 6 – Stability analysis of evolutionary game between food-delivery platform and drivers (case 3).

Equilibrium point	Determinant symbol	Eigenvalue	Eigenvalue symbol	Stability
$A(0,0)$	+	$\lambda_1 = -C_{12}$ $\lambda_2 = R_{21} - C_{21} - C_{22} + C_{23}$	$\lambda_1 < 0$ $\lambda_2 < 0$	Stable
$B(0,1)$	+	$\lambda_1 = C_{11} - C_{12}$ $\lambda_2 = C_{21} + C_{22} - C_{23} - R_{21}$	$\lambda_1 > 0$ $\lambda_2 > 0$	Unstable
$C(1,0)$	+	$\lambda_1 = C_{12}$ $\lambda_2 = R_{21} - C_{21} + C_{23}$	$\lambda_1 > 0$ $\lambda_2 < 0$	Unstable
$D(1,1)$	+	$\lambda_1 = C_{12} - C_{11}$ $\lambda_2 = C_{21} - C_{23} - R_{21}$	$\lambda_1 < 0$ $\lambda_2 < 0$	Stable
$E\left(1 - \frac{R_{21} - C_{21} + C_{23}}{C_{22}}, \frac{C_{12}}{C_{11}}\right)$ (Internal equilibrium point)	−	λ_1 λ_2	$\lambda_1 < 0$ $\lambda_2 > 0$	Saddle point

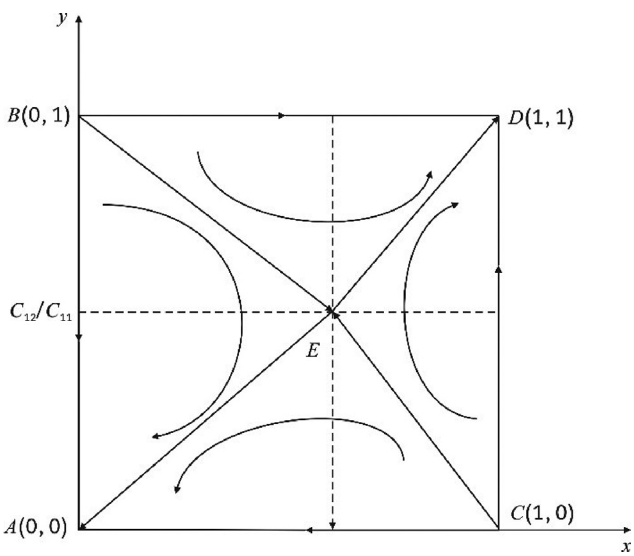

Fig. 4 – Copying dynamic phase diagram of evolutionary game between food-delivery platform and drivers (case 3).

game between the drivers and the food-delivery platform is shown in Fig. 4.

As Fig. 4 shows, when the net income of the strictly managed food-delivery platform is greater than the net income of those firms that take a passive management approach, and $C_{21} - C_{23} - R_{21} < 0$ is satisfied, the result of the game equilibrium between the drivers and the food-delivery platform is related to the initial state and the relative position of saddle point E. When the initial state is in the $ABECA$ area, the game equilibrium will converge to the stable equilibrium point $A(0, 0)$, which is the least optimal result for the TADs. When the initial state is in the $DBECD$ area, the game equilibrium will converge to the stable equilibrium point $D(1,1)$, which is the most stable equilibrium state. Therefore, the TADs need to take certain measures to expand the $DBECD$ area, while also reducing the size of the $ABECA$ area, that is, the saddle point $E\left(1 - \frac{R_{21} - C_{21} + C_{23}}{C_{22}}, \frac{C_{12}}{C_{11}}\right)$ moves to the lower left.

Therefore, it is important to analyze which factors can promote the equilibrium result of the game to move to point $D(1, 1)$, that is, the parameters affecting the area of $DBECD$ region need to be analyzed. Where, the area of $DBECD$ region can be expressed as Eq. (12).

Table 7 – Analysis of parameter influence.

Parameter	Partial derivative	Impact on S_{DBECD}
C_{11}	> 0	+
C_{12}	< 0	−
C_{21}	< 0	−
C_{22}	< 0	−
C_{23}	> 0	+
R_{21}	> 0	+

$$S_{DBECD} = 1 - \frac{1}{2}\left(1 - \frac{R_{21} - C_{21} + C_{23}}{C_{22}} + \frac{C_{12}}{C_{11}}\right) \tag{12}$$

Eq. (12) shows the parameters affecting the area of $DBECD$ include C_{11}, C_{12}, C_{21}, C_{22}, C_{23} and R_{21}. S_{DBECD} was used to take partial derivatives of these parameters respectively. "+" was used to represent the positive correlation, "−" was used to represent the negative correlation, and "/" was used to indicate that the correlation could not be identified. The results obtained were shown in Table 7.

As shown in Table 7, there is a positive correlation between S_{DBECD} and the penalty cost (C_{11}) paid by takeout delivery personnel for choosing the strategy of "not abiding by traffic rules", the penalty cost (C_{23}) incurred by traffic management departments for takeout delivery platform adopting a negative management strategy, and the reputation incentive (R_{21}) brought by platform adopting strict management measures. As C_{11}, C_{23}, and R_{21} increase, S_{DBECD} increases. On the contrary, the cost C_{12} paid by the delivery staff for choosing a "complying with traffic rules" strategy, the time and material cost C_{21} for the delivery platform choosing the "strict management" strategy, and the risk cost C_{22} brought to the platform due to strict supervision are all negative to S_{DBECD}. Furthermore, when C_{12}, C_{21} and C_{22} increase, S_{DBECD} will decrease instead.

Therefore, in order to expand the area of the $DBECD$ and achieve an ideal game equilibrium result, the government can play an influential role in guiding the types of managerial approaches adopted by the food-delivery platforms. For example, increases in the reputation incentive (R_{21}) of adopting a strict management strategy or by increasing the penalty of negative management (C_{23}) which encourages the movement of the saddle point to the lower left, so that the game equilibrium converges to the equilibrium point $D(1, 1)$, and in doing so achieve an ideal and stable equilibrium strategy that

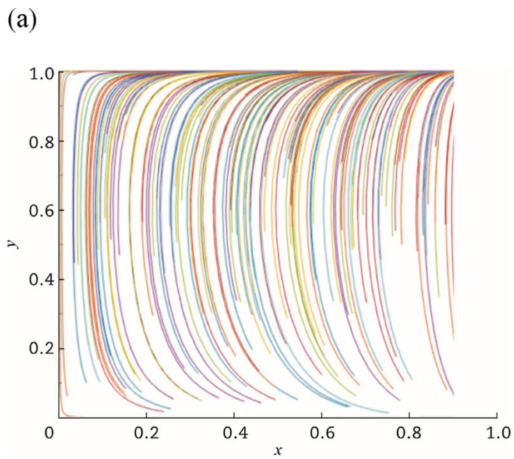

Fig. 5 – Trajectory of the evolutionary game between the drivers and the food-delivery platform (case 1). (a) $C_{11} = 5$, $C_{12} = 3$, $C_{21} = 2$, $C_{22} = 3$, $C_{23} = 5$, $R_{21} = 5$. (b) $C_{11} = 6$, $C_{12} = 4$, $C_{21} = 3$, $C_{22} = 4$, $C_{23} = 6$, $R_{21} = 6$.

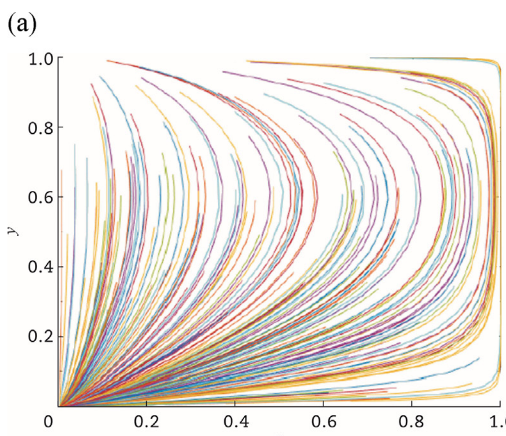

Fig. 6 – Trajectory of the evolutionary game between the drivers and the food-delivery platform (case 2). (a) $C_{11} = 5$, $C_{12} = 3$, $C_{21} = 11$, $C_{22} = 3$, $C_{23} = 5$, $R_{21} = 5$. (b) $C_{11} = 6$, $C_{12} = 4$, $C_{21} = 13$, $C_{22} = 4$, $C_{23} = 6$, $R_{21} = 6$.

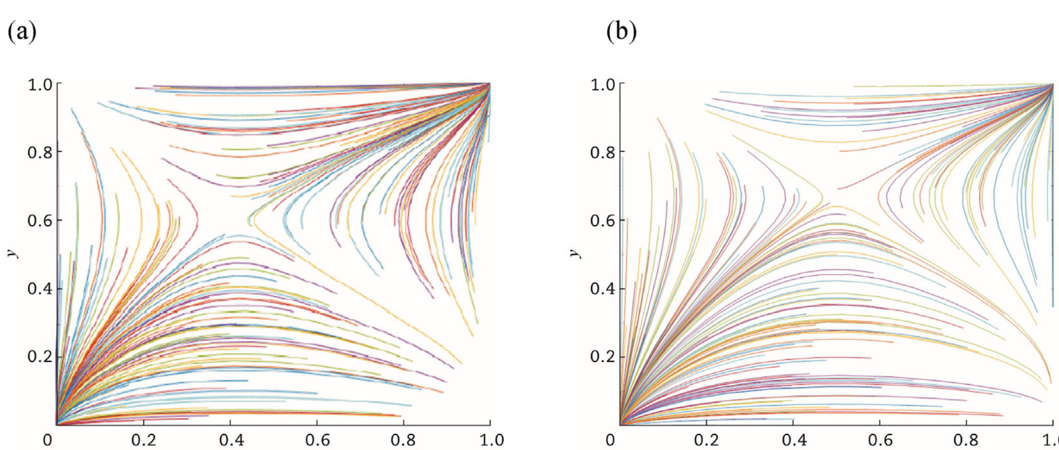

Fig. 7 – Trajectory of the evolutionary game between the drivers and the food-delivery platform (case 3). (a) $C_{11} = 5$, $C_{12} = 3$, $C_{21} = 9$, $C_{22} = 3$, $C_{23} = 5$, $R_{21} = 5$. (b) $C_{11} = 6$, $C_{12} = 4$, $C_{21} = 11$, $C_{22} = 4$, $C_{23} = 6$, $R_{21} = 6$.

is not only compliant with traffic rules but also embraces a strict management approach.

4. Discussion

To present the above theoretical research results more intuitively, a model application was conducted in this study which is based on numerical simulations. This model assesses the traffic safety aspects of the food-delivery industry, by testing the impacts of different factors on the decision-making behaviors of both the food-delivery drivers and the food-delivery platform.

(1) When the net income of the "strict management" strategy used by the food-delivery platform is greater than the net income of a "negative management" strategy, that is $R_{21} - C_{21} - C_{22} + C_{23} > 0$, let $C_{11} = 5$, $C_{12} = 3$, $C_{21} = 2$, $C_{22} = 3$, $C_{23} = 5$, $R_{21} = 5$ be the initial value. The dynamic evolution trajectory of the equilibrium strategy of the game between the drivers and the delivery platform is shown in Fig. 5. In this instance, when the TADs introduce control measures to strictly manage the traffic violations of the drivers, it will at the same time increase the costs a food-delivery platform will face for applying a strict management strategy, while also increasing its penalties associated with adopting a negative management approach. It is therefore imperative that platforms work to encourage drivers to comply with traffic rules. At different initial probabilities, the game equilibrium gradually approaches point $D(1,\ 1)$. The strategy of compliance with traffic rules and strict management becomes the only evolutionary equilibrium strategy, which is the most ideal and stable equilibrium strategy. To verify the reliability of this result, we select a different set of initial values again, and let $C_{11} = 6$, $C_{12} = 4$, $C_{21} = 3$, $C_{22} = 4$, $C_{23} = 6$, $R_{21} = 6$ be the initial value. We can see that the results are consistent.

(2) When the net income of the "strict management" delivery platform is less than the net income of the "negative management" strategy, that is, $C_{21} - C_{23} - R_{21} > -C_{22}$, and $C_{21} - C_{23} - R_{21} > 0$, let $C_{11} = 5$, $C_{12} = 3$, $C_{21} = 11$, $C_{22} = 3$, $C_{23} = 5$ and $R_{21} = 5$ be the initial values. The dynamic evolution trajectory of the equilibrium strategy of the game between the drivers and the delivery platform is shown in Fig. 6. According to Fig. 6, under different initial probabilities of compliance with traffic rules, and the adoption of strict management strategies, the system will eventually converge to the only stable equilibrium point $A(0,\ 0)$, and the strategy combination is one of non-compliance with traffic rules and a passive management approach. This is due to the cost of a delivery platform adopting a strict management approach is too high, so that it has no incentive to strictly manage its drivers, which leads to the prevalence of poor driving behavior in which the drivers do not follow the traffic rules. This result is the most unreasonable from the perspective of urban public traffic safety or the long-term development of the food-delivery industry. Again, we select a different set of initial values to verify the reliability of the results, and let $C_{11} = 6$, $C_{12} = 4$, $C_{21} = 13$, $C_{22} = 4$, $C_{23} = 6$, $R_{21} = 6$ be the initial value. We can see that the trend of the two graphs is roughly the same.

(3) When the net income of the "strict management" food-delivery platform is less than the net income of the "passive management" strategy, that is, $C_{21} - C_{23} - R_{21} > -C_{22}$, and $C_{21} - C_{23} - R_{21} < 0$, let $C_{11} = 5$, $C_{12} = 3$, $C_{21} = 9$, $C_{22} = 3$, $C_{23} = 5$ and $R_{21} = 5$ be the initial values. The dynamic evolution trajectory of the equilibrium strategy of the game between the drivers and the delivery platform is shown in Fig. 7. According to Fig. 7, under different initial probabilities of traffic rule compliance and the adoption of a strict management strategy, the game equilibrium may converge at point $A(0,\ 0)$ or point $D(1,\ 1)$. The specific convergence position is related to the initial state and the position of the saddle point. The government can change the position of the

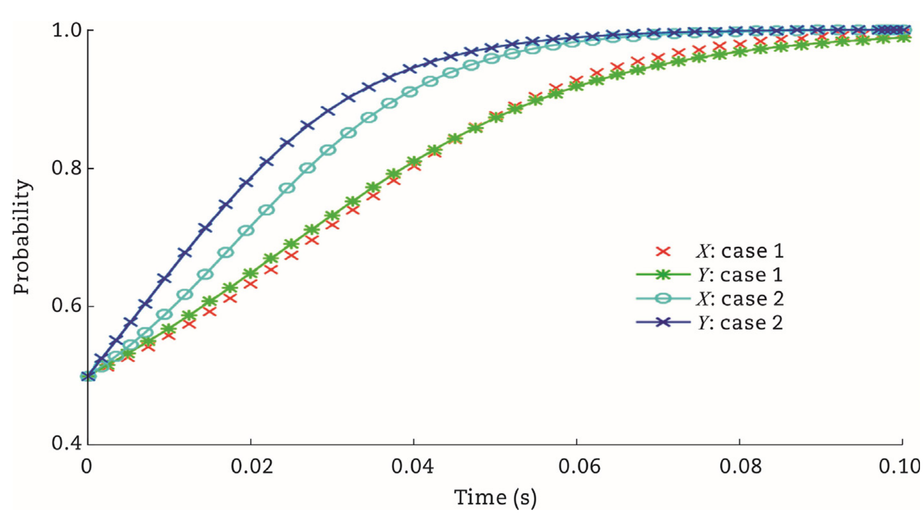

Fig. 8 – Dynamic evolution results of parameter changes.

saddle point by increasing its level of regulation and control over the industry, so as to make the equilibrium approach the ideal state point $D(1,\ 1)$, which is one of compliance with traffic rules and the adoption of a strict management strategy; representing the most stable and balanced approach by government. When we select a different set of initial values again, let $C_{11} = 6$, $C_{12} = 4$, $C_{21} = 11$, $C_{22} = 4$, $C_{23} = 6$ and $R_{21} = 6$ be the initial value. We see a slight shift in the position of the saddle points, but the result remains the same.

Meanwhile, according to Table 7, the size of parameters (C_{11}, C_{12}, C_{21}, C_{22}, C_{23} and R_{21}) in the equation has a certain influence on the final evolution result of the game. For example, assuming the initial value (case 1) $C_{11} = 100$, $C_{12} = 30$, $C_{21} = 90$, $C_{22} = 100$, $C_{23} = 50$, $R_{21} = 90$, $x = 0.5$ and $y = 0.5$, according to the different influence relationship of each parameter on S_{DBECD} in Table 7, We make the corresponding changes to the variables (case 2), and let $C_{11} = 110$, $C_{12} = 25$, $C_{21} = 80$, $C_{22} = 90$, $C_{23} = 60$ and $R_{21} = 100$, so as to analyze the comprehensive influence of these parameters on the game evolution results. The dynamic evolution results are shown in Fig. 8.

We found that after making a parameters adjustment, the decision-making probability of each game subject tends to get to "1" more quickly. Next, we analyze these parameters and their effect on S_{DBECD} respectively and observe the influence of

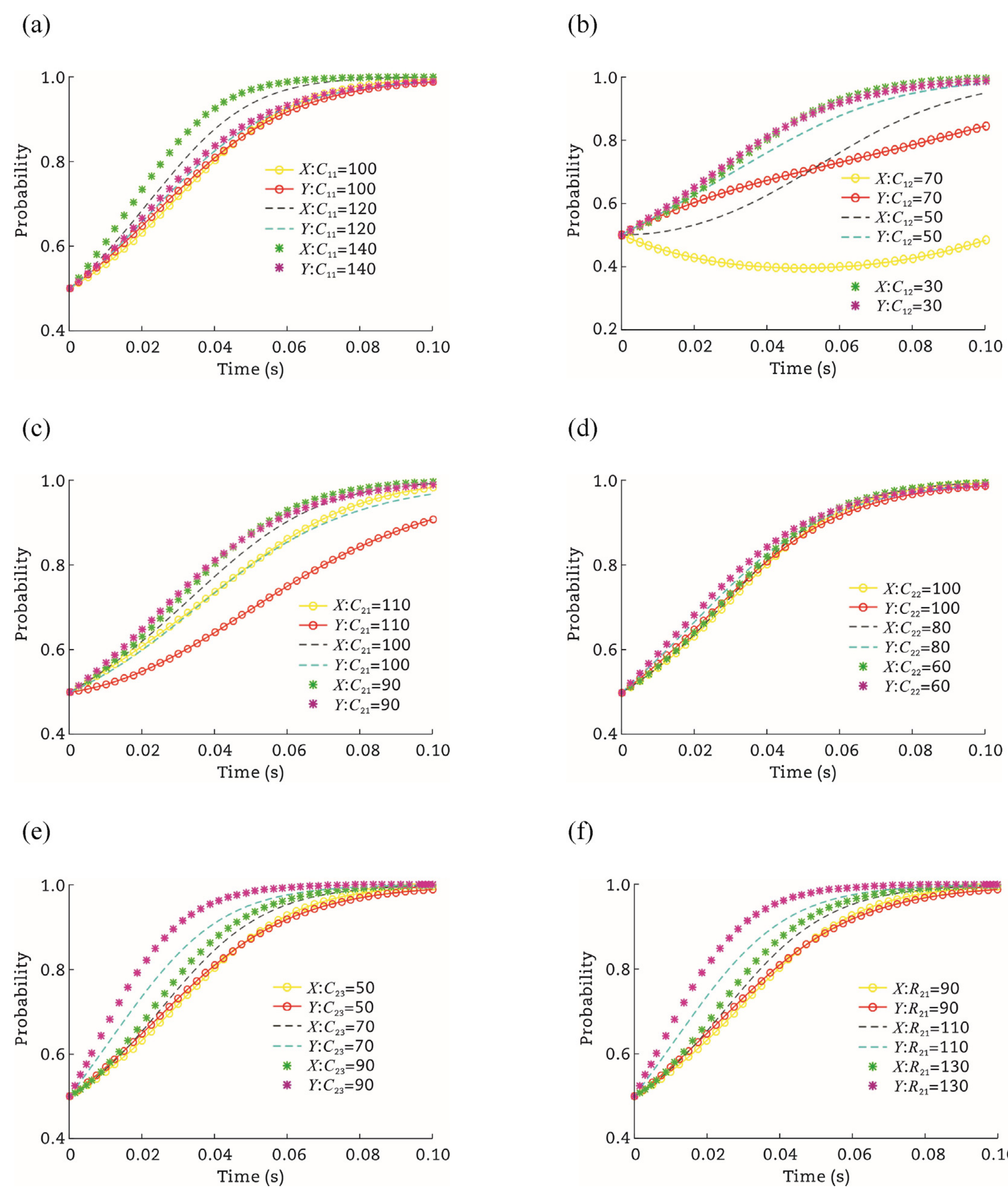

Fig. 9 – Dynamic influence of each parameter on evolution result. (a) Evolutionary trajectory under different C_{11}. (b) Evolutionary trajectory under different C_{12}. (c) Evolutionary trajectory under different C_{21}. (d) Evolutionary trajectory under different C_{22}. (e) Evolutionary trajectory under different C_{23}. (f) Evolutionary trajectory under different R_{21}.

an increase or decrease of these parameters on the game evolution process and results.

Fig. 9 illustrates the trend of the evolution results of each game subject, when adjusted for each parameter. The figure shows that parameters C_{11}, C_{23} and R_{21} have a positive correlation with the dynamic evolution results for both sides of the game, while parameters C_{12}, C_{21} and C_{22} have a negative correlation with the dynamic evolution results for both sides of the game. When the parameters C_{11}, C_{23} and R_{21} increase or the parameters C_{12}, C_{21} and C_{22} decrease, the probability of delivery personnel choosing to "obey traffic rules" and the probability of delivery platform choosing to adopt a "strict management" will rapidly increase.

5. Conclusions

This study uses evolutionary game theory to analyze the game evolution process and stabilization strategies that exist between the food-delivery platform and their drivers, when the TADs have increased their management and enforcement of electric vehicle traffic violations. For the purpose of this study, we examine the crowd-sourced food-delivery service, which differs from the traditional food-delivery service industry. Our research showed that when the net income of the "strict management" strategy used within the food-delivery platform is greater than the income of its "negative management" strategy, the business is able to achieve a stable and balanced state of operation that complies with the relevant traffic rules and embraces a strict management approach; which is the kind of operational state the TADs expect to see from businesses operating in this industry. Such behavior, is conducive to developing an effective food-delivery market and the formation of a safe urban transportation system. From an evolutionary game theory perspective, when the net income of the "strict management" delivery platform is less than its "negative management" strategy and $C_{21} - C_{23} - R_{21} > 0$, the stable equilibrium strategy of the two players is one of non-compliance with traffic rules and the adoption of a passive management approach, which provides for a so-called "prisoner's dilemma" situation. This balanced result is not conducive to forming a normal delivery mechanism within the food-delivery industry, moreover, it can also endanger the safety of the urban public transportation system. When the net income of the "strict management" delivery platform is less than its "negative management" alternative and $C_{21} - C_{23} - R_{21} < 0$, the game equilibrium has two stable equilibrium strategies. The first, is one of compliance with traffic rules and the adoption of a strict management strategy, which is an ideal evolutionary state. The other, is one is non-compliance with traffic rules and the adoption of a passive management strategy, which represents a failed evolutionary state. In this context, the TADs can promote the evolution of the game towards a stable equilibrium state in which traffic rules are complied with and a strict management approach is followed by changing the intensity of its macro-control mechanisms. By increasing their macro-controls, by either providing addition compensation or incentives to business, the TADs can facilitate organizational change that sees the number of food-delivery platforms that use stricter management approaches increase. The TADs can also increase the types of penalties or fines that food-delivery drivers must face for traffic violations, thereby controlling or reducing the risk that food-delivery drivers will not follow the relevant traffic rules, while at the same time promoting the evolution of the game direction to ensure compliance with the traffic rules and the adoption of strict management strategies. When government regulation is relatively weak, the cost of a strict management approach by the food-delivery platform is greater than the penalty cost associated with the use of a passive management style. In this instance, the platform will be more inclined to choose a passive management strategy which allows the organization to operate in a manner that represents its own best interests. In doing so, it will condone illegal driving behavior in which food-delivery drivers do not comply with the traffic rules.

Under the control of the TADs, the evolutionary game between the food-delivery platform and drivers contains different stability strategies that are created based around different initial conditions. Moreover, the development of an organized and well-regulated food-delivery industry will also improve the overall status of the urban public transport travel system. In terms of the differences in net income that exist across the strict and passive management strategies, the TADs need to change their regulatory provisions surrounding compensation (for strict management) and punishment (for passive management) for those operating within the delivery platform. This can be done by strengthening the management of the food-delivery platform, so that it can be more proactive and ensure that drivers are more strictly managed. These fundamental changes would ensure that the overall Internet plus food-delivery industry employs drivers that not only abide by traffic rules when delivering meals, but also play a pivotal role in reducing the number of traffic accidents occurring across the urban landscape. Furthermore, this study can provide important insight as to how an instant delivery platform can optimize its orders improve traffic safety, while also reducing social logistics costs and security risks.

Despite its important contributions, this study has limitations that could be addressed in future research. The research on traffic safety management for takeout distribution platforms is constantly evolving. Although out study uses game theory to discuss and analyze the industry, there are still some deficiencies in the methodological approach we adopted. First, the numerical simulation part should use actual cases as part of future analyses (Wang et al., 2021b). Moreover, as this study shows, the control of TADs has a great influence on the game stability strategy. In the future, we will consider introducing "platform enterprises" to discuss the tripartite evolutionary game analysis of introducing TADS. Finally, using an evolutionary game with multi-agent participation will also help to improve the shortcomings of the study.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

Acknowledgments

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Appendix A. Calculation process of the Jacobian matrix.

In this paper, the calculation method of the Jacobian matrix of case 1, case 2, and case 3 is the same. Simultaneous Eqs. (7) and (9),

$$\begin{cases} F(x) = \dfrac{dx}{dt} = x(E_1 - E_{average}) = x(1-x)(yC_{11} - C_{12}) \\ F(y) = \dfrac{dy}{dt} = y(E_3 - E_{average}) = y(1-y)[R_{21} - C_{21} - (1-x)C_{22} \\ \qquad +C_{23}] \end{cases} \tag{A1}$$

the two equations respectively take partial derivatives of x and y, we can get the following results.

$$\frac{dF(x)}{dx} = (1-2x)(yC_{11} - C_{12}) \tag{A2}$$

$$\frac{dF(x)}{dy} = x(1-x)C_{11} \tag{A3}$$

$$\frac{dF(y)}{dx} = y(1-y)C_{22} \tag{A3}$$

$$\frac{dF(y)}{dy} = (1-2y)[R_{21} - C_{21} - (1-x)C_{22} + C_{23}] \tag{A4}$$

Appendix B. Example code

In this article, we use MATLAB software for example simulation, the code of the simulation process is as follows.

```
function dy = wm(t, y)
dy = zeros (2, 1);
C21 = 9;
C22 = 3;
C23 = 5;
R21 = 5;
C11 = 5;
C12 = 3;
dy (1) = y(1) * (1 − y(1)) * (y(2) *C11 − C12);
dy (2) = y(2) * (1 − y(2)) *(−(1 − y(1)) ^2 * C22 − C21+C23+R21);
a = rand (1, 200);
b = rand (1, 200);
for i = 1:1:200.
[T, Y] = ode45 ('wm', [0 10], [a(i) b(i)]);
Plot (Y (:, 1), Y (:, 2))
hold on
end
axis ([0 1 0 1]);
xlabel ('x');
ylabel ('y');
```

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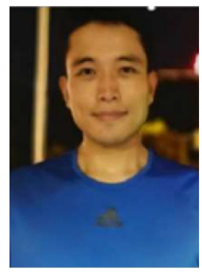

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