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Network Evolution Analysis of Vehicle Road-Driving Behavior Strategies and Design of Information Guidance Algorithm

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Abstract: By analyzing the influence of time and safety factors on the behavior strategies of vehicles on the road, a network game evolution model between drivers that considers the behavior strategies of the driving vehicle itself and its neighbors is constructed, and the competition relationship between different types of cars is studied. The influence of the proportion of driving vehicle types on the potential risk of the road is also discussed. This paper presents a guidance algorithm for vehicle dynamic behavior preference information. The correctness of the algorithm is verified by an example. Research shows: The choice of behavior strategies, such as speeding and lane changing, is related to the expected benefits of time, safety, and neighboring vehicle strategies, and the critical value of payable benefits is obtained. The higher the proportion of aggressive vehicles on the road, the greater the potential risk on the road. Whether there is a vehicle in the adjacent lane of the driving vehicle will affect the type of driving vehicle. Information guidance helps to stabilize the state of vehicles on the road, and the policy transition probability also helps stabilize the form of vehicles cars on the road. Still, information guidance has a more significant impact on the transition of vehicle types. Finally, the guidance strategy of managers is given when the road is smooth and congested.

Key words: user portrait; information guidance; network game; risk appetite

1 Introduction

1.1 Background

With the rapid development of urban transportation, modern urban transportation networks have been becoming more complex and causing many concomitant problems such as traffic congestion and accidents as well as environmental pollution, all of which make the promotion of the governmental capacity over the urban traffic system seem very urgent[1]. To mitigate these problems and meanwhile not limiting the number of vehicles unduly, designing an efficient and reliable intelligent transportation system usually is viewed as a necessary way[2, 3] in which an information guidance system is its core component[4–6], consisting of the critical part of intelligent networked vehicles system[7–9]. In ideal scenarios, the traffic information guidance system (IGS) is expected to improve the efficiency of urban traffic operation, thus reducing the possibility of traffic congestion and accidents by guiding vehicle drivers' driving behaviors[10]. Moreover, the rapid development of road-related information technologies, e.g., Internet of Things technology and comprehensive platform technology, lay a steady foundation for vision realization[11, 12]. Therefore, the discussion around traffic information guidance becomes the research focus in the field of transportation management.

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1.2 Literature review

Generally, traffic information guidance research topics mainly contain the following aspects. Some scholars discussed the effect of introducing traffic information guidance. For example, Zhang and Huang[13] and Lv et al.[14] argued that the dissemination of extra traffic information would be beneficial to alleviate congestion. Tang and Wang[15] measured the aggregated effectiveness of building IGS from the aspects of economic rationality, technical rationality, and social and economic benefits. Other studies focused on the driving behavior changes of vehicle drivers. Some discussed the impact of traffic information signs on drivers' route[16], travel mode selection[17, 18], and departure time selection[19, 20] as well as the payment willingness for obtaining extra transportation information[21, 22]. Besides, many studies have recently paid attention to relevant issues in background smart transportation. For example, Lv et al.[23] argued that utilizing big data analysis techniques to improve electric vehicle transportation networks can significantly reduce network data transmission performance and change the path to suppress the spread of congestion effectively. Gargoum and El-Basyouny[24] studied the influence of point density on extracting traffic signs from lidar data sets. Zhao et al.[25] learned the strategies of regional route guidance for an autonomous driving vehicle. Li et al.[26] deemed that the mixed-use of description and specification information in an appropriate proportion can improve traffic flow stability. Dong et al.[27] argued that networked autonomous-driving vehicles could favor disseminating traffic-related information with the assistance of vehicular wireless communication technology.

Before releasing guidance information, it is necessary to comprehensively consider its expected effectiveness[28]. To this aspect, most studies argued that providing extra information for guiding the driving of vehicles could reduce drivers' cognitive uncertainties, thus enhancing their driving efficiency[29, 30]; however, ignoring the possible negative impact. To specify the unexpected latent outcomes, Ben-Elia et al.[31] discussed the relationship between information accuracy and drivers' route choice, confirming that travelers' choices are sensitive to the accuracy of travel information. Similarly, Liu and Zhou[32] argued that the effect of information guidance is affected by the information permeability of the situations the drivers are in, exhibiting an inverted U-shaped trend. The reasons incurring the negative influence of traffic information guidance partly could be attributed to the mutual relation between drivers' factors and the information factors. For example, Tang et al.[11] and Iraganaboina et al.[33] argued that people with different travel purposes would pay special attention to various information before and on the way. In an account of the personal factors, Zhang et al.[34] proposed the intelligent transportation service recommendation (Masr) model, which comprehensively considered the personalized behavior of users from many aspects.

Generally speaking, compared with the existing road traffic system, the intelligent traffic represented by the information guidance system could provide a more convenient, reliable, and economical traffic environment[35], laying a foundation not only for the current person-centered driving mode but also for future autonomous driving. To this end, the research on the deigns of the information-guidance scheme has become a hot topic in intelligent transportation. Nevertheless, a lot of issues should be addressed further. For instance, the extant studies pay little attention to the dynamic information induction according to real-time road situations, especially according to the different characteristics of drivers to make guidance strategies. This may be due to the difficulty that it is hard to get private information in terms of the driving features of drivers.

1.3 Contribution and organization

In response to the above challenges, based on the idea of a network evolution game, this paper analyzes and classifies the driving vehicle behavior, realizes the overall accurate perception and personalized service of the road network through comprehensive portraits, releases guidance information, improves the level of traffic service, and coordinates the operation efficiency of the road network. Compared with the existing research, the innovations of this paper are as follows:

(1) The vehicle behavior strategy selection is analyzed, and a vehicle network game evolution model is constructed.

(2) The conversion relationship of different types of vehicles in different environments is studied.

(3) An information guidance algorithm for vehicle behavior selection is proposed.

The rest of this paper will be structured as follows: A network evolutionary game model is established in Section 2. Then the influence of manager information guidance on vehicles is analyzed in Section 3. Next, we build a set of algorithms for identifying vehicle types and conducting traffic information guidance in Section 4. And then, an example is given to verify the rationality of the proposed model and algorithm in Section 5. Finally, the conclusion is given in Section 6.

2 Traffic Network Analysis

The road could be viewed as areas where moving vehicles affect each other and compete for limited road rights[36]. All vehicles on the road consist of a typically dynamic network game[37], in which one vehicle as the node of the network interacts with others, as shown in Fig. 1. To analyze the features of this dynamic network game, the network evolutionary game model is employed in this section.

2.1 Network structure description

In the process of the traffic game, the moving vehicles, as shown in Fig. 1, constitute the main body of the game, which are affected by the road environment (traffic density/road saturation), driving speed, and lane change frequency of other vehicles, and accordingly choose the driving strategy of themselves (i.e., driving speed and whether changing lane). All these factors make the traffic network complicated. Yet, the game could also be described as a game made up of multiple two-player games in which the neighboring vehicles influence mutually[38−40]. Thus, the traffic network game could be abstracted as $G=(V,e)$, in which $V=\{v_1,v_2,...,v_n\}$ is the set of driving vehicles $(v_1,v_2,...,v_n)$ on the road and $e=\{e_{11},e_{12},...,e_{nn}\}$ represents the traffic network relationships (named edges of the network in this paper) among driving cars in the network. If the driving vehicles v_i and v_j are neighbors, e_{ij} is 1, otherwise,

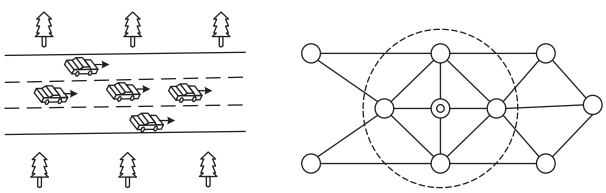


Fig. 1 Network topology of driving vehicles.

$e_{ij}=0$. In addition, N_i represents the number of neighbor vehicles of the vehicles $v_i \in V$, and d_i is the aggregated amount of all edges of the v_i.

In the traffic network game, one driving vehicle gleans the information of other neighbor vehicles and adjusts the driving strategy in real-time according to the principle of utility maximum. Taking all introduced factors together, the game could be described as $\Gamma_G=(G,S,U)$ in which G represents the traffic network, $S=\{S_i|v_i \in V\}$ represents driving strategy set of the driving vehicles on the road (S_i is the strategy of vehicle i), and $U=\{u_i|v_i \in V\}$ represents the utility set of the driving vehicles (u_i is the utility of the vehicle i). The symbolic meaning of this paper is shown in Table 1.

2.2 Game model construction

The utility functions of different vehicles usually determine their choice of game behavior. To better describe the driving behavior of vehicles, the vehicles are categorized into three types: the aggressive (often performing impatiently in driving) represented by V_A, the slow (often performing inactively in driving) represented by V_C, and the stable (lying the mediate state between the above types) defined by V_B[41−44]. x_A, x_B, and x_C are used to represent numbers of the three types of vehicles on the road, respectively. Besides, as the information on vehicle types is grey information that can not be obtained directly, the vehicle type judgments are often described as some probabilities. Hence, set the possibility that one vehicle is aggressive vehicles r_A, the probability of stable vehicles r_B, and the probability of slow vehicles r_C. The vehicles of different types have different driving strategy sets represented by $P_i=\{p_{1,i},p_{2,i},...,p_{m,i}\}$, $i \in \{A,B,C\}$.

2.2.1 Individual income function of driving vehicle

Running vehicles' state benefit function can be composed of time and safety benefits[45]. Time benefit refers to the time utility brought by road travel time, and safety benefit refers to the potential accident risk mitigated by paying attention to the possibility of an accident. When a driving vehicle overtakes or accelerates, it is necessary to judge the vehicle's speed in front and the distance between the vehicle and the vehicle in front. When meeting, it is necessary to judge the lateral clearance between the two vehicles. Otherwise, a traffic accident may occur. If a traffic accident occurs, money will be lost, and the travel time

Table 1 Nomenclature.

Symbol	Meaning
Γ_G	Traffic network game
G	Traffic network
V	Set of driving vehicles
e	Traffic network relationships among driving cars in the network
N_i	Number of neighbor vehicles of the vehicles $v_i \in V$
d_i	Aggregated amount of all edges of the v_i
S	Driving strategy set of the driving vehicles
U	Utility set of the driving vehicles
V_A	Aggressive vehicles
V_B	Stable vehicles
V_C	Slow vehicles
x_A	Number of the aggressive vehicles
x_B	Number of the stable vehicles
x_C	Number of the slow vehicles
r_A	Possibility of aggressive vehicles
r_B	Possibility of stable vehicles
r_C	Possibility of slow vehicles
R_i	Individual income function of driving vehicle v_i
α_i	Driver's emphasis on safety benefits
β_i	Driver's emphasis on temporal benefits
D	Safety benefit of running vehicles
ε_i	Probability of traffic accident risk
c_i	Accident cost
Z	Time benefit of driving vehicles
η^{ij}	Headway of the *j* type driving vehicle in front and the *i* type driving vehicle in the back
$\bar{\eta}_a^{ij}$	Average headway of η_a^{ij}
C_a	Capacity of the road section a
$\hat{C}_a^A$	Road capacity when the road a is full of aggressive vehicles
R_{Si}	Vehicle strategic benefit function
r_{ij}	Vehicle strategy transfer probability
π_i	Total income of driving vehicles
$\bar{E}v_i$	Average expected return on a vehicle v_i
Ev_i	Expected return on a vehicle v_i
y_A	Proportion of aggressive vehicles
y_B	Proportion of stable vehicles
y_C	Proportion of slow vehicles
L_R	Road network system loss
J	Traffic congestion degree
E	Safety factor damage
μ	Impact of issuing information to the manager on the strategy transfer
D_i	Actual driving behavior preference set

will be increased, which means that the income of the driving vehicle will be reduced. The degree of attention paid to safety and temporal benefits is determined by the driver's personality and safety awareness[46–49]. Based on this, the individual income equation of driving vehicles v_i is constructed as follows:

$$R_i = \alpha_i D + \beta_i Z \tag{1}$$

where α_i is the driver's emphasis on safety benefits, β_i is the driver's emphasis on temporal benefits, and

$\alpha_i+\beta_i=1$ $(i=A,B,C)$. A represents the aggressive type. B represents the stable type. C represents the slow type. α_A, α_B, and α_C represent the emphasis of aggressive, stable, and slow vehicles on safety benefits, respectively. β_A, β_B, and β_C represent the emphasis of aggressive, stable, and slow vehicles on time benefit, respectively.

The safety benefit of running vehicles is inversely proportional to the accident rate. When the accident rate is low, the safety benefit is significant. Let D be the safety benefit of running vehicles, and its equation is

$$D=-\varepsilon_I\times c_i(v) \tag{2}$$

where ε_I is the probability of traffic accident risk when driving vehicles overtake and change lanes $(I\in\{A,B,C\})$. c_i is the accident cost.

The time benefit of driving vehicles is inversely proportional to the road section saturation. When the road section saturation is more minor, the time benefit is fantastic[46]. Let Z be the time benefit of driving vehicles. The equation is

$$Z=-bt_0\left(1+\xi\left(\frac{x_A^{t,a}+x_B^{t,a}+x_C^{t,a}}{C_a}\right)^{\psi}\right) \tag{3}$$

where b is the contribution of the road travel time of the driving vehicle to the utility of the driving vehicle, ξ and ψ are the parameters, t_0 is the free flow time, C_a is the capacity of the road section a, $\rho=\left(x_A^{t,a}+x_B^{t,a}+x_C^{t,a}\right)/C_a$ is the saturation of the road section, $x_A^{t,a}$ is the number of aggressive driving vehicles on the road a at the time t, $x_B^{t,a}$ is the number of stable driving vehicles on the road a at the time t, and $x_C^{t,a}$ is the number of slow driving vehicles on the road a at the time t.

For road capacity, this paper adopts the model proposed by Liu and Song[50], which is based on the relationship between road capacity and average minimum headway. As shown in Fig. 2, there are nine different headways. η^{ij} $(i\in\{A,B,C\},j\in\{A,B,C\})$ represents the headway of the j type driving vehicle in front and the i type driving vehicle in the back, for example, η^{BA} represents the headway of the aggressive driving vehicle in front and the stable driving vehicle in the back.

Let $\bar{\eta}_a^{ij}$ $(i\in\{A,B,C\},j\in\{A,B,C\})$ be the average headway of η_a^{ij} $(i\in\{A,B,C\},j\in\{A,B,C\})$ on the road a. Assuming that all vehicles are randomly distributed,

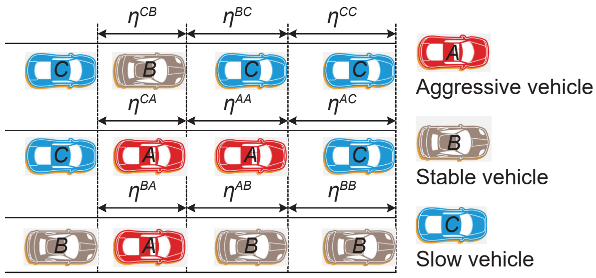


Fig. 2 Schematic diagram of headway.

the vehicle type arrival model is Bernoulli distribution[51]. Then the average headway of mixed traffic flow on the road a is

$$\begin{aligned}\bar{\eta}_a=&\sum_{i\in\{A,B,C\}}\sum_{j\in\{A,B,C\}}\bar{\eta}_a^{ij}r_i^a r_j^a=\\&\bar{\eta}_a^{AA}r_A^a r_A^a+\bar{\eta}_a^{BA}r_A^a r_B^a+\bar{\eta}_a^{CA}r_A^a r_C^a+\bar{\eta}_a^{AB}r_B^a r_A^a+\\&\bar{\eta}_a^{BB}r_B^a r_B^a+\bar{\eta}_a^{CB}r_B^a r_C^a+\bar{\eta}_a^{AC}r_C^a r_A^a+\bar{\eta}_a^{BC}r_C^a r_B^a+\\&\bar{\eta}_a^{CC}r_C^a r_C^a\end{aligned} \tag{4}$$

where r_i^a $(i\in\{A,B,C\})$ is the proportion of i type vehicles on the road a, A represents aggressive type vehicles, B represents stable type vehicles, C represents slow type vehicles, and $r_A^a+r_B^a+r_C^a=1$. The ratio of aggressive vehicles on the street is

$$r_A^a=\frac{x_A^{t,a}}{x_A^{t,a}+x_B^{t,a}+x_C^{t,a}} \tag{5}$$

The lane change behavior of vehicles in other lanes will affect the proportion of different types of vehicles. The impact of lane change will be described in detail in the next section.

According to the traffic flow theory, the capacity of each lane of the section is equal to the reciprocal of the average minimum headway.

$$\begin{aligned}C_a=\frac{\phi_a}{\bar{\eta}_a}=\phi_a/\big[&(\bar{\eta}_a^{BA}+\bar{\eta}_a^{AB})r_A^a r_B^a+(\bar{\eta}_a^{CA}+\bar{\eta}_a^{AC})r_A^a r_C^a+\\&(\bar{\eta}_a^{CB}+\bar{\eta}_a^{BC})r_B^a r_C^a+\bar{\eta}_a^{AA}r_A^a r_A^a+\bar{\eta}_a^{BB}r_B^a r_B^a+\bar{\eta}_a^{CC}r_C^a r_C^a\big]\end{aligned} \tag{6}$$

Equation (6) is the number of lanes on the road and the minimum headway on the road a.

Let $\hat{C}_a^A$ indicate the road capacity when the road a is full of aggressive vehicles. Bring $\hat{C}_a^A=\phi_a/\bar{\eta}_a^{AA}$ into Eq. (6):

$$\begin{aligned}C_a=\frac{\phi_a}{\bar{\eta}_a}=\hat{C}_a^A/\Bigg[&\frac{(\bar{\eta}_a^{BA}+\bar{\eta}_a^{AB})}{\bar{\eta}_a^{AA}}r_A^a r_B^a+\frac{(\bar{\eta}_a^{CA}+\bar{\eta}_a^{AC})}{\bar{\eta}_a^{AA}}r_A^a r_C^a+\\&\frac{(\bar{\eta}_a^{CB}+\bar{\eta}_a^{BC})}{\bar{\eta}_a^{AA}}r_B^a r_C^a+r_A^a r_A^a+\frac{\bar{\eta}_a^{BB}}{\bar{\eta}_a^{AA}}r_B^a r_B^a+\frac{\bar{\eta}_a^{CC}}{\bar{\eta}_a^{AA}}r_C^a r_C^a\Bigg]\end{aligned} \tag{7}$$

Substituting Eqs. (2), (3), (5) and (7) into Eq. (1), the individual revenue equation of running vehicles v_i of type I can be obtained as

$$R_i = -\alpha_i \varepsilon_I \times c_i(v) - \beta_i b t_0 \left[1 + \xi \left(\frac{H x_A^{t,a} + \bar{\eta}_a^{BB} x_B^{t,a} + K x_C^{t,a}}{\hat{C}_a^A \bar{\eta}_a^{AA}} \right)^{\psi} \right] \tag{8}$$

where H and K are respectively:

$$H = \bar{\eta}_a^{BA} + \bar{\eta}_a^{AB} - \bar{\eta}_a^{BB} + (\bar{\eta}_a^{AA} + 2\bar{\eta}_a^{BB} - \bar{\eta}_a^{BA} - \bar{\eta}_a^{AB}) r_A^{t,a} + (\bar{\eta}_a^{CA} + \bar{\eta}_a^{AC} + \bar{\eta}_a^{BB} - \bar{\eta}_a^{CB} - \bar{\eta}_a^{BC} - \bar{\eta}_a^{BA} - \bar{\eta}_a^{AB}) r_C^{t,a},$$

$$K = \bar{\eta}_a^{CB} + \bar{\eta}_a^{BC} - \bar{\eta}_a^{BB} + (\bar{\eta}_a^{CC} + \bar{\eta}_a^{BB} - \bar{\eta}_a^{CB} - \bar{\eta}_a^{BC}) r_C^{t,a}.$$

2.2.2 Benefit function of a moving vehicle affected by adjacent vehicles

The profitability of a vehicle is related to its operating status and is affected by its adjacent vehicles. The vehicle interacts with adjacent vehicles through the automobile network and learns the strategy from the middle side of the game and the side to decide whether to change the design after weighing the benefits of the individual state and transferring the help of the design. The micro decision of a single-vehicle ultimately determines the operational efficiency of the entire road network at the macro level. From the previous section setting, it can be seen that the number of all neighbors of the vehicle v_i of type I is d_i. Due to the influence of the adjacent vehicle strategies, the vehicle strategic benefit function R_{Si} is constructed as

$$R_{Si} = \sum_{j \in V_{-i}} e_{ij} \cdot r_{ij} \cdot R_j \tag{9}$$

The car v_i randomly selects a neighbor v_j to compare the benefits by observing. Suppose that the probability of vehicle strategy transfer is only related to income, that is, $r_{i \to j}(t+1) \sim (\pi_j(t) - \pi_i(t))$. When the revenue of a car v_i is less than that of the vehicle v_j at the time t, the car v_i will choose to learn its neighbor car's strategy at the time t, that is, $s_i(t+1) = s_j(t)$. According to the Fermi update rule[52], the vehicle strategy transfer probability r_{ij} is

$$r_{ij} = \begin{cases} r_{i \to j}(t+1), R_j > R_i; \\ 0, R_j < R_i \end{cases} \tag{10}$$

where $r_{i \to j}(t+1) = 1 \Big/ \left[1 + \exp\left(\frac{R_i(t) - R_j(t)}{\zeta} \right) \right]$, and ζ is the degree of individual rationality.

2.2.3 Total revenue function of running vehicles

In the network game, each individual's income depends not only on itself but also on the strategies of neighbor individuals. In the pair interaction mode, each neighbor pair plays a two-person game. The income of each individual is the sum of the revenue generated by the match between him and all neighbors. Because the driving state of the driving vehicle will be affected by the behavior preference of the surrounding cars, the driving state of the front and rear cars and the left and suitable vehicles of the driving vehicle needs to be observed in the process of safe road driving, and the subsequent driving decision should be made. After each game, individuals decide their next strategy according to the obtained income information and the strategy information of other neighbor individuals. Therefore, the total income of driving vehicles v_i is

$$\pi_i = U_i(s_i, s_{-i}) = U_i\left(s_i, \sum_{v_j \in N_i} s_j \right) \tag{11}$$

To sum up, by substituting Eqs. (8) and (9) into Eq. (11), the total income function of running vehicles v_i of type I is

$$\pi_i = -\beta_i b t_0 \left[1 + \xi \left(\frac{H x_A^{t,a} + \bar{\eta}_a^{BB} x_B^{t,a} + K x_C^{t,a}}{\hat{C}_a^A \bar{\eta}_a^{AA}} \right)^{\psi} \right] - \alpha_i \varepsilon_I \times c_i(v) + \sum_{j \in V_{-i}} e_{ij} \cdot r_{ij} \cdot R_j \tag{12}$$

where e_{ij} indicates whether there is a vehicle near the driving vehicle v_i. If there is a vehicle near the driving vehicle v_i, $e_{ij} = 1$, otherwise, $e_{ij} = 0$.

2.3 Evolution rule

Based on the above analysis and according to Eq. (12), the income function of different types of vehicles can be obtained, and the income function at this time is the expected income of this type of vehicles. The average expected income of vehicles can be obtained according to the proportion of vehicles with blocked roads. Finally, the corresponding replication dynamic equation can be obtained, which will pave the way for the discussion of evolutionary equilibrium results in the next section.

At the time t, the expected benefits of each type of vehicle v_i (aggressive, stable, or slow) are

$$E v_{i,A} = -\beta_i b t_0 \left[1 + \xi \left(\frac{H x_A^{t,a} + \bar{\eta}_a^{BB} x_B^{t,a} + K x_C^{t,a}}{\hat{C}_a^A \bar{\eta}_a^{AA}} \right)^{\psi} \right] - \alpha_i \varepsilon_A \times c_i(v) + \sum_{j \in V_{-i}} e_{ij} \sum_{x=1}^{16} r^{i \to x, j} \cdot R_j^x \tag{13}$$

$$Ev_{i,B}=-\beta_i bt_0\left[1+\xi\left(\frac{Hx_A^{t,a}+\bar{\eta}_a^{BB}x_B^{t,a}+Kx_C^{t,a}}{\hat{C}_a^A\bar{\eta}_a^{AA}}\right)^{\psi}\right]-$$
$$\alpha_i\varepsilon_B\times c_i(v)+\sum_{j\in V_{-i}}e_{ij}\sum_{x=1}^{16}r^{i\to x,j}\cdot R_j^x \tag{14}$$

$$Ev_{i,C}=-\beta_i bt_0\left[1+\xi\left(\frac{Hx_A^{t,a}+\bar{\eta}_a^{BB}x_B^{t,a}+Kx_C^{t,a}}{\hat{C}_a^A\bar{\eta}_a^{AA}}\right)^{\psi}\right]-$$
$$\alpha_i\varepsilon_C\times c_i(v)+\sum_{j\in V_{-i}}e_{ij}\sum_{x=1}^{16}r^{i\to x,j}\cdot R_j^x \tag{15}$$

The average expected return on a vehicle v_i is

$$\bar{E}v_i=y_A\cdot Ev_{i,A}+y_B\cdot Ev_{i,B}+y_C\cdot Ev_{i,C} \tag{16}$$

The replica dynamic equations are

$$\mathrm{d}y_A=y_A\cdot(Ev_{i,A}-\bar{E}v_i)=$$
$$y_A\cdot[(y_B+y_C)Ev_{i,A}-(y_BEv_{i,B}+y_CEv_{i,C})] \tag{17}$$

$$\mathrm{d}y_B=y_B\cdot(Ev_{i,B}-\bar{E}v_i)=$$
$$y_B\cdot[(y_A+y_C)Ev_{i,B}-(y_AEv_{i,A}+y_CEv_{i,C})] \tag{18}$$

$$\mathrm{d}y_C=y_C\cdot(Ev_{i,C}-\bar{E}v_i)=$$
$$y_C\cdot[(y_A+y_B)Ev_{i,C}-(y_AEv_{i,A}+y_BEv_{i,B})] \tag{19}$$

where y_A represents the proportion of aggressive vehicles in the road section a, y_B represents the ratio of stable vehicles in the road section, and y_C represents the proportion of slow vehicles in the road section.

In the above equations, $Ev_{i,A}$ represents the expected income when the driving vehicle v_i is aggressive, $Ev_{i,B}$ represents the expected income when the driving vehicle v_i is stable, and $Ev_{i,C}$ represents the expected income when the driving vehicle v_i is slow. $\sum_{x=1}^{16} r^{i\to x,j}\cdot R_j^x$ represents the benefit of a moving car v_i affected by its neighbor strategy. $r^{i\to x,j}$ represents the probability that the vehicle v_i strategy is transferred to its neighbor v_j's method S_x. $\bar{E}v_i$ represents the average expected return.

2.4 Equilibrium solution

According to the replicated dynamic equations of Eqs. (17)−(19), the critical value of the expected revenue for aggressive vehicles is

$$E^*(v_{i,A})=\frac{y_BEv_{i,B}+y_CEv_{i,C}}{1-y_A} \tag{20}$$

The critical value of the expected revenue for stable vehicles is

$$E^*(v_{i,B})=\frac{y_AEv_{i,A}+y_CEv_{i,C}}{1-y_B} \tag{21}$$

The critical value of the expected revenue for slow vehicles is

$$E^*(v_{i,C})=\frac{y_AEv_{i,A}+y_BEv_{i,B}}{1-y_C} \tag{22}$$

Theorem 1: When the expected return of the driving vehicle of type I is less than the critical value $E^*(v_{i,I})$, the driving vehicle will not continue the current strategy over time.

Proof: Assuming that the driving vehicles on the road are divided into aggressive type, stable type, and slow type, the driving cars are discussed, respectively.

(1) When the driving vehicle is aggressive:

If $Ev_{i,A}<E^*(v_{i,A})$, the replicated dynamic equation of the proportion of aggressive driving vehicles is less than zero, which means that in this case, the balance of aggressive driving vehicles will tend to be zero.

(2) When the driving vehicle is stable:

If $Ev_{i,B}<E^*(v_{i,B})$, the replicated dynamic equation of the proportion of stable vehicles is less than zero, which means that in this case, the balance of stable vehicles will tend to be zero.

(3) When the driving vehicle is slow:

If $Ev_{i,C}<E^*(v_{i,C})$, the replicated dynamic equation of the proportion of slow vehicles is less than zero, the balance of slow vehicles will tend to be zero in this case.

Therefore, when the expected return of the vehicle is less than the critical value $E^*(v_{i,I})$, the driving vehicle will not drive on the road over time. □

Based on Theorem 1, it can further push the vehicle affected by adjacent vehicles when driving strategy change. For the convenience of analysis, the vehicle in the adjacent lane is referred to as “neighbor vehicle”. Centered on a particular vehicle (the vehicle in the following referred to as “main vehicle”), the subsequent deduction to explore its affected by surrounding vehicles can be got.

Inference 1: When the front vehicle is stable and the neighbor vehicles is existence, the main vehicle types will only change in the following situation. Details are as follows:

(1) When the front vehicle is stable and the neighbor vehicle is stable, the aggressive main vehicle transitions stable.

(2) When the front vehicle is stable and the neighbor

vehicle is slow, the aggressive main vehicle transitions stable.

Proof: When the front vehicle is stable, and the main vehicle is aggressive, if the neighbor vehicle is aggressive, it will be urged to accelerate, then change lanes, and the main vehicle will keep the same type. If the neighbor vehicle is stable, the main vehicle will not change lanes to avoid a collision, and the main vehicle will become a stable type. If the neighbor vehicle is a slow type, the main vehicle will not change lanes in order to avoid a collisionm, and the main vehicle will become stable.

When the front car is stable and the main vehicle is stable, the main vehicle will keep the same type regardless of the type of the neighbor vehicle. When the front vehicle is stable and the main vehicle is slow, the main vehicle will keep the same type regardless of the type of the neighbor vehicle, as shown in Fig. 3. □

Inference 2: When the front vehicle is slow and neighbor vehicles is existence, the main vehicle type will only change in the following situations. The specifics are as follows:

(1) When the front vehicle is slow and the neighbor vehicle is aggressive, the stable main vehicle becomes slow.

(2) When the front vehicle is slow and the neighbor vehicle is stable, the aggressive main vehicle and the stable main vehicle become slow.

(3) When the front vehicle is slow and the neighbor vehicle is slow, the aggressive main vehicle and the stable main vehicle become slow.

Proof: When the front vehicle is slow, and the main vehicle is aggressive, if the neighbor vehicle is aggressive, it is urged to accelerate and then change lanes, and the main vehicle remains the same type. If the neighbor vehicle is stable, the main vehicle will not change lanes to avoid a collision, and the main vehicle will become slow. If the neighbor vehicle is slow, the main vehicle will not change lanes to avoid a collision, and the main vehicle will become slow type.

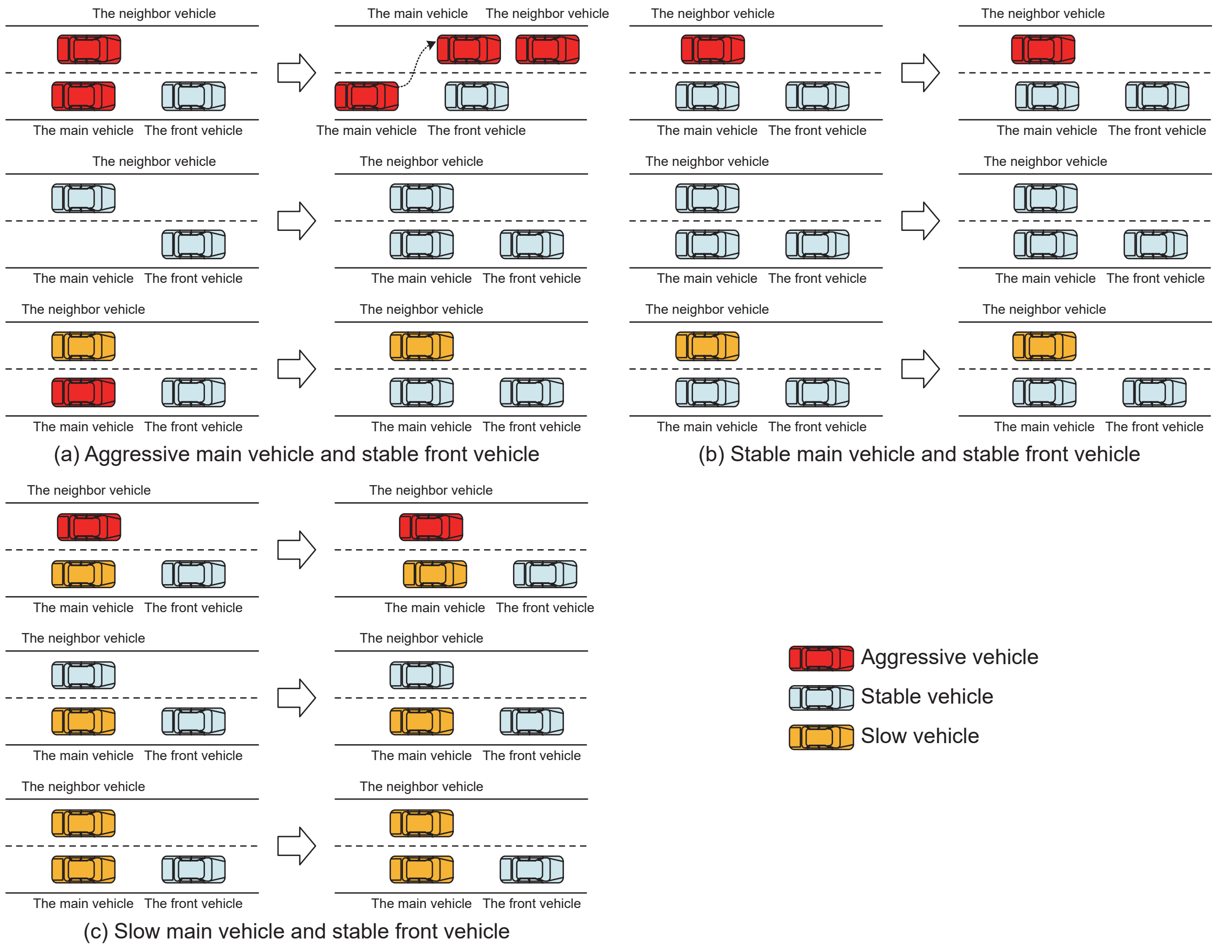


Fig. 3 Change diagram of the main vehicle type when the front vehicle is stable and the neighbor vehicle is existence.

When the front vehicle is slow, and the main vehicle is stable type, if the neighbor vehicle is aggressive, the main vehicle will not change lanes to avoid a collision, and the main vehicle will become a slow type. If the neighbor vehicle is stable, the main vehicle will not change lanes to avoid a collision, and the main vehicle will become a slow type. If the neighbor vehicle is slow, the main vehicle will not change lanes to avoid a collision, and the main vehicle will become a slow type.

When the front vehicle is slow and the main vehicle is slow, the main vehicle will remain the same type regardless of the type of the neighbor vehicle. This is shown in Fig. 4. □

Theorem 2: When the expected benefit of vehicle is more than its critical value $E^{*}(v_{i,I})$, each type of vehicle will continue to drive the previous driving strategy over time.

Proof: When the expected return of aggressive vehicles is more than its critical value, that is, $Ev_{i,A} > \dfrac{y_B Ev_{i,B} + y_C Ev_{i,C}}{y_B + y_C}$, the stable solution of the proportion of aggressive vehicles is

$$y_A{}^{*} = \left[y_B{}^2 M\left(r_A^{i\to x,j} - r_B^{i\to x,j}\right) + y_B y_C M\left(2r_A^{i\to x,j} - r_B^{i\to x,j} - r_C^{i\to x,j}\right) + y_C{}^2 M\left(r_A^{i\to x,j} - r_C^{i\to x,j}\right)\right] / \left[(y_B + y_C)M(r_B^{i\to x,j} + r_C^{i\to x,j} - 2r_A^{i\to x,j})\right].$$

When the expected return of stable vehicles is more than its critical value, that is, $Ev_{i,B} > \dfrac{y_A Ev_{i,A} + y_C Ev_{i,C}}{y_A + y_C}$, the stable solution of the proportion of stable vehicles is

$$y_B{}^{*} = \left[y_A{}^2 M\left(r_B^{i\to x,j} - r_A^{i\to x,j}\right) + y_A y_C M\left(2r_B^{i\to x,j} - r_A^{i\to x,j} - r_C^{i\to x,j}\right) + y_C{}^2 M\left(r_B^{i\to x,j} - r_C^{i\to x,j}\right)\right] / \left[(y_A + y_C)M\left(r_A^{i\to x,j} + r_C^{i\to x,j} - 2r_B^{i\to x,j}\right)\right].$$

When the expected return of slow vehicles is more than its critical value, that is, $Ev_{i,C} > \dfrac{y_A Ev_{i,A} + y_B Ev_{i,B}}{y_A + y_B}$, the stable solution of the proportion of slow vehicles is

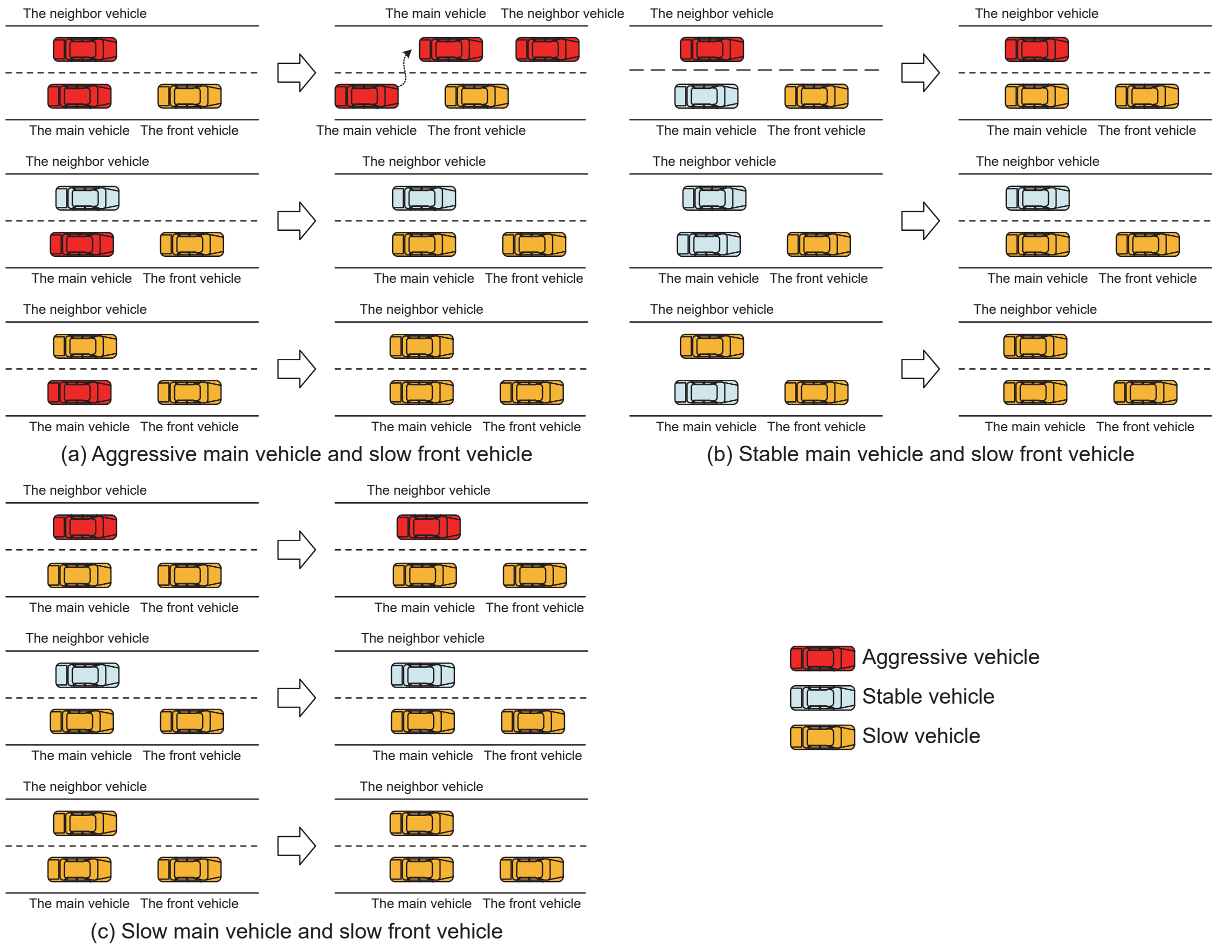


Fig. 4 Change diagram of the main vehicle type when the front vehicle is slow and the neighbor vehicle is existence.

$$
\begin{aligned}
{y_C}^* = \Big[&{y_A}^2 M\left(r_C^{i\to x,j} - r_A^{i\to x,j}\right) + \\
&y_B y_A M\left(2r_C^{i\to x,j} - r_B^{i\to x,j} - r_A^{i\to x,j}\right) + \\
&{y_B}^2 M\left(r_C^{i\to x,j} - r_B^{i\to x,j}\right)\Big] / \\
&\Big[(y_A + y_B) M\left(r_B^{i\to x,j} + r_A^{i\to x,j} - 2r_C^{i\to x,j}\right)\Big],
\end{aligned}
$$

where $M(x) = \sum_{j\in V_{-i}} e_{ij}\left(\sum_{x=1}^{16} x \cdot R_j^{x,z}\right)$ represents the sum of the payoffs of a car v_i affected by its neighbor policy.

The above analysis shows that aggressive, stable, and slow vehicles will be stabilized. Over time, each type of vehicle will continue to drive the previous driving strategy, so it is proven. □

Theorem 2 gives the conditions for the vehicle to maintain its own driving strategy, based on which an Inference 3 can be drawn:

Inference 3: When there is no the neighbor vehicle, the main vehicle type will not be affected by the type of the front vehicle, and the main vehicle will still maintain its own driving strategy.

Proof: When the main vehicle is aggressive, since there is no the neighbor vehicle, the main vehicle can be changed lanes regardless of the front vehicle, keeping it still aggressive.

When the main vehicle is a stable type, the aggressive front vehicle and the stable front vehicle will not hinder the stable main vehicle, so that the main vehicle type will not change; the slow type front vehicle will affect the stable main vehicle driving, but because there is no the neighbor vehicle, the main vehicle type can remain unchanged by changing lanes.

When the main vehicle is a slow type, the main vehicle can be kept slow regardless of the type of the front vehicle.

Therefore, it is proved. The change of the main vehicle type when there is no the neighbor vehicle is shown in Fig. 5. □

Inference 4: When the front vehicle is aggressive, the main vehicle type does not change, regardless of the type of the neighbor vehicle.

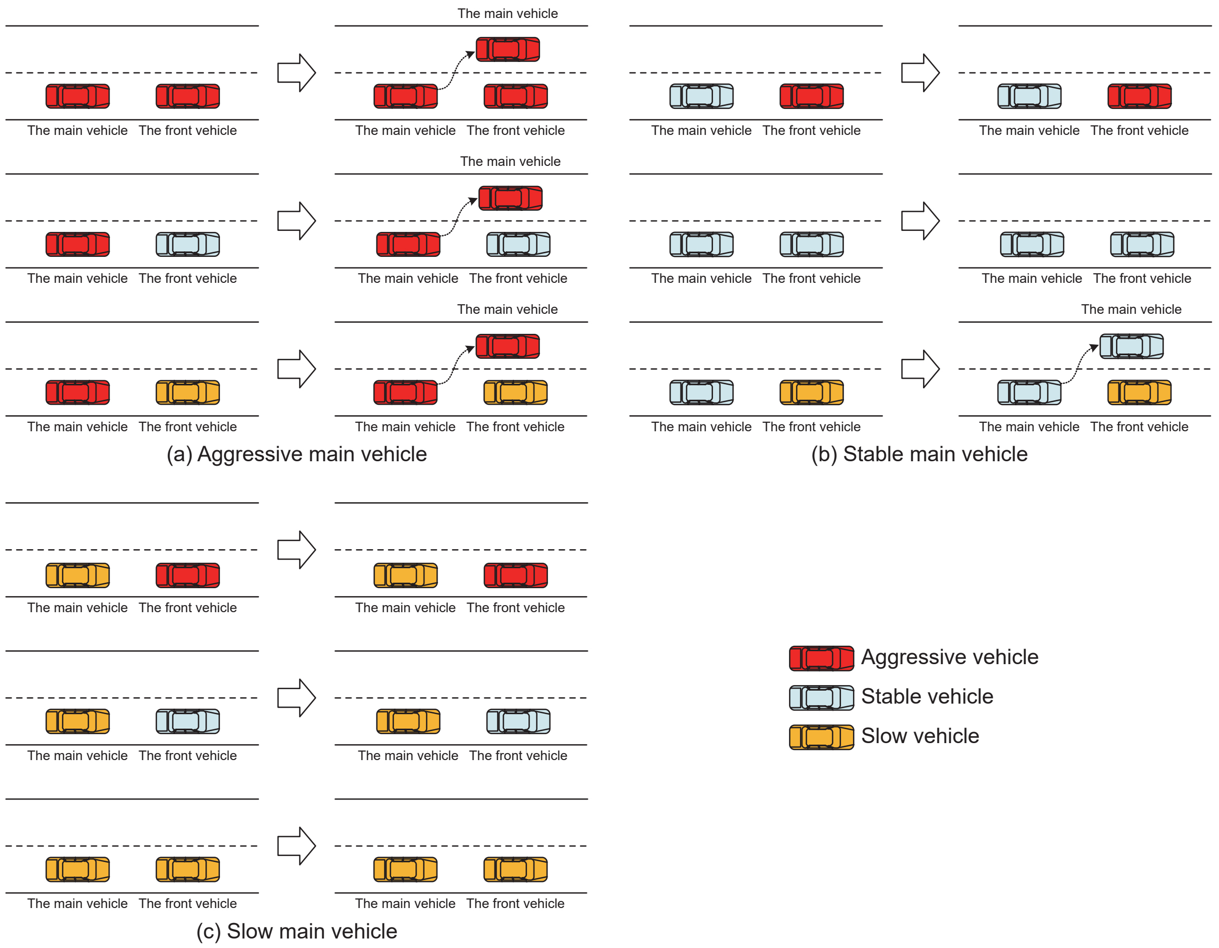


Fig. 5 Change diagram of the main vehicle type when the neighbor vehicle is inexistence.

Proof: When the front vehicle is aggressive, and the main vehicle is also aggressive, if the neighbor vehicle is aggressive, it is urged to accelerate and then change lanes; if the neighbor vehicle is stable, it will not change lanes; if the neighbor vehicle is slow, it will not change lanes, and eventually it will remain unchanged from the original type.

When the front vehicle is aggressive and the main vehicle is stable, the main vehicle will remain the same regardless of the type of the neighbor vehicle. When the front vehicle is aggressive, and the main vehicle is slow, the main vehicle remains the same type regardless of the type of the neighbor vehicle. This is shown in Fig. 6. □

Theorem 3: The proportion of aggressive vehicles has an inverted U-shaped relationship with the accident probability and a U-shaped relationship with the accident probability of stable and slow cars.

Proof: Bring Eqs. (14)−(16) into Eq. (17) to get

$$\begin{aligned}
&\mathrm{d}y_A = y_A\cdot[(y_B+y_C)Ev_{i,A}-(y_B Ev_{i,B}+y_C Ev_{i,C})]=\\
&y_A\cdot[y_B(Ev_{i,A}-Ev_{i,B})+y_C(Ev_{i,A}-Ev_{i,C})]=\\
&y_A\cdot\left\{y_B\left[-\beta_i b t_0\left(1+\xi\left(\frac{Hx_A^{t,a}+\bar{\eta}_a^{BB}x_B^{t,a}+Kx_C^{t,a}}{\hat{C}_a^A\bar{\eta}_a^{AA}}\right)^{\psi}\right)+\right.\right.\\
&\left.\beta_i b t_0\left(1+\xi\left(\frac{Hx_A^{t,a}+\bar{\eta}_a^{BB}x_B^{t,a}+Kx_C^{t,a}}{\hat{C}_a^A\bar{\eta}_a^{AA}}\right)^{\psi}\right)\right]+\\
&y_C\left[-\beta_i b t_0\left(1+\xi\left(\frac{Hx_A^{t,a}+\bar{\eta}_a^{BB}x_B^{t,a}+Kx_C^{t,a}}{\hat{C}_a^A\bar{\eta}_a^{AA}}\right)^{\psi}\right)+\right.\\
&\left.\beta_i b t_0\left(1+\xi\left(\frac{Hx_A^{t,a}+\bar{\eta}_a^{BB}x_B^{t,a}+Kx_C^{t,a}}{\hat{C}_a^A\bar{\eta}_a^{AA}}\right)^{\psi}\right)\right]+\\
&\alpha_i\cdot c_i(v)[y_B(\varepsilon_B-\varepsilon_A)+y_C(\varepsilon_C-\varepsilon_A)]+\\
&y_B\left(\sum_{j\in V_{-i}}e_{ij}\sum_{x=1}^{16}r^{i\to x,j}\cdot R_j^x-\sum_{j\in V_{-i}}e_{ij}\sum_{x=1}^{16}r^{i\to x,j}\cdot R_j^x\right)+\\
&\left.y_C\left(\sum_{j\in V_{-i}}e_{ij}\sum_{x=1}^{16}r^{i\to x,j}\cdot R_j^x-\sum_{j\in V_{-i}}e_{ij}\sum_{x=1}^{16}r^{i\to x,j}\cdot R_j^x\right)\right\}=\\
&y_A\cdot\alpha_i\cdot c_i(v)[y_B\varepsilon_B+y_C\varepsilon_C-(y_B+y_C)\varepsilon_A]
\end{aligned} \tag{23}$$

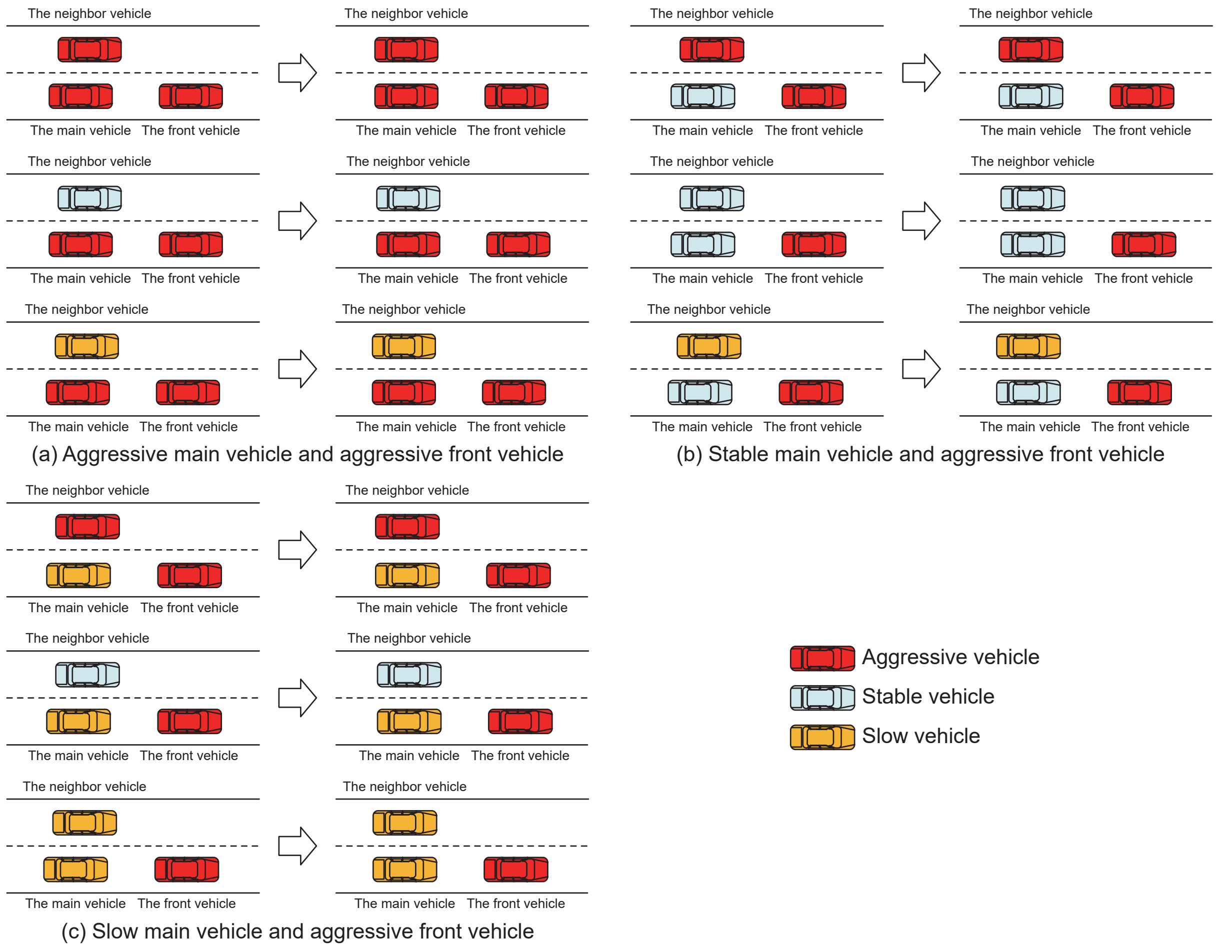


Fig. 6 Change diagram of the main vehicle type when the front vehicle is aggressive and the neighbor vehicle is existence.

From Eq. (23), the following conclusions can be obtained under the condition that other conditions remain unchanged.

When $\varepsilon_A < (y_B\varepsilon_B + y_C\varepsilon_C)/(1-y_A)$, $\mathrm{d}y_A > 0$. when $\varepsilon_A > (y_B\varepsilon_B + y_C\varepsilon_C)/(1-y_A)$, $\mathrm{d}y_A < 0$, as shown in Fig. 7a.

When $\varepsilon_B < [(y_B+y_C)\varepsilon_A - y_C\varepsilon_C]/y_B$, $\mathrm{d}y_A < 0$; when $\varepsilon_B > [(y_B+y_C)\varepsilon_A - y_C\varepsilon_C]/y_B$, $\mathrm{d}y_A > 0$, as shown in Fig. 7b.

When $\varepsilon_C < [(y_B+y_C)\varepsilon_A - y_B\varepsilon_B]/y_C$, $\mathrm{d}y_A < 0$; when $\varepsilon_C > [(y_B+y_C)\varepsilon_A - y_B\varepsilon_B]/y_C$, $\mathrm{d}y_A > 0$, as shown in Fig. 7c.

Therefore, it can be seen that the proportion of aggressive driving vehicles has an inverted U-shaped relationship with the accident probability and has a U-shaped relationship with the accident probability of stable and slow type. □

From Theorem 3, one derives the following Inference 5:

Inference 5: The higher the proportion of aggressive vehicles, the greater the potential risk on the road, and the potential risk is $\varepsilon = y_A\varepsilon_A + y_B\varepsilon_B + y_C\varepsilon_C$.

Proof: From Theorem 3, it can be concluded that the critical values of the vehicle accident probability for aggressive type, stable type, and slow type can be concluded.

The critical value of the accident probability of the aggressive vehicles, the maximum proportions, and the minimum proportions of aggressive vehicles are

$$\varepsilon_A^* = (y_B\varepsilon_B + y_C\varepsilon_C)/(1-y_A),$$
$$y_A^{\max} = 1 - (y_B\varepsilon_B + y_C\varepsilon_C)/\varepsilon_A,$$
$$y_A^{\min} = 1 - (y_B + y_C)^2\varepsilon_A/(y_B\varepsilon_B + y_C\varepsilon_C).$$

Similarly, the critical value of accident probability of stable vehicles, the maximum proportion, and the minimum proportion of stable vehicles are

$$\varepsilon_B^* = (y_A\varepsilon_A + y_C\varepsilon_C)/(1-y_B),$$
$$y_B^{\max} = 1 - (y_A\varepsilon_A + y_C\varepsilon_C)/\varepsilon_B,$$
$$y_B^{\min} = 1 - (y_A + y_C)^2\varepsilon_B/(y_A\varepsilon_A + y_C\varepsilon_C).$$

The critical value of accident probability of slow vehicles, the maximum proportion, and the minimum proportion of slow vehicles are

$$\varepsilon_C^* = (y_B\varepsilon_B + y_A\varepsilon_A)/(1-y_C),$$
$$y_C^{\max} = 1 - (y_B\varepsilon_B + y_A\varepsilon_A)/\varepsilon_C,$$
$$y_C^{\min} = 1 - (y_B + y_A)^2\varepsilon_C/(y_B\varepsilon_B + y_A\varepsilon_A).$$

Figure 7 shows the relationship between vehicle proportion and accident probability. According to Theorem 3, the proportion of type I vehicles has an inverted U-shaped relationship with the accident probability of this type of vehicles, and a U-shaped relationship with the accident probability of non-type I

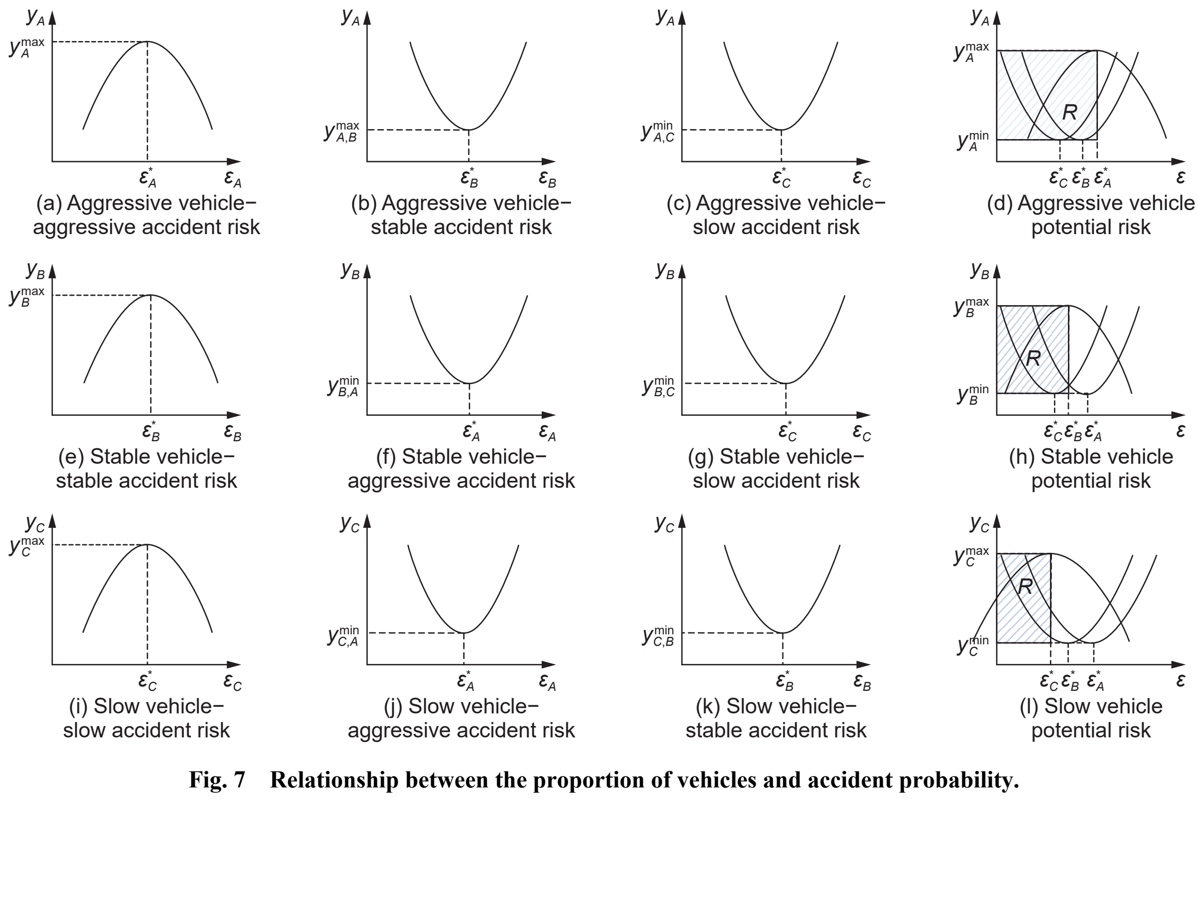


Fig. 7 Relationship between the proportion of vehicles and accident probability.

vehicles. Figure 7a shows, all else being equal, the effect of accident risk generated by aggressive vehicle behavior on the proportion of aggressive vehicles. Figure 7b shows, all else being equal, the effect of accident risk arising from stable vehicle behavior on the proportion of aggressive vehicles. Figure 7c shows, all else being equal, the effect of accident risk arising from slow vehicle behavior on the proportion of aggressive vehicles. Figure 7d shows the combined effect of aggressive, slow, and stable behavior on the proportion of aggressive vehicles. The shaded part R is the maximum potential risk of the bold type.

Similarly, it can be seen that the maximum potential risk of the stable type is the shaded part shown in Fig. 7h. The maximum potential risk of the slow type is the shaded section shown in Fig. 7l. As shown in Fig. 7, the potential road risk caused by different proportions of vehicles is different, and the higher the proportion of aggressive vehicles, the greater the road potential risk. So it is proven. □

Figure 7 shows the relationship between the proportion of vehicles and the accident rate, respectively, describing the mixed potential accident risk between different types of vehicles.

Take aggressive vehicles as an example. With the increasing number of aggressive vehicles on the road, their accident risk is increasing, and when the number of aggressive vehicles increases to the maximum, it will reach the critical value of risk that aggressive vehicles are willing to bear. When the accident risk exceeds this critical value, some aggressive vehicles will change their driving behavior because they are unwilling to bear too much accident risk, and the proportion of aggressive vehicles will continue to decrease, as shown in Fig. 7a.

In addition to vehicles affected by their own type, they are also affected by vehicles other than their own type. When there are only aggressive vehicles and stable vehicles on the road, the aggressive vehicles constantly change their behavior into stable vehicles, which increases the accident risk of stable vehicles. When the critical value of stationary accident risk is reached, the proportion of aggressive vehicles reaches the minimum value, at which time it will be profitable to change their behavior to aggressive, so the proportion of aggressive vehicles will increase, as shown in Fig. 7b.

When there are only aggressive vehicles and slow vehicles on the road, with the increase in accident risk, aggressive vehicles constantly change their behavior into slow vehicles. When the critical value of accident risk is reached, the proportion of aggressive vehicles reaches a minimum value, after which it will be profitable to change their behavior to the aggressive class, so the proportion of aggressive vehicles will increase, as shown in Fig. 7c.

When the road is mixed with three types of vehicles: aggressive, stable, and slow, the potential accident risk of aggressive vehicles can be obtained according to the difference in accident risk tolerance of different types of vehicles, as shown in Fig. 7d. The analysis of Figs. 7e−7l is similar to that of Figs. 7a−7d, so it is not necessary to go into details here.

In summary, whether a vehicle on the road exhibits a particular characteristic (such as aggressive, stable, or slow) is the result of its careful consideration of time gains and safety gains, that is, whether there is a specific type of vehicle on the road is related to its individual perceived total benefits. The original driving strategy will only be continued if its total return is more significant than its critical return. Otherwise, it will change its approach. When there are three types of vehicles on the road in a particular proportion, the car will consider how its safety benefits and time benefits are distributed to maximize the total benefits. The ratio of vehicles is affected by the combination of aggressive, slow, and stable accident risks. The higher the proportion of aggressive cars, the greater the potential danger on the road.

The above analysis shows that in the early days, under the condition of smooth roads, the competition for road rights between different vehicles was not apparent. The proportion of cars increased, and the accident rate also increased. When the critical value is reached, the balance of cars of various types has reached its maximum, and the road is close to saturation. People will think more about security factors to be more secure at the expense of time. After reaching the threshold, the proportion of vehicles is constantly reduced in order to avoid increasing the likelihood of accidents.

3 Information Guidance Model for Managers to Drive Vehicles

Traffic information is an essential factor affecting the travel behavior choice of driving vehicles[32]. With the development of intelligent automobiles, the popularity of mobile and onboard terminals, as well as the result of extensive data analysis and mining and wireless communication technology, the vehicle road coordination system based on wireless interconnection allows managers to accurately perceive the overall situation of the road network and road transportation, and provide personalized services. Managers and vehicles work together to achieve the goal of safe, efficient, and green travel.

3.1 Problem description

The process of traffic information guidance is also a dynamic interaction process in which traffic managers and driving vehicle drivers play each other (as shown in Fig. 8):

(1) The manager observes the traffic capacity of the road network and determines whether the operation efficiency of the road network needs to be optimized.

(2) After determining the need for optimization, the manager actively releases guidance information to the driving vehicle according to the driving vehicle profile defined by the information platform.

(3) The driving vehicle receives the induction information, judges the data according to the road environment in which it is located, and decides whether to adopt it.

(4) The driving vehicle combines the existing prior probability of road capacity (congestion, non-congestion), selects the optimal behavior strategy, and updates the posterior probability judgment of the road condition.

(5) After observing the behavior selection of the moving vehicle, the manager determines whether the operation efficiency of the road network is optimal.

(6) Cycle through the above processes until the optimum road network operation efficiency.

3.2 Construction of information guidance model

The purpose of choosing different driving modes during road driving is to minimize the impedance of its road section. Still, it may make the road network environment unable to operate normally. According to the analysis in the previous area, the accident probability of different types of vehicles is different, and the accident probability is related to the proportion of different types of cars. The information publisher

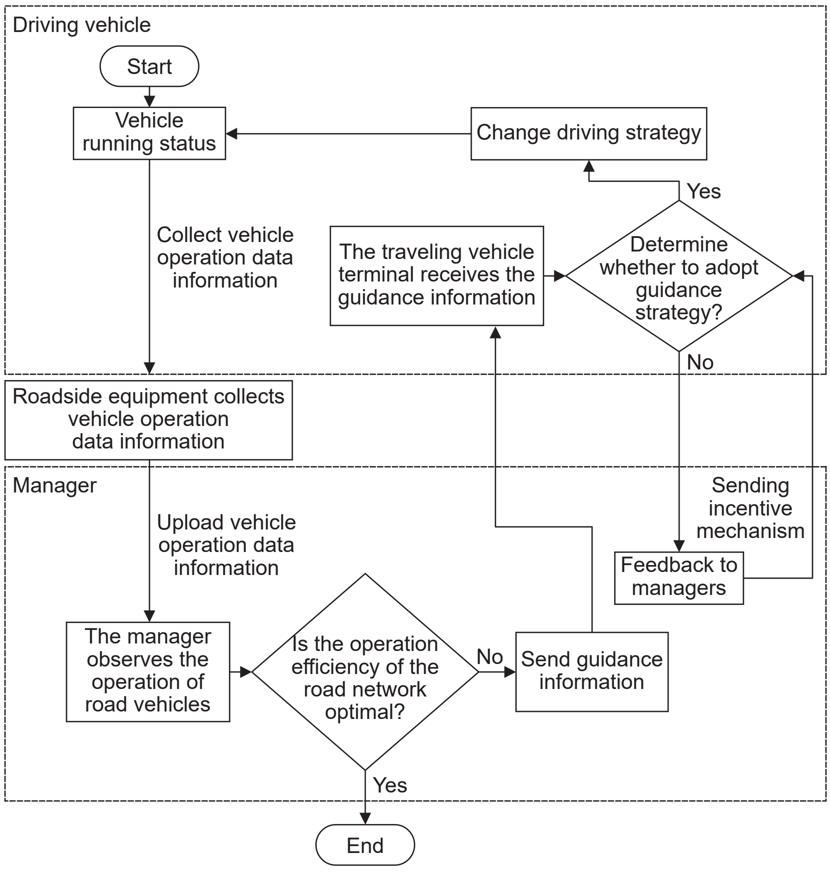


Fig. 8 Flow chart of mutual information feed between manager and driving vehicle.

accurately judges the driving vehicles through the user's accurate portrait and releases accurate guidance information to the target user to change the dangerous behavior strategy to reduce the possibility of traffic accidents. For example, warning information is issued for radical driving vehicles to stop speeding up road congestion such as running traffic lights, changing lanes at will, and speeding, and warning information is given for slow driving vehicles to improve their driving speed.

3.2.1 Manager objective function

The manager's purpose is to minimize the loss of the road network and ensure the safety and reliability of the road network. The goal of driving vehicles is to reduce their section impedance.

In this stage t, the objective function of the manager is

$$\min U_D(t) = L_R(t) = J(t-1)\cdot E(t-1) \tag{24}$$

Road network system loss (L_R) refers to the loss of road network environment caused by the disorderly behavior of driving vehicles, including loss of individual travel efficiency, loss of travel efficiency of the whole road network, traffic congestion, reduction of road capacity, and reduction of road capacity traffic travel safety factor. Road network system loss can be described by traffic congestion degree (J) and safety factor damage (E). This paper sets the traffic congestion degree as high, medium, and low. The higher the congestion level, the greater the system loss when damaged road network stability. The safety factor damage is quantified by five factors: traffic violation rate, safe vehicle operation, accident rate, mortality, and injury rate.

3.2.2 Objective function of moving vehicle

The goal of the driving vehicle is to minimize the impedance of its road section, and the pursuit is to pass through the road section in a short time based on safety.

In this stage t, the objective function of driving vehicles on the road a is

$$\max \quad U_V(t) = \sum_i (R_i(t) + R_{Si}(t)) \tag{25}$$

s.t.,

$$R_i = -\alpha_i\varepsilon_I \times c_i(v) - \beta_i b t_0\left(1+\xi\left(\frac{Hx_A^{t,a} + \bar{\eta}_a^{BB} x_B^{t,a} + Kx_C^{t,a}}{\hat{C}_a^A \bar{\eta}_a^{AA}}\right)^{\psi}\right),$$

$$R_{Si}(t) = \sum_{j\in V_{-i}} e_{ij}\cdot r_{ij}(t)\cdot R_j(t-1),$$

$$n_a(t) = n_a(t-1) + u_a(t-1) - g_a(t-1),$$

where $R_i(t)$ is the individual income of the vehicle v_i in the phase t. $R_{Si}(t)$ is the income of the car after the stage t manager guidance the information of the driving vehicle v_i. $u_a(t-1)$ is the number of vehicles flowing in on stage $t-1$, on the road a. $g_a(t-1)$ is the number of vehicles drifting out of phase $t-1$, on the road a. $n_a(t-1)$ is the number of reserved vehicles on stage $t-1$, on the road a. $n_a(t)$ is the number of stocked vehicles on the scene t, route a.

3.2.3 Mutual feed mode between manager and driving vehicle

When the manager releases the information, it will affect the strategy transfer probability of the driving vehicle, so the strategy transfer probability is updated as

$$r_{ij}(t) = \frac{1}{1+\exp\left(\dfrac{R_i(t-1)-R_j(t-1)}{\zeta}\right)} + \mu(t) \tag{26}$$

where μ is the impact of issuing information to the manager on the strategy transfer.

At time t, the revenue function of the vehicle is

$$U_V(t) = \sum_i \left\{ -\beta_i b t_0\left[1+\xi\left(\frac{Hx_A^{t,a} + \bar{\eta}_a^{BB} x_B^{t,a} + Kx_C^{t,a}}{\hat{C}_a^A \bar{\eta}_a^{AA}}\right)^{\psi}\right] - \alpha_i\varepsilon_I \times c_i(v) + \sum_{j\in V_{-i}} e_{ij}\cdot \left[\frac{1}{1+\exp\left(\frac{R_i(t-1)-R_j(t-1)}{\zeta}\right)} + \mu(t)\right]\cdot R_j(t-1)\right\} \tag{27}$$

4 Algorithm Analysis

At present, the information guidance is mainly through traffic lights, variable information boards, on-board terminals, etc., and rarely provides targeted induction information to vehicles based on their behavioral preferences. Based on this, this study starts from the dynamic behavioral preferences of vehicles, constructs user portraits, obtains the real-time changing behavioral preferences of vehicles, and proposes targeted information induction algorithms. This not only helps to identify the true type of vehicle, but also helps to promote stable traffic flow.

4.1 Portrait of the user of the moving vehicle

The user portrait label of the driving vehicle is composed of the dynamic label and static label, of which the static label is composed of the essential attributes of the driving vehicle such as age, gender, and driving age[53−56]. Dynamic labels consist of driving speed, lane change frequency, traffic light crossing behavior, safety distance to follow the car, steering response time, and brake reaction time[57−60]. The user portrait of the driving vehicle can be expressed in the following form.

$$\begin{aligned}
&\text{Userprofile} = \text{Static} \cup \text{Dynamic},\\
&\text{Static} = \{(m_1,\omega_{m_1}),(m_2,\omega_{m_2}),\ldots,(m_i,\omega_{m_i}),\ldots,(m_l,\omega_{m_l})\},\\
&\text{Dynamic} = \{(k_1,\omega_{k_1}),(k_2,\omega_{k_2}),\ldots,(k_j,\omega_{k_j}),\ldots,(k_n,\omega_{k_n})\},
\end{aligned}$$

where Static represents the static attribute tag set. Dynamic represents the dynamic attribute tag set. m_i stands for a static attribute tag ($i = 1,2,\ldots,l$). ω_{m_i} means the weight of the label m_i. k_j represents the active attribute tag ($j = 1,2,\ldots,n$). ω_{k_j} represents the weight of the dynamic attribute label k_j. The label table of the driving vehicle user portrait is shown in Table 2.

In this paper's dynamic generation method, the static attribute label remains unchanged, and the active attribute label is in change. As shown in Table 2, the dynamic labels of the driving vehicle in this paper include 16 types of potential behaviors, which constitute a collection of optional driving behaviors of

Table 2　User behavior preference portrait label table.

Label	Criteria		Describe	Sign
Dynamic label	Speed	Standard speed (speed_0)	Accelerate driving ($\text{speed}_A > \text{speed}_0$)	k_1
			Steady speed driving ($\text{speed}_B = \text{speed}_0$)	k_2
			Slow driving ($\text{speed}_C < \text{speed}_0$)	k_3
	Lane change	Standard lane change (lanec_0)	Frequent lane change ($\text{lanec}_A > \text{lanec}_0$)	k_4
			Normal lane change ($\text{lanec}_B = \text{lanec}_0$)	k_5
			Low-frequency lane change ($\text{lanec}_C < \text{lanec}_0$)	k_6
	Traffic light	Number	Pass the yellow light	k_7
			Pass the green light	k_8
	Safety distance	Standard safety distance (dist_0)	Close safety distance ($\text{dist}_A < \text{dist}_0$)	k_9
			Moderate safety distance ($\text{dist}_B = \text{dist}_0$)	k_{10}
			Far safety distance ($\text{dist}_C > \text{dist}_0$)	k_{11}
	Steering reaction time	Standard steering reaction time (steer_0)	Quick steering ($\text{steer}_A < \text{steer}_0$)	k_{12}
			Smooth steering ($\text{steer}_B = \text{steer}_0$)	k_{13}
			Slow steering ($\text{steer}_C > \text{steer}_0$)	k_{14}
	Braking reaction time	Standard braking reaction time (brak_0)	Emergency braking ($\text{brak}_A < \text{brak}_0$)	k_{15}
			Smooth braking ($\text{brak}_{B/C} < \text{brak}_0$)	k_{16}
Static label	Age		18−30	m_1
			31−50	m_2
			51−70	m_3
			More than 70	m_4
	Gender		Male	m_5
			Female	m_6
	Driving age		0−6 years	m_7
			7−16 years	m_8
			More than 16 years	m_9

driving vehicles. In different driving environments, the priority of each car's operating behavior selection is represented by the set of behavioral preferences.

In this paper, the dynamic behavior preference set of the driving vehicle v_i is composed of the top six behaviors of driving behavior weight values, and the other ten behaviors constitute its candidate preference set. As shown in Fig. 9, dynamic labels and behavioral preference sets for moving vehicles often change over time. To accurately predict the behavior preference of the driving vehicle v_i and make timely information induction, it is necessary to characterize the behavior preference set of the driving vehicle. To this end, it can be reversed based on the historical driving data of the car v_i. The number of occurrences of driving behavior in the car v_i can be constructed as a set of behaviors:

$$S_i^t = \{s_{k_1}^{t,i}, s_{k_2}^{t,i}, \ldots, s_{k_{16}}^{t,i}\},$$

where $s_{k_j}^{t,i}$ represents the number of times the j label of the vehicle v_i appears. Based on the set of behaviors obtained, follow these steps to receive a collection of dynamic behavior preferences ($D_i^{t_j} = \{d_1^{t_j}, d_2^{t_j}, \ldots, d_6^{t_j}\}$) of the vehicle v_i at different times t_j ($1 \leqslant j \leqslant n$):

(1) Determine the weight of the vehicle's historical behavior

The initial weights of driving behavior within each S_i ($1 \leqslant i \leqslant n$) are estimated to explore the historical behavioral preferences of the moving vehicle. After preprocessing all the behavior information in the behavior set S_i, the driving behavior weight is calculated by the term frequency-inverse document frequency (TF-IDF) method, and the weight of the k_j

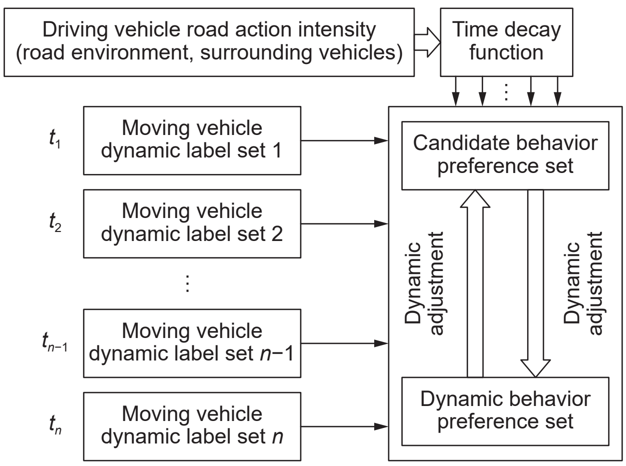


Fig. 9 Diagram of the generation and update process of dynamic attribute tags.

tag of the driving vehicle v_i can be obtained. The weight of the k_j is

$$\omega_{k_j}^i = \mathrm{TF}(k_j^i) \times \mathrm{IDF}(k_j^i) \tag{28}$$

$$\text{s.t.,} \quad \mathrm{TF}(k_j^i) = \frac{s_{k_j}^i}{\sum\limits_{j \in k} s_{k_j}^i},$$

$$\mathrm{IDF}(k_j^i) = \frac{\sum\limits_{i \in V} \sum\limits_{j \in k} s_{k_j}^i}{\sum\limits_{i \in V} x_i(k_j^i)},$$

where $\mathrm{TF}(k_j^i)$ represents the proportion of the tag k_j in all tags of the user v_i. $\mathrm{IDF}(k_j^i)$ indicates how scarce the label k_j is among all labels. $s_{k_j}^i$ represents the number of times the j-th label of the vehicle v_i appears. $x_i(k_j^i)$ means whether the moving vehicle v_i contains a k_j^i label if the driving vehicle v_i contains a k_j^i label otherwise $x_i(k_j^i) = 0$. k_j^i represents the j-th label of the moving vehicle v_i. $\omega_{k_j}^i$ represents the weight of the j-th label of the traveling vehicle v_i. The set of weights for the candidate behavior preferences of the vehicle v_i is $\omega^i = \{\omega_{k_j}^i | 1 \leqslant j \leqslant 16\}$. $k = \{k_j | 1 \leqslant j \leqslant 16, j \in \mathbb{N}^+\}$ represents a collection of dynamic tags.

(2) Determine the temporal correlation of vehicle behavior

Considering the degree of correlation between the behavioral preferences before and after driving the vehicle (the subsequent selections are often affected by choice of previous likes) and the time series characteristics of the impact (the preference sets in different periods in the past often have other influences on the choice of current preferences), this paper introduces a time decay function to characterize this unbalanced relationship[61]. Let t represent the period during which the current set of behaviors has changed. $T_{\min}$ defines the minimum time interval at which the behavior of the moving vehicle has shifted. $T_{\max}$ represents the maximum time interval at which the behavior of the moving vehicle has been transferred. Suppose that the behavior of the driving vehicle is quickly completed. In that case, it indicates that the driving vehicle prefers the behavior after the transformation, and the intensity of this behavior is relatively large. Suppose that the driving vehicle takes a long time to complete a specific behavior change. In that case, it may be affected by the influence of the surrounding environment to change the behavior, rather than spontaneous behavior, indicating that the driving vehicle's preference for this behavior is not strong. The build time decay function based on this is

$$g(t)=\begin{cases}1, & t<T_{\min};\\ e^{-\frac{t-T_{\min}}{T_{\max}-T_{\min}}}, & T_{\min}\leqslant t\leqslant T_{\max};\\ 0, & t>T_{\max}\end{cases} \tag{29}$$

(3) Update the behavior weights in the dynamic behavior preference set

Changes in driving behavior in each period of the vehicle impact the weight of that behavior. When considering the behavior weight of the current time point, it is necessary to comprehensively assess the weight of the behavior in the historical behavior set. The new weight generated by the recent behavior set on the behavior and the combination of the two can calculate the cumulative weight of the behavior after the current behavior set. The result is a dynamic update of the behavior weights. According to Eqs. (28) and (29), the weights available to update the formula are as follows:

$$\omega_i^{[n]}=\begin{cases}\omega_{\text{acti}}^{[1]}, & n=1;\\ \omega_i^{[n-1]}\times g(t)+\omega_{\text{acti}}^{[1]}, & n\geqslant 2\end{cases} \tag{30}$$

where $\omega_i^{[n]}$ represents the cumulative weight of behavioral characteristics k_i after the current behavior set S. When n = 1, that is, the first occurrence of the behavior word k_i, its weight is the weight $\omega_{\text{acti}}^{[1]}$ in the current set of behaviors. When $n\geqslant 2$, its weight is the sum of the accumulated preference weights of the historical behavior set ($n-1$) and the newly generated preference weights of the current behavior set.

After updating the weight of the driving behavior according to Eq. (30), the driving behavior weight is sorted by size. The first six driving behaviors are added to the dynamic behavior preference set Dynamic, and the remaining driving behaviors are grouped into the candidate behavior preference set Candidate. Every time a driving behavior change occurs in a moving vehicle, the corresponding driving behavior weight changes. The dynamic behavior preference set is updated when the last six driving behaviors change. Vehicles v_i traveling on the road, when the observation vehicle is driven for a sufficiently long period, its dynamic behavior preference set is updated enough times to stabilize eventually, so the final dynamic behavior preference set will be able to represent the actual driving behavior preference set D_i of the vehicle, that is, $D_i=\lim\limits_{t\to+\infty}D_i^t$.

4.2 Algorithm step

Based on the above analysis, the algorithm steps are shown as follows. The flow of the algorithm is shown in Fig. 10.

(1) Construct a set of dynamic behavior preferences for moving vehicles from user portraits $D=\{D_i^t|i\in(1,n)\}$.

(2) Construct a collection of induced signal strategies $\text{SI}=\{\text{SI}_1,\text{SI}_2,\ldots,\text{SI}_\gamma\}$, For example, if the road saturation is low, the signal could remind the vehicles to speed up. If the road is congested, the signal could remind the vehicles to slow down. Change lanes in front of the barrier, and so on. Construct an array of driving vehicle behavior strategies $\text{DS}=\{\text{DS}_1,\text{DS}_2,\ldots,\text{DS}_\varepsilon\}$, For example, slow down, speed up, change lanes, etc. Construct an initial state set A_0 and a steady-state set A, and initialize the driving vehicle strategy transfer probability $r_{ij}(\text{DS}_j|\text{DS}_i)$.

(3) Get the manager objective function $U_D^k=L_R$ and the driving vehicle objective function $U_V^k=\sum\limits_i(R_i+R_{Si})$ of the k stage.

Due to the uncertainty of the future, there is a series of noise effects such as signal attenuation, and the next stage of revenue will be attenuated accordingly. Therefore, this paper introduces the discount expected return criterion function to obtain the actual return value. That is, the discounted expected return criterion function:

$$R_D^k=U_D^k+\gamma\sum_{g,h\in[k,\lambda]}r_{gh}(\text{DS}_h|\text{DS}_g)R_D^h \tag{31}$$

$$R_V^k=U_V^k+\gamma\sum_{g,h\in[k,\lambda]}r_{gh}(\text{DS}_h|\text{DS}_g)R_V^h \tag{32}$$

where $r_{gh}(\text{DS}_h|\text{DS}_g)$ denotes the probability that the vehicle transforms action DS_g into action DS_h. γ represents the discount factor.

When the return of individual strategies is higher than the average return of the group, the proportion of strategies will increase. On the contrary, when the return of individual strategy is lower than the average return of the group, its strategy proportion will decrease. Based on this, the vehicle replication dynamic equation is established respectively to obtain the optimal

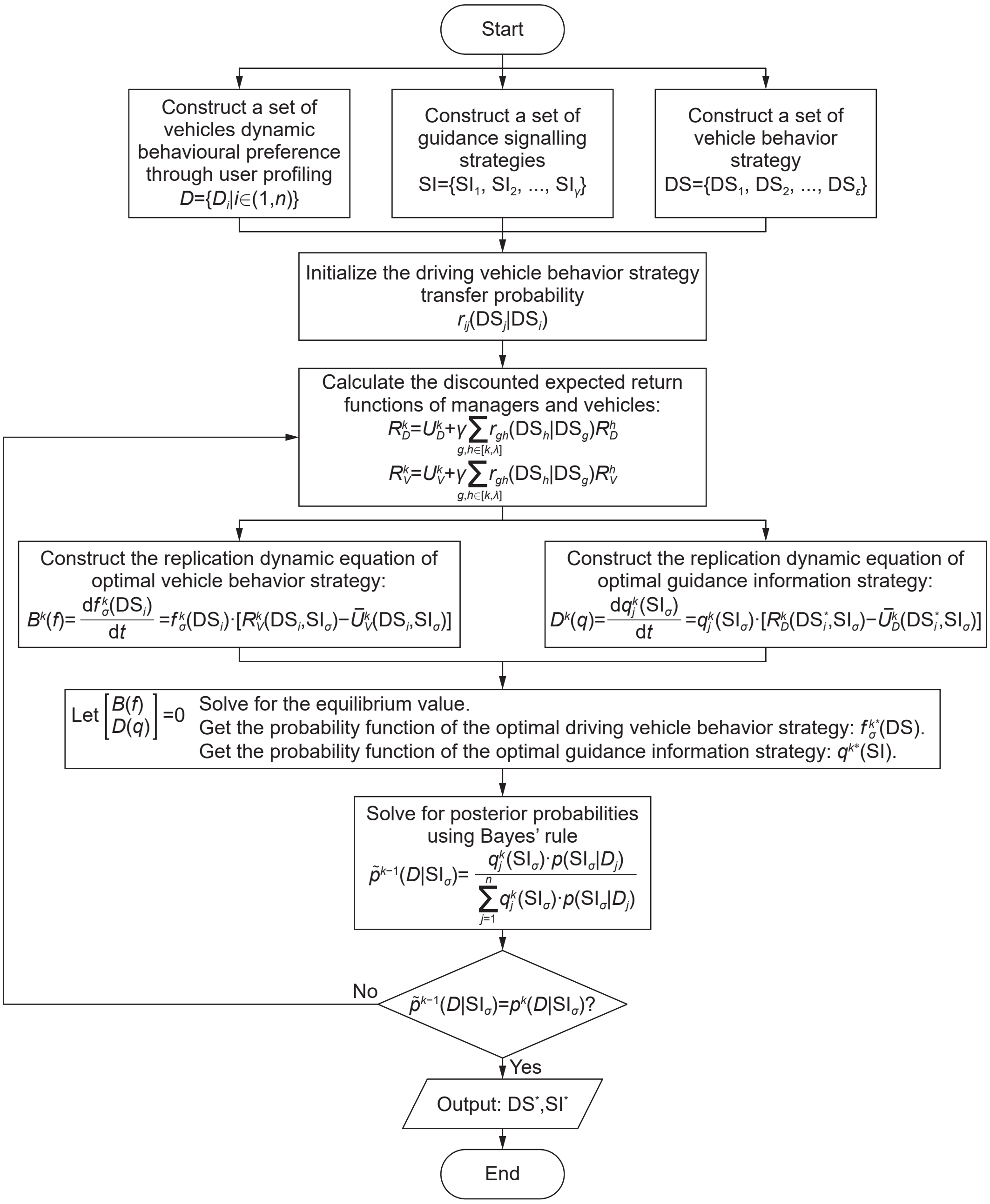


Fig. 10 Algorithm flow chart.

behavior strategy of the vehicle. The optimal vehicle behavior strategy obtained here is put into the manager's income function. Accordingly, the probability function of the optimal driving vehicle behavior strategy and the probability function of the optimal guidance information strategy are obtained. In this step, Bayes' law can be used to solve the posterior probability to obtain the probability of taking the strategy under the induced information in $k-1$ stage until the posterior probability no longer changes, then the driving behavior and the induced information are optimal at this time.

(4) Obtain the k-phase optimal action strategy to copy the dynamic equation:

$$B^k(f)=\frac{\mathrm{d}f_\sigma^k(\mathrm{DS}_i)}{\mathrm{d}t}=f_\sigma^k(\mathrm{DS}_i)\cdot[R_V^k(\mathrm{DS}_i,\mathrm{SI}_\sigma)-\overline{U}_V^k(\mathrm{DS},\mathrm{SI}_\sigma)] \tag{33}$$

where $f_\sigma^k(\mathrm{DS}_i)$ denotes the driving vehicle behavioral strategy probability function under the guidance information SI_σ.

Obtain the k-phase optimal guidance information strategy to copy the dynamic equation:

$$D^k(q)=\frac{\mathrm{d}q_j^k(\mathrm{SI}_\sigma)}{\mathrm{d}t}=q_j^k(\mathrm{SI}_\sigma)\cdot[R_D^k(\mathrm{DS}_i^*,\mathrm{SI}_\sigma)-\overline{U}_D^k(\mathrm{DS}_i^*,\mathrm{SI}_\sigma)] \tag{34}$$

where $q_j^k(\mathrm{SI}_\sigma)$ denotes the guidance information strategy probability function for DS_i^*.

Let $\begin{bmatrix} B(f) \\ D(q) \end{bmatrix}=0$, solve for the equilibrium value. The probability function of the optimal driving vehicle behavior strategy in the k-stage ($f_\sigma^{k^*}(\mathrm{DS})$) and the probability function of the optimal induction information strategy ($q^{k^*}(\mathrm{SI})$) are obtained.

(5) Solve for posterior probabilities using Bayes' law.

$$\tilde{p}^{k-1}(D|\mathrm{SI}_\sigma)=\frac{q_j^k(\mathrm{SI}_\sigma)\cdot p(\mathrm{SI}_\sigma|D_j)}{\sum\limits_{j=1}^{n} q_j^k(\mathrm{SI}_\sigma)\cdot p(\mathrm{SI}_\sigma|D_j)} \tag{35}$$

(6) If $\tilde{p}^{k-1}(D|\mathrm{SI}_\sigma)=p^k(D|\mathrm{SI}_\sigma)$, output the optimal driving vehicle behavior strategy DS^* and optimal guidance information strategy SI^*.

(7) End.

5 Case Analysis

To verify the feasibility of the above conclusions and algorithms, the simulation idea is as follows: Firstly, MATLAB software is used to simulate the impact of accident rate and road saturation on the income of different types of vehicles. Secondly, the behavior characteristics of 40 vehicles were randomly generated by MATLAB software. Finally, AnyLogic is used to simulate vehicle strategy selection.

5.1 Analysis of inter-driver information induction studies

For ease of analysis, this research assumed that the length of the road section is 1 km. Take $\xi=1$ and $\psi=4$ according to Ref. [62]. MATLAB software is used to simulate the impact of accident rate and road saturation on the income of different types of vehicles. Take the accident rate $\varepsilon=0.1$, 0.3, 0.5, 0.7, and 0.9, and the road saturation is $\rho=0.1$, 0.3, 0.5, 0.7, and 0.9. The following simulation results can be obtained.

The change in revenue of aggressive, stable, and slow vehicles under the combined impact of accident rate and road saturation is shown in Fig. 11. Regardless of the type of vehicle, the benefits of the vehicle decrease as the saturation of the road increases. However, different types of vehicles have different preferences for time benefit and accident risk. The details are as follows:

Different types of vehicles have different preferences for time benefit and accident risk.

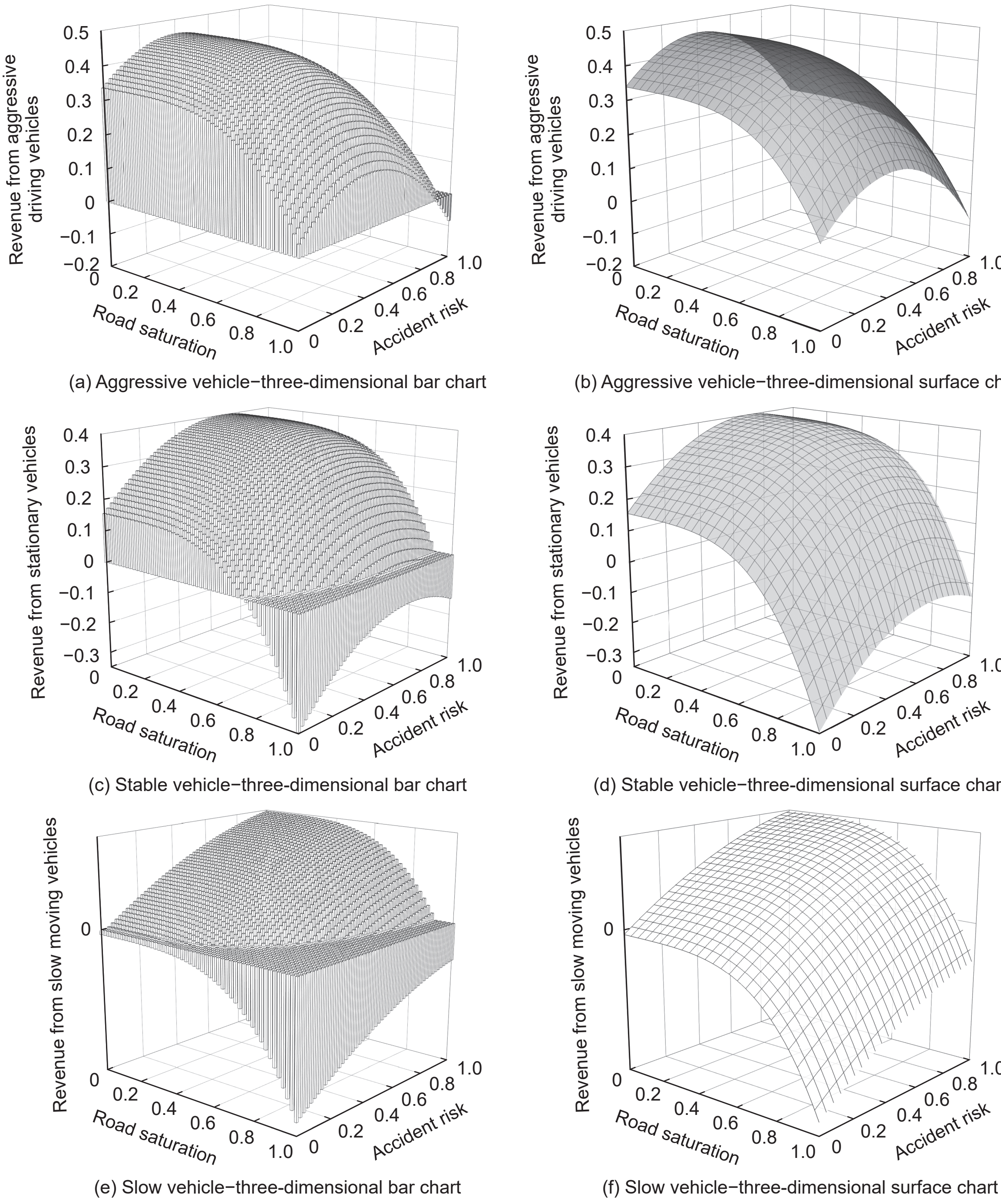
(1) When the vehicle is aggressive, the preference for time gains is greater than for safety gains. Vehicles are not sensitive to risk but to time saved. Therefore, in the early days, as the risk of accidents increases, the benefits of the vehicle increase. After reaching the threshold, the vehicle's benefits decrease as the risk of accidents increases, as shown in Figs. 11a and 11b.

(2) When the vehicle is stable, the preference for time benefits is not much different from safety benefits. When road saturation is low, vehicles can trade safety risks for time gains, and there is a maximum cut-off value for benefits. When the road saturation is high, the return of the vehicle is negative, and it is not profitable at this time, as shown in Figs. 11c and 11d.

(3) When the vehicle is slow, the preference for time gains is less than for safety gains. The vehicle's revenue decreases with the increase in road saturation throughout the period, and the revenue is negative, indicating that the vehicle is susceptible to road saturation. When the road saturation is low, the road is smooth, and vehicles can only obtain high returns by increasing the risk. As the saturation of the road increases, the willingness of the vehicle to exchange risk for returns is getting lower and lower, as shown in Figs. 11e and 11f.

After simulating and analyzing the comprehensive effects of accident incidence and road saturation on revenue. The effect of road saturation on the revenue of the three types of vehicles at different accident rates is shown in Fig. 12. The impact of accident rates on the benefits of the three types of vehicles at different road saturation levels is shown in Fig. 13.

Figure 12 indicates that the revenue of vehicles decreases with the increase of road saturation, which is consistent with the fact that the revenue of vehicles decreases in the event of road congestion. Aggressive vehicles prefer risk, and the greater the risk, the higher the return. Stable vehicles remain neutral, and returns stabilize when risk reaches a certain level. Slow vehicles avoid the wind direction, and when the risk is small, it has little impact on the change of its returns, and when the risk is significant, its return will decrease significantly.



(a) Aggressive vehicle−three-dimensional bar chart
(b) Aggressive vehicle−three-dimensional surface chart
(c) Stable vehicle−three-dimensional bar chart
(d) Stable vehicle−three-dimensional surface chart
(e) Slow vehicle−three-dimensional bar chart
(f) Slow vehicle−three-dimensional surface chart

Fig. 11 Income chart of different types of vehicles.

Figures 13 shows that aggressive vehicles prefer to risk, and their returns are proportional to risk. Both stable and slow vehicles have acceptable critical risks, and when the critical risks are exceeded, their benefits are reduced.

Under the same accident rate, the change in the earning difference of aggressive vehicles is the most stable, and the change in the earning difference of slow vehicles is the steepest, indicating that aggressive vehicles are not sensitive to risk and slow vehicles are sensitive to risk, as shown in Fig. 14.

Under the same road saturation, the earning difference of slow vehicles changes the most smoothly. The earning difference of aggressive vehicles changes the most steeply, indicating that slow vehicles are not sensitive to road saturation and aggressive vehicles are sensitive to road saturation, as shown in Fig. 15.

The average income variations for three different

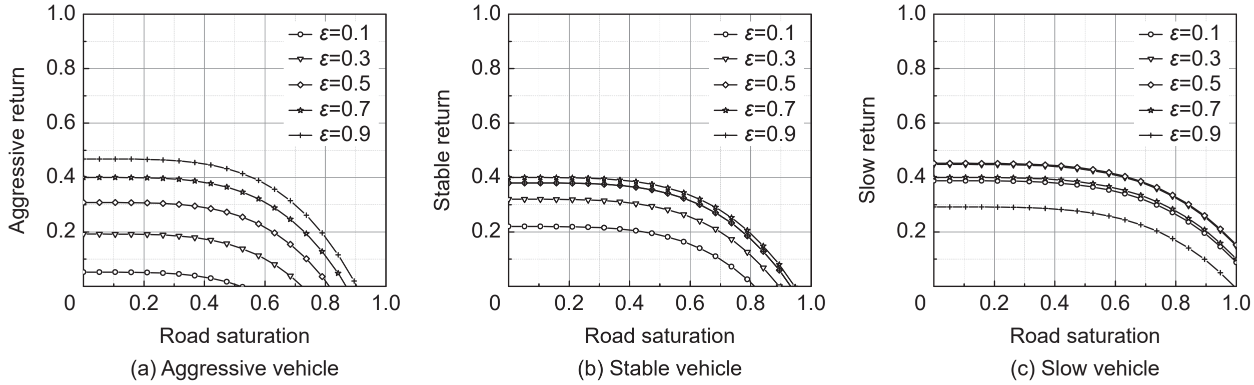


Fig. 12 Effect of road saturation on vehicle revenue at different accident rates.

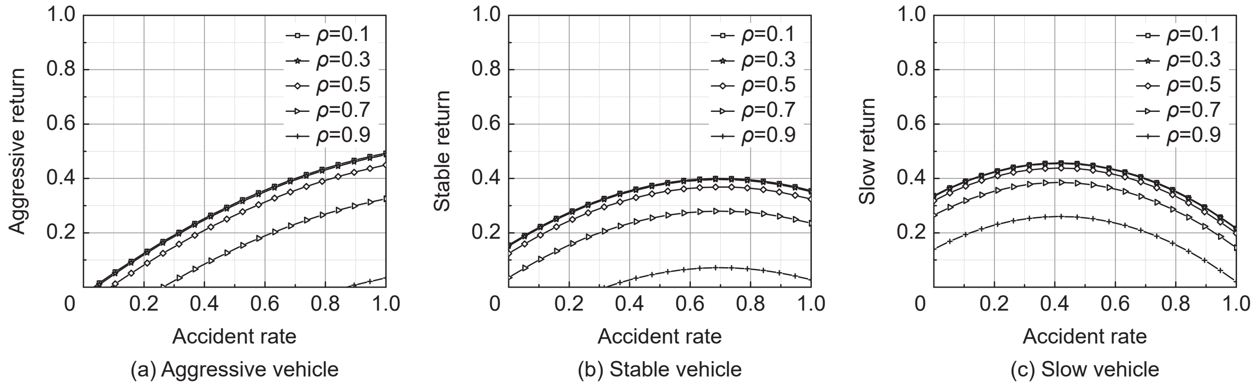


Fig. 13 Effect of accident rates on vehicle revenue at different road saturation levels.

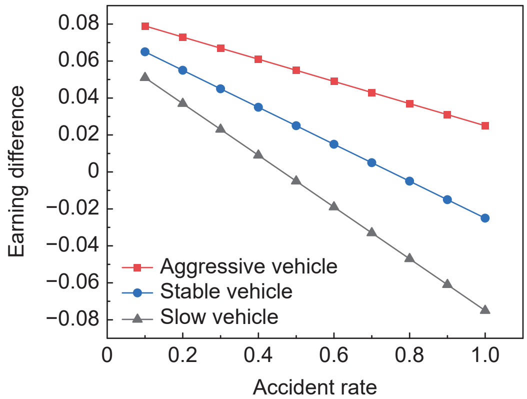


Fig. 14 Variation in earning differential at different accident rates.

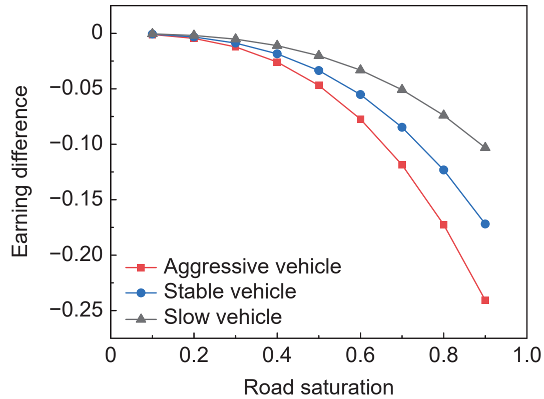


Fig. 15 Variation of earning differential under different road saturation levels.

types of vehicles are examined in terms of accident rates and road saturation. The higher the accident rate, the greater the average return of aggressive vehicles on the road, indicating that aggressive vehicles are risk-conscious. Stable vehicles are risk-neutral, and the average benefit is maximized when the accident rate reaches 0.7. Slow vehicles are risk-averse, and the average benefit is maximized when the accident rate reaches 0.4, as shown in Table 3.

Aggressive vehicles are sensitive to road saturation, and their benefits are significantly reduced when the roads are too congested. Slow vehicles are insensitive to road saturation, and changes in road saturation have little impact on changes in their earnings. Stable vehicles are somewhere between aggressive and slow. This is shown in Table 4.

5.2 Analysis of manager information induction studies

In this paper, 40 vehicles driving on the road are selected as the research object. The dynamic label of

Table 3 Average revenue of the three types of vehicles under different accident rates.

Vehicle type	Average return										
	Accident rate=0	Accident rate=0.1	Accident rate=0.2	Accident rate=0.3	Accident rate=0.4	Accident rate=0.5	Accident rate=0.6	Accident rate=0.7	Accident rate=0.8	Accident rate=0.9	Accident rate=1.0
Aggressive vehicle	0.000	0.044	0.100	0.158	0.207	0.248	0.280	0.323	0.360	0.370	0.395
Stable vehicle	0.122	0.177	0.220	0.265	0.285	0.310	0.325	0.330	0.325	0.310	0.285
Slow vehicle	0.272	0.323	0.360	0.383	0.392	0.387	0.368	0.335	0.288	0.240	0.175

Table 4 Average revenue of three types of vehicles under different road saturation levels.

Vehicle type	Average return									
	Road saturation= 0.1	Road saturation= 0.2	Road saturation= 0.3	Road saturation= 0.4	Road saturation= 0.5	Road saturation= 0.6	Road saturation= 0.7	Road saturation= 0.8	Road saturation= 0.9	Road saturation= 1.0
Aggressive vehicle	0.296	0.295	0.291	0.294	0.268	0.237	0.201	0.119	0.021	0.000
Stable vehicle	0.334	0.333	0.330	0.321	0.303	0.269	0.214	0.147	0.052	0.000
Slow vehicle	0.387	0.387	0.385	0.380	0.369	0.349	0.315	0.265	0.191	0.111

the driving vehicle is represented by six sets of characteristics: driving speed, lane change frequency, traffic light behavior, safe distance following the vehicle, steering reaction time, and braking reaction time. The basic data in this paper are derived from the METR-LA dataset. However, because some driving behaviors are difficult to obtain, this paper uses simulation to verify them.

Since vehicles and their driving behavior are random events, and normal distribution can well describe the occurrence rule of random time, MATLAB is used in this section to generate random numbers conforming to normal distribution. According to the above analysis, the vehicle has 6 types of dynamic behavior characteristics, namely 16 kinds of behavior choices, and the vehicle makes behavior choices in 6 types of behavior characteristics. Since driver behavior is difficult to obtain, in order to better analyze vehicle behavior characteristics and easily distinguish important vehicle behavior characteristics, the total number of each type of behavior characteristic needs to be constrained by a fixed value. Therefore, this paper assumes that the maximum value of each behavior selection is 10, the total number of behavior features of speed, lane change, safety distance, and steering reaction time is 30, and the total number of behavior features of traffic light and braking reaction time is 20.

For example, in the category of steering reaction time, the vehicle has three choices, and the total number of such behavioral characteristics is 30. To better fit the actual simulation, 3 × 40 random numbers with a normal distribution and a sum of 30 for each column are generated. In the category of braking reaction time, the vehicle has two choices, and the total number of such behavioral features is 20. 2 × 40 random numbers with a normal distribution and a column sum of 20 are generated.

By analogy, in order to better simulate vehicle behavior characteristics, this paper uses MATLAB to randomly generate six types of behavior characteristics of 40 vehicles, whose behavior characteristics obey normal distribution, and the number sum of each type of behavior characteristic is a fixed value.

Due to space limitation, only 16 vehicle characteristics were shown in this paper. Since driving vehicles will show hidden driving behavior with changes in the road environment, it is organized into the forms of Table 5.

When road congestion is low, the behavior of the vehicle exhibits an objective vehicle type. However, when the road congestion is above moderate, the vehicle will be affected by the external environment, and show the false behavioral characteristics, as shown in Table 5. Specific performance is as follows:

(1) When the road congestion is high, aggressive and stable vehicles will show slow behavior.

(2) When road congestion is moderate, aggressive

Table 5 Number of vehicle behaviors when road congestion is medium and high.

Feature	Frequency of occurrence															
	"1"	"2"	"3"	"4"	"5"	"6"	"7"	"8"	"9"	"10"	"11"	"12"	"13"	"14"	"15"	"16"
Accelerate driving	8	7	5	0	11	5	7	12	7	9	12	6	8	6	8	9
Frequent lane change	18	0	18	15	20	8	17	9	3	27	15	10	16	16	20	9
Pass the yellow light	12	11	8	4	8	11	1	7	6	8	6	16	7	2	7	11
Close safety distance	14	8	8	3	2	16	27	24	20	23	24	15	1	23	12	20
Quick steering	2	26	13	8	28	19	10	13	9	2	0	14	1	18	5	3
Emergency braking	1	1	4	14	3	2	9	2	11	9	11	1	3	3	3	2
Steady speed driving	9	7	5	8	14	3	22	17	18	11	16	19	20	23	19	5
Normal lane change	4	6	5	7	9	0	11	14	17	2	14	10	9	8	8	7
Moderate safety distance	7	2	6	11	26	2	2	4	10	6	6	12	28	5	11	1
Smooth steering	7	1	6	10	2	3	18	9	11	23	16	14	18	9	24	8
Smooth braking	19	19	16	6	17	18	11	18	9	11	9	19	17	17	17	18
Pass the green light	8	9	12	16	12	9	19	13	14	12	14	4	13	18	13	9
Slow driving	13	16	19	22	5	23	2	1	4	9	2	5	2	1	3	15
Low frequency lane change	8	24	8	8	1	21	2	7	9	1	2	10	6	6	1	13
Far safety distance	10	20	16	17	2	12	1	2	1	2	0	3	1	1	7	9
Slow steering	21	3	11	12	0	7	2	8	10	6	14	3	10	3	2	19
Real vehicle type	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A
Fake performance	C	C	C	C	B	C	B	B	B	B	B	B	B	B	B	C
Road congestion	H	H	H	H	M	H	H	H	H	M	M	M	M	M	M	H

Note: "1"–"16" represent the vehicle number, H represents high, M represents middle, pink represents aggressive, blue represents stable, and yellow represents slow.

vehicles exhibit a stable behavior.

Based on the above analysis, the influence of information induction on vehicle behavior change is further explored. AnyLogic simulation software was used for information induction simulation analysis. For the convenience of discussion, this calculation example only discusses the type change between the two pairs, taking the aggressive type change to the slow type as an example. Suppose that the total number of vehicles on the road is 40, and the number of vehicles in contact with neighbors is 4. Assume that the initial vehicles on the road are all aggressive. Then, the effects of information guidance and strategy transfer on vehicle type change are discussed. The details are as follows:

Figure 16 analyzes the transformation of aggressive vehicles under different information guidance rates and strategy transfer probabilities when the vehicle behavior changes will not change to the previous behavior (that is, the vehicle behavior changes are permanent).

When the information guidance rate and the strategy transfer probability are both 0, that is, the vehicle itself has no idea of transferring strategy and the outside world has not induced it to change strategy, then all vehicles will not change their own strategy, as shown in Fig. 16a.

With the increase in information guidance rate, when the information guidance rate is 0 and the strategy transfer probability is 1, that is, the vehicle itself has the idea of transferring policy, but if there is no external security information to help it change strategy, all vehicles will not change their own strategy, as shown in Fig. 16c. When the information guidance rate is 0.5 and the strategy transfer probability is 1, that is, the vehicle itself has the idea of transferring the strategy completely, and the outside world provides some information to help it change the strategy, then all the vehicles will change their own strategy, as shown in Fig. 16e.

With the increase in strategy transfer probability, when the information guidance rate is 1 and the strategy transfer probability is 0, that is, the vehicle itself has no idea of policy transfer. However, if the outside world provides complete safety information to help it change its policy, all vehicles will change their own policies, as shown in Fig. 16b. When the

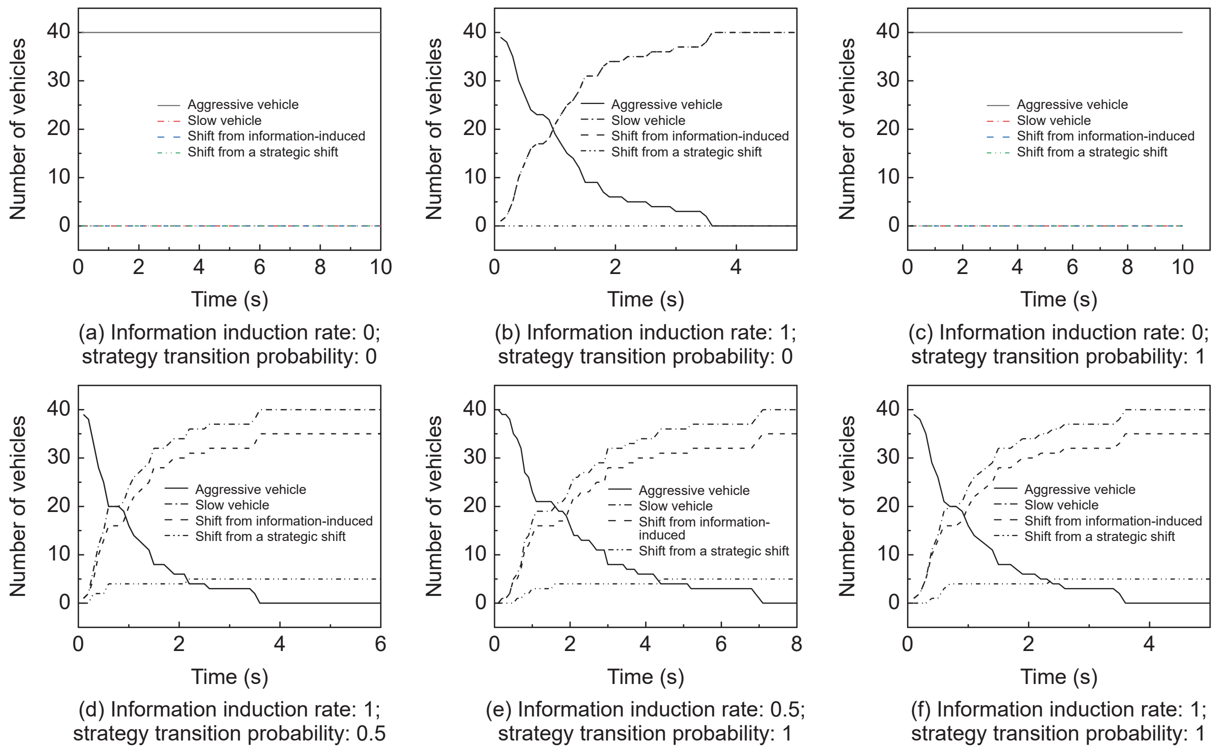


Fig. 16 Transition from aggressive vehicles to slow vehicles. The total number of vehicles is 40, and the number of contact neighbors is 4.

information guidance rate is 1 and the strategy transfer probability is 0.5, that is, the vehicles themselves have some ideas of policy transfer, and the outside world provides complete safety information to help them change their policies, then all vehicles will change their own policies, as shown in Fig. 16d. When the information guidance rate is 1 and the strategy transfer probability is 1, that is, the vehicle itself fully intends to transfer the policy, and the outside world provides complete safety information to help it change the policy, then all the vehicles will change their own policies, as shown in Fig. 16f. Based on the above analysis, the following conclusions can be drawn.

(1) When the vehicle type changes and does not change again, the following situations exist.

(a) When the information guidance rate and the likelihood of strategy transfer are 0, the type change of aggressive vehicles will not occur.

(b) When the information guidance rate and the strategy transfer probability are 1, the aggressive vehicle will change to a slow type.

(c) As the rate of information guidance increases, the faster the road vehicle state tends to stabilize. The increase of the policy transition probability will also speed up the stabilization of the vehicle's state on the road. However, the influence of the policy transition probability on the vehicle type transition is not as significant as that guidance by the information guidance for the neighbor policy, as shown in Fig. 16.

Figure 17 analyzes the transformation of aggressive vehicles under different information guidance rates and strategy transfer probabilities, when vehicle behavior changes will also change to the previous behavior (that is, vehicle behavior changes are not permanent).

When the information guidance rate and the strategy transfer probability are both 0, it indicates that the vehicle itself has no idea of transferring strategy, and the outside world has not induced it to change strategy. Then all aggressive vehicles will not change their own strategy, as shown in Fig. 17a.

With the increase in information guidance rate, when the information guidance rate is 0.5 and the strategy transfer probability is 0, it indicates that the vehicle itself has no idea of transferring strategy at all, but the outside world can provide some safety information to help it change strategy. In this case, the aggressive vehicle will change its own strategy, but because the change in vehicle behavior is not permanent, the vehicle will change its own strategy. At this time, the number of aggressive vehicles and slow vehicles is

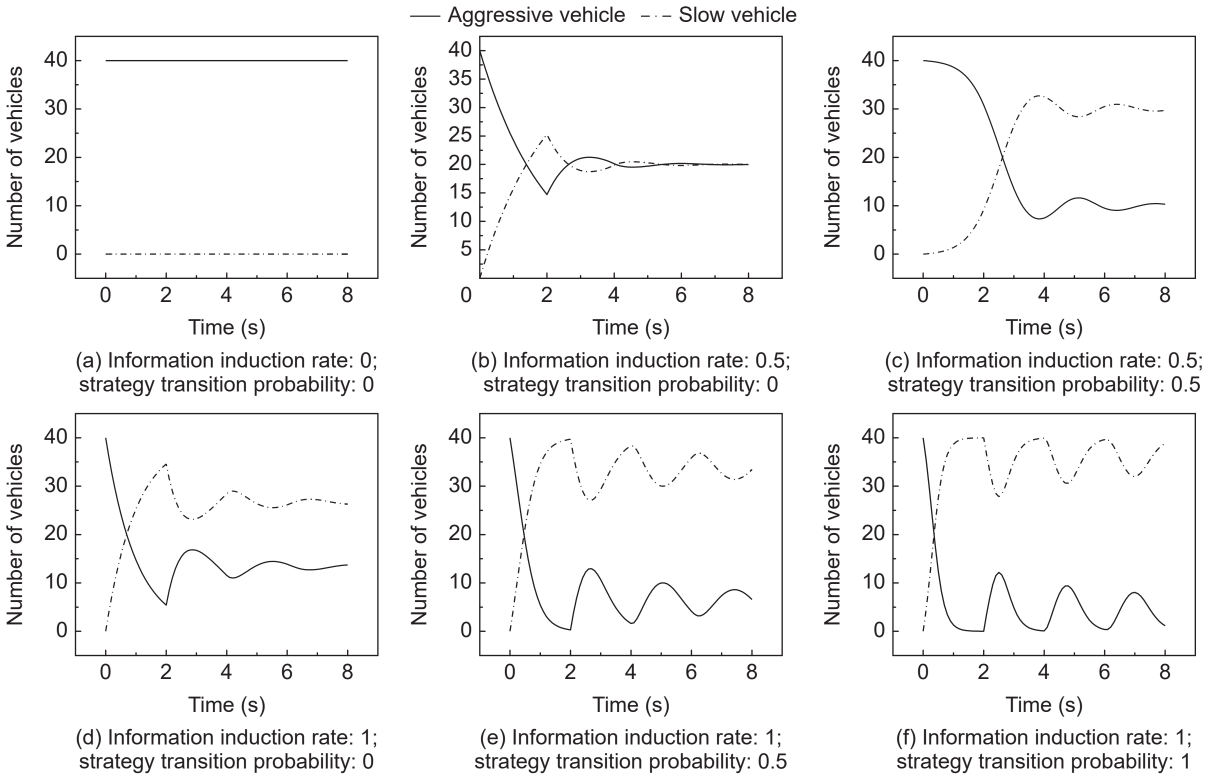


Fig. 17 Coexistence diagram of the transition from aggressive vehicles to slow vehicles. The total number of vehicles is 40, and the number of contact neighbors is 4.

equal and will tend to stabilize, as shown in Fig. 17b. When the information guidance rate is 1 and the strategy transfer probability is 0, the number of slow vehicles exceeds the number of aggressive vehicles, but because the behavior change of vehicles is not permanent, the aggressive vehicles will not be completely transformed into slow vehicles, as shown in Fig. 17d.

When the information guidance rate is 0.5 and the strategy transfer probability is 0.5, it indicates that when the vehicle itself has some idea of the transfer strategy and the outside world provides some safety information to help it change strategy, the number of slow vehicles exceeds the number of radical vehicles. However, since the behavior change of vehicles is not permanent, the radical vehicles will not be completely transformed into slow vehicles, as shown in Fig. 17c.

With the increase in strategy transfer probability, when the information guidance rate is 1 and the strategy transfer probability is 0.5, it indicates that when the vehicle itself has some ideas of policy transfer and the outside world provides complete safety information to help it change its strategy, the number of slow vehicles exceeds the number of aggressive vehicles. However, since the change in vehicle behavior is not permanent, aggressive vehicles do not fully transform into slow vehicles, and the volatility of their number changes increases, as shown in Fig. 17e. When the information guidance rate is 1 and the strategy transfer probability is 1, it indicates that when the vehicle itself fully has the idea of a transfer strategy and the outside world provides complete safety information to help it change strategy, the number of slow vehicles exceeds the number of aggressive vehicles. However, since the behavior change of vehicles is not permanent, the aggressive vehicles will not be completely transformed into slow vehicles. And the volatility of its quantity change further increases, as shown in Fig. 17f. Based on the above analysis, the following conclusions can be drawn.

(2) When the vehicle type changes after the change, the following situations exist.

(a) When the information guidance rate and the probability of strategy transfer are 0, the type transformation of aggressive vehicles will not occur.

(b) When the information guidance rate and the probability of strategy transfer are both 1, the aggressive vehicle coexists with the slow type.

(c) Information guidance helps speed up the transition of vehicle types, and the increase in the probability of policy transition increases the volatility of the number of vehicles, as shown in Fig. 17.

When the number of vehicles is 40 and the number of neighboring vehicles is 4, the information induction rate is 0, 0.2, 0.5, or 1, and the strategy transfer probability is 0, 0.5, or 1. The test results shown in Table 6 can be obtained by running the information induction algorithm. It can be seen from Table 6 that the information guidance algorithm proposed in this paper can improve the efficiency of vehicle behavior strategy change while shortening the running time.

Based on the above simulation analysis, the driving vehicle guidance strategy for different roads is as follows:

(1) When the road saturation is low, that is, the road is smooth. Aggressive vehicles prefer risks, and managers can release information such as road safety to aggressive vehicles to increase the safety factor of their road passage. Slow vehicles are not sensitive to road saturation, and changes in road saturation have little impact on their income changes. Managers can release information such as acceleration or lane change to slow vehicles, thus improving the operation efficiency of the road network. Stable vehicles are between aggressive and slow vehicles, and managers should not only release safe driving information to them, but also make them properly accelerate information, so as to increase the operating efficiency of the road network and the time benefit of the driving vehicle itself.

(2) When the road saturation is high, that is, the road is congested. Aggressive vehicles are the most sensitive to road saturation and are also the most prone to accidents. The manager’s induction strategy is to send warning messages to aggressive vehicles to encourage aggressive vehicles to reduce aggressive behaviors, thereby reducing the risk of accidents and increasing the profits of driving vehicles.

6 Conclusion

In this paper, considering the factors of time, safety, and neighbor vehicle behavior strategy, the vehicle behavior strategy selection is analyzed, and a vehicle network game evolution model is constructed to study the competition relationship between different types of vehicles. Then, an algorithm for vehicle dynamic behavior preference information induction is proposed. Finally, an example is given to verify the algorithm. The results show that:

(1) In the network evolutionary game of vehicle behavior, different types of vehicles have different dynamic behavior preferences, and vehicle behavior selection is not only affected by safety and time gain but also by neighboring vehicle types and behavior strategies.

(2) Different combinations of road vehicle types lead to different potential accident risks, among which the higher the proportion of aggressive vehicles, the greater the potential road risk. In order to reduce the accident probability, aggressive vehicles should be guided to transform into other types.

(3) With the change in road environment, vehicles will hide their real driving behavior, and information guidance of vehicles will help to change vehicle types.

(4) Vehicle type identification also contributes to road risk assessment. Information guidance helps to promote the stability of vehicle states, and information guidance helps to change vehicle types and promote road traffic safety.

(5) Managers can provide differentiated information guidance strategies according to different road

Table 6 Experimental results of information guidance algorithm.

No.	Information guidance rate	Strategy transfer rate	Time (s)	Conversion rate (%)	Number of vehicles	Number of neighbors
1	0	0	$+\infty$	0.00	40	4
2	0.2	1.0	9.8	87.50	40	4
3	0.5	0.5	7.2	74.26	40	4
4	0.5	1.0	7.1	100.00	40	4
5	0.5	0	6.9	50.02	40	4
6	1.0	0	6.1	65.75	40	4
7	1.0	0.5	3.6	100.00	40	4
8	1.0	1.0	3.6	100.00	40	4

saturation states. For example, when road saturation is low, managers can release inducements related to time preference. When road saturation is high, managers can release inducements related to safety preferences.

This study analyzed the evolutionary game of vehicle networks, and only discussed vehicle behavior choice and the influence of information guidance on vehicle behavior strategy, but did not discuss the incentive mechanism design of information guidance. Therefore, future research can consider how to establish an information guidance incentive mechanism to encourage individual vehicles to transmit valuable information, and ultimately achieve the purpose of smoothing the operation of the road network.

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References

[1] F. Y. Wang, Y. Lin, P. A. Ioannou, L. Vlacic, X. Liu, A. Eskandarian, Y. Lv, X. Na, D. Cebon, J. Ma, et al., Transportation 5.0: The DAO to safe, secure, and sustainable intelligent transportation systems, *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 10, pp. 10262–10278, 2023.

[2] B. Zhou, A. Liu, V. Lau, J. Wen, S. Mumtaz, A. K. Bashir, and S. H. Ahmed, Performance limits of visible light-based positioning for internet-of-vehicles: Time-domain localization cooperation gain, *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 8, pp. 5374–5388, 2021.

[3] S. Rasool, A. Saleem, M. Iqbal, T. Dagiuklas, S. Mumtaz, and Z. U. Qayyum, Docschain: Blockchain-based IoT solution for verification of degree documents, *IEEE Trans. Comput. Soc. Syst.*, vol. 7, no. 3, pp. 827–837, 2020.

[4] I. I. Sirmatel and N. Geroliminis, Economic model predictive control of large-scale urban road networks via perimeter control and regional route guidance, *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 4, pp. 1112–1121, 2018.

[5] M. Rezaei, H. Noori, M. Mohammadkhani Razlighi, and M. Nickray, ReFOCUS: Multi-layers real-time intelligent route guidance system with congestion detection and avoidance, *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 1, pp. 50–63, 2021.

[6] D. Calabuig, D. Martín-Sacristán, J. F. Monserrat, M. Botsov, and D. Gozálvez, Distribution of road hazard warning messages to distant vehicles in intelligent transport systems, *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 4, pp. 1152–1165, 2018.

[7] I. Rasheed, F. Hu, Y. K. Hong, and B. Balasubramanian, Intelligent vehicle network routing with adaptive 3D beam alignment for mmWave 5G-based V2X communications, *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 5, pp. 2706–2718, 2021.

[8] G. Xie, L. T. Yang, W. Wu, K. Zeng, X. Xiao, and R. Li, Security enhancement for real-time parallel in-vehicle applications by CAN FD message authentication, *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 8, pp. 5038–5049, 2021.

[9] M. Yang, B. Ai, R. He, C. Shen, M. Wen, C. Huang, J. Li, Z. Ma, L. Chen, X. Li, et al., Machine-learning-based scenario identification using channel characteristics in intelligent vehicular communications, *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 7, pp. 3961–3974, 2021.

[10] C. Tang, W. Hu, S. Hu, and M. E. J. Stettler, Urban traffic route guidance method with high adaptive learning ability under diverse traffic scenarios, *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 5, pp. 2956–2968, 2021.

[11] L. Tang, H. Zhou, and X. Zhang, An ordered selection model of travel information demand based on quantitative phenotypic selection set, (in Chinese), *Journal of Transportation Engineering*, vol. 19, no. 4, pp. 151–160, 2019.

[12] G. Manogaran, R. Alsabet, A. Uprety, and D. B. Rawat, GTSM—Graph-transient security model for intelligent transportation system information exchange, *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 8, pp. 8421–8430, 2023.

[13] Z. Zhang and H. Huang, The influence of social network information on travel time choice behavior, (in Chinese), *Transportation System Engineering and Information*, vol. 17, no. 5, pp. 22–28, 2017.

[14] Q. Lv, M. Xu, G. Xu, Y. Liu, and X. Zhou, Vehicle multi station target selection and impact analysis under different information modes, (in Chinese), *Transportation System Engineering and Information*, vol. 19, no. 1, pp. 62–68, 2019.

[15] M. Tang and J. Wang, Research on evaluation content of traffic guidance electronic information screen, (in Chinese), *Highway Engineering*, vol. 44, no. 3, pp. 258–263, 2019.

[16] F. Romero, J. Gomez, T. Rangel, R. Jurado-Piña, and J. M. Vassallo, The influence of variable message signs on en-route diversion between a toll highway and a free competing alternative, *Transportation*, vol. 47, no. 4, pp. 1665–1687, 2020.

[17] H. Gan, To switch travel mode or not? Impact of Smartphone delivered high-quality multimodal information, *IET Intell. Transp. Syst.*, vol. 9, no. 4, pp. 382–390, 2015.

[18] H. Gan and X. Ye, Will commute drivers switch to park-and-ride under the influence of multimodal traveler information? A stated preference investigation, *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 56, pp. 354–361,

2018.
[19] X. M. Lou, L. Cheng, and Z. M. Chu, Modelling travellers' en-route path switching in a day-to-day dynamical system, *Transp. B Transp. Dyn.*, vol. 5, no. 1, pp. 15–37, 2017.
[20] A. Rapoport, E. J. Gisches, T. Daniel, and R. Lindsey, Pre-trip information and route-choice decisions with stochastic travel conditions: Experiment, *Transp. Res. Part B Methodol.*, vol. 68, pp. 154–172, 2014.
[21] E. Ben-Elia and E. Avineri, Response to travel information: A behavioural review, *Transp. Rev.*, vol. 35, no. 3, pp. 352–377, 2015.
[22] C. Pronello, A. Duboz, and V. Rappazzo, Towards smarter urban mobility: Willingness to pay for an advanced traveller information system in Lyon, *Sustainability*, vol. 9, no. 10, p. 1690, 2017.
[23] Z. Lv, L. Qiao, K. Cai, and Q. Wang, Big data analysis technology for electric vehicle networks in smart cities, *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 3, pp. 1807–1816, 2021.
[24] S. Gargoum and K. El-Basyouny, Effects of LiDAR point density on extraction of traffic signs: A sensitivity study, *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2673, no. 1, pp. 41–51, 2019.
[25] C. Zhao, F. Liao, X. Li, and Y. Du, Macroscopic modeling and dynamic control of on-street cruising-for-parking of autonomous vehicles in a multi-region urban road network, *Transp. Res. Part C Emerg. Technol.*, vol. 128, p. 103176, 2021.
[26] M. Li, J. Lu, and J. Sun, Network traffic flow evolution model under multi type information, (in Chinese), *Transportation System Engineering and Information*, vol. 20, no. 4, pp. 97–105, 2020.
[27] J. Dong, S. Chen, Y. Li, R. Du, A. Steinfeld, and S. Labi, Space-weighted information fusion using deep reinforcement learning: The context of tactical control of lane-changing autonomous vehicles and connectivity range assessment, *Transp. Res. Part C Emerg. Technol.*, vol. 128, p. 103192, 2021.
[28] K. Tang, H. Zhang, and B. Y. Xie, Efficiency evaluation of traffic guidance system based on multi-agent simulation, (in Chinese), *Journal of System Simulation*, vol. 30, no. 7, pp. 2630–2639, 2018.
[29] G. N. Bifulco, G. E. Cantarella, F. Simonelli, and P. Velonà, Advanced traveller information systems under recurrent traffic conditions: Network equilibrium and stability, *Transp. Res. Part B Methodol.*, vol. 92, pp. 73–87, 2016.
[30] L. Cheng, X. M. Lou, J. Zhou, and J. Ma, A mixed stochastic user equilibrium model considering influence of advanced traveller information systems in degradable transport network, *J. Cent. South Univ.* , vol. 25, no. 5, pp. 1182–1194, 2018.
[31] E. Ben-Elia, R. Di Pace, G. N. Bifulco, and Y. Shiftan, The impact of travel information's accuracy on route-choice, *Transp. Res. Part C Emerg. Technol.*, vol. 26, pp. 146–159, 2013.
[32] K. Liu and J. Zhou, Research on mixed user equilibrium model under traffic information guidance, (in Chinese), *System Engineering Theory and Practice*, vol. 40, no. 2, pp. 415–425, 2020.
[33] N. C. Iraganaboina, T. Bhowmik, S. Yasmin, N. Eluru, and M. A. Abdel-Aty, Evaluating the influence of information provision (when and how) on route choice preferences of road users in Greater Orlando: Application of a regret minimization approach, *Transp. Res. Part C Emerg. Technol.*, vol. 122, p. 102923, 2021.
[34] Y. Zhang, Y. Li, R. Wang, M. S. Hossain, and H. Lu, Multi-aspect aware session-based recommendation for intelligent transportation services, *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 7, pp. 4696–4705, 2021.
[35] L. Zhu, F. R. Yu, Y. Wang, B. Ning, and T. Tang, Big data analytics in intelligent transportation systems: A survey, *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 1, pp. 383–398, 2019.
[36] Y. Gong, Evolutionary game analysis of travel path selection behavior under information guidance, (in Chinese), *Highway*, vol. 60, no. 1, pp. 108–113, 2015.
[37] Y. Wang, J. Yu, W. Qiu, H. Shen, X. Cheng, and C. Lin, Evolutionary game model and analysis method of network group behavior, (in Chinese), *Journal of Computer Science*, vol. 38, no. 2, pp. 282–300, 2015.
[38] G. Comert, Z. Khan, M. Rahman, and M. Chowdhury, Grey models for short-term queue length predictions for adaptive traffic signal control, *Expert Syst. Appl.*, vol. 185, p. 115618, 2021.
[39] J. Lee, S. Kwak, S. Park, and S. Park, Cluster-based stable BSM dissemination system for safe autonomous platooning, *Comput. Mater. Continua*, vol. 71, no. 1, pp. 321–338, 2022.
[40] P. Li, J. Shi, and X. Liu, Modeling of competitive driving behavior based on theory of planned behavior, (in Chinese), *Transportation System Engineering and Information*, vol. 16, no. 1, pp. 92–98, 2016.
[41] P. Baran, P. Zieliński, and Ł. Dziuda, Personality and temperament traits as predictors of conscious risky car driving, *Saf. Sci.*, vol. 142, p. 105361, 2021.
[42] H. Hu, X. Jia, K. Liu, and B. Sun, Self-adaptive traffic control model with behavior trees and reinforcement learning for AGV in industry 4.0, *IEEE Trans. Ind. Inform.*, vol. 17, no. 12, pp. 7968–7979, 2021.
[43] D. J. Sun and L. Elefteriadou, A driver behavior-based lane-changing model for urban arterial streets, *Transp. Sci.*, vol. 48, no. 2, pp. 184–205, 2014.
[44] B. Yu, H. Zhou, L. Wang, Z. Wang, and S. Cui, An extended two-lane car-following model considering the influence of heterogeneous speed information on drivers with different characteristics under honk environment, *Phys. A Stat. Mech. Appl.*, vol. 578, p. 126022, 2021.
[45] Y. Guo, X. Wang, X. Lan, and T. Su, Traffic target location estimation based on tensor decomposition in intelligent transportation system, *IEEE Trans. Intell. Transp. Syst.*, vol. 25, no. 1, pp. 816–828, 2024.
[46] X. Chen, J. Sun, Z. Ma, J. Sun, and Z. Zheng, Investigating the long- and short-term driving characteristics and incorporating them into car-following models, *Transp. Res. Part C Emerg. Technol.*, vol. 117, p. 102698, 2020.
[47] Z. H. Khattak, M. D. Fontaine, and B. L. Smith, Exploratory investigation of disengagements and crashes

in autonomous vehicles under mixed traffic: An endogenous switching regime framework, *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 12, pp. 7485–7495, 2021.
[48] D. Xu, Z. Ding, X. He, H. Zhao, M. Moze, F. Aioun, and F. Guillemard, Learning from naturalistic driving data for human-like autonomous highway driving, *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 12, pp. 7341–7354, 2021.
[49] T. Shang, P. Wu, B. Tang, J. Bai, and L. Zhou, Study on vehicle lane changing game behavior in small distance section from tunnel to interchange, (in Chinese), *Chinese Journal of Safety Science*, vol. 31, no. 10, pp. 68–75, 2021.
[50] Z. Liu and Z. Song, Strategic planning of dedicated autonomous vehicle lanes and autonomous vehicle/toll lanes in transportation networks, *Transp. Res. Part C Emerg. Technol.*, vol. 106, pp. 381–403, 2019.
[51] D. A. Lazar, S. Coogan, and R. Pedarsani, Capacity modeling and routing for traffic networks with mixed autonomy, in *Proc. IEEE 56th Annual Conf. Decision and Control* (*CDC*), Melbourne, Australia, 2017, pp. 5678–5683.
[52] J. Zha, C. Li, and S. Fan, The effect of stability-based strategy updating on cooperation in evolutionary social dilemmas, *Appl. Math. Comput.*, vol. 413, p. 126603, 2022.
[53] H. Li, X. Li, X. Xu, J. Liu, and B. Ran, Modeling departure time choice of metro passengers with a smart corrected mixed logit model—A case study in Beijing, *Transp. Policy*, vol. 69, pp. 106–121, 2018.
[54] Z. R. Moghaddam, M. Jeihani, S. Peeta, and S. Banerjee, Comprehending the roles of traveler perception of travel time reliability on route choice behavior, *Travel. Behav. Soc.*, vol. 16, pp. 13–22, 2019.
[55] M. Thorhauge, E. Cherchi, and J. Rich, How flexible is flexible? Accounting for the effect of rescheduling possibilities in choice of departure time for work trips, *Transp. Res. Part A Policy Pract.*, vol. 86, pp. 177–193, 2016.
[56] M. Thorhauge, J. Swait, and E. Cherchi, The habit-driven life: Accounting for inertia in departure time choices for commuting trips, *Transp. Res. Part A Policy Pract.*, vol. 133, pp. 272–289, 2020.
[57] J. Lizbetin and L. Bartuska, The influence of human factor on congestion formation on urban roads, *Procedia Eng.*, vol. 187, pp. 206–211, 2017.
[58] F. W. Siebert and F. L. Wallis, How speed and visibility influence preferred headway distances in highly automated driving, *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 64, pp. 485–494, 2019.
[59] A. Talebpour and H. S. Mahmassani, Influence of connected and autonomous vehicles on traffic flow stability and throughput, *Transp. Res. Part C Emerg. Technol.*, vol. 71, pp. 143–163, 2016.
[60] M. R. Yanko and T. M. Spalek, Route familiarity breeds inattention: A driving simulator study, *Accid. Anal. Prev.*, vol. 57, pp. 80–86, 2013.
[61] S. Wu, C. Wu, and J. Zhu, Microblog user dynamic portrait generation based on interest transfer, (in Chinese), *Information Science*, vol. 39, no. 8, pp. 103–111, 2021.
[62] H. K. Lo, X. W. Luo, and B. W. Y. Siu, Degradable transport network: Travel time budget of travelers with heterogeneous risk aversion, *Transp. Res. Part B Methodol.*, vol. 40, no. 9, pp. 792–806, 2006.

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