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Mode choice between autonomous vehicles and manually-driven vehicles: An experimental study of information and reward

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ABSTRACT

An increase in autonomous vehicles (AVs) would result in a decline in traffic congestion; however, the travel cost associated with AVs is always higher than that of manually-driven vehicles (MV). This situation is interpreted as a so-called multi-player social dilemma. This study designed an economic experiment to investigate the effect of AVs on mode choice in mixed traffic flows. Participants were informed about the cost function in both modes and were asked to choose the travel mode for more than 60 rounds. In full information (FI) treatment, participants received information about the travel costs of the AV and MV modes at the end of each round. In the partial information (PI) treatment, participants received information only about the travel cost of the mode they chose. We found that participants were sensitive to cost differences in the FI treatments. Based on inequality aversion models, we proposed a perceived cost that could better explain the experimental equilibrium. A monetary reward was provided to encourage participants to take AVs and solve social dilemmas. The results demonstrated that the reward mechanism reduces traffic congestion and increases social benefits, especially in the FI treatment. Finally, a learning model that considers inertia and perceived cost is proposed to explain the decision-making process of the participants during the experiment. The findings have implications for traffic forecasting in the mixed flow of MVs and AVs and provide insights and policy suggestions for AV management.

1. Introduction

Advanced autonomous vehicles (AVs) have enormous potential for reducing traffic congestion. Equipped with multiple sensors and artificial intelligence technologies, AVs collect data on their surroundings and plan routes in real time. Studies have proved that in mixed traffic of AVs and manually-driven vehicles (MVs), an increasing proportion of AVs substantially enhance traffic capacity (Childress et al., 2015; Aria et al., 2016; Arnaout & Bowling, 2011). Furthermore, the car-sharing business might be a novel segment for AVs. Companies sell mobility instead of cars, and travelers take on-demand or shared services, such as driverless taxis (Firnkorn & Müller, 2012; Krueger et al., 2016). However, little research has been done to study the impact of AVs on travel choice behavior, and previous research largely ignores the effect of social interaction on travelers' mode choices. In this study, a laboratory experiment was designed to shed light on mode choice behavior in mixed traffic of AVs and MVs. The results may have implications for government and AV-related enterprises in predicting public acceptance of AVs and promoting the use of AVs.

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Table 1
Cost matrix for the simplified version of two players.

	MV	AV
MV	(H, H)	($\underline{L}$, $\underline{M}$)
AV	($\underline{L}$, $\underline{M}$)	(M, M)

It is difficult to obtain AV data on real roads because AVs are still in the testing phase; therefore, this study adopts an experimentation approach to understand the behavior of travelers' mode choice. We assume that in a mixed single road, an increased number of AVs can improve road capacity. Traffic congestion will be reduced as the proportion of AVs increases, which allows all travelers to save travel time (Dixit et al., 2017). If the proportion of AVs is sufficiently high, most travelers are driving at free-flow speed. However, AVs are more expensive than MVs because they are equipped with high-tech hardware (Milakis et al., 2017; Fagnant & Kockelman, 2015). In summary, travelers take a higher cost for driving AVs than driving MVs, but all travelers are better off if most of them choose AVs. The decision-making process is the so-called social dilemma for travelers who must decide whether to cooperate (choose AV) or to defect (choose MV). The cost matrix for a simplified two-player version is given in Table 1, where H is the cost of MV on a congested road, and L (M) is the cost of AV (MV) on a free-flowing road. It is assumed that the cost on a free-flowing road is less than the cost on a congested road, and the cost of MV is less than the cost of AV, that is $H > M > L$. The resulting structure is a feature of the chicken game, which is a classical social dilemma game. In multi-player social dilemma games, cooperation may be encouraged through interactions in social networks (Tanimoto, 2013). To reflect the nature of mode choice behavior in a mixed traffic flow, participants were recruited to repeatedly make their decisions in this multi-player travel mode choice game.

The second objective of this study was to understand the impact of information. Previous research (Ben-Elia & Shiftan, 2010; Ben-Elia et al., 2013a) has confirmed that travelers with more information are better informed of their travel behavior, which could be provided by variable message signals (VMS) or advanced traveler information systems (ATIS). However, an increasing amount of information is not always beneficial to travelers. For example, Wijayaratna et al. (2017) observed an online information paradox in which the cost for all travelers is much higher if online information is provided. In this study, two types of information feedback are provided. In one treatment (partial information [PI]), travelers received feedback information on travel mode cost they chose in this round; in the other treatment (full information [FI]), subjects received feedback information on travel mode cost on both AVs and MVs. The results of the experiment showed that information makes a difference in treatments, with fewer travelers choosing AVs in the FI treatment than in the PI treatment. Such an information paradox is important for understanding the transition of travel behavior and promoting public acceptance of AVs.

Punishment or reward mechanisms are common institutional designs to solve social dilemmas, which propose to eliminate the gap in travel costs. In this study, we set up a reward mechanism to induce travelers to choose AVs, thus reducing traffic congestion on the mixed road and improving social efficiency. To evaluate the effectiveness of the reward mechanism, we applied the concept of the social efficiency deficit (SED) proposed by Arefin et al. (2019). If a small reward for AVs can induce more travelers to choose this travel mode, traffic congestion could be reduced, and social benefits would be generated.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the details of the experimental setting and the predicted equilibrium. The subjects and experimental procedures are introduced in Section 4. Section 5 reports the results of the experiment, including basic data analysis, followed by a modeling approach applied in behavioral mode choice. Section 6 presents the conclusion and discussion of our experiments and addresses policy implications.

2. Literature review

This study conducted an experiment based on the assumption that AVs can reduce congestion under mixed traffic. In this section, previous research on the ability of AVs in traffic, experimental analysis of travel behavior, social dilemma structures, and social interaction models are summarized.

In recent studies, the effects of autonomous vehicles on transportation have been broadly discussed. Arnaout and Bowling (2011) and Aria et al. (2016) conducted microscopic simulation studies to prove that AVs can enhance capacity by increasing the speed on the road. Shladover et al. (2012) estimated that lane capacity with 100% connected AVs is nearly double that of unconnected AVs. Levin and Boyles (2016) suggested that adopting AVs could increase capacity, reduce congestion, and ensure safe movement. Lazar et al. (2017) proposed a road capacity function for mixed AV and MV roads and found that road capacity increases convexity as the ratio of AV on the road increases. An et al. (2020) reported that the travel time in mixed traffic flow reduces as the proportion of AVs increases. Yao et al. (2019) analyzed the stability of mixed traffic flow and suggested that travel time can be saved under high penetration rates of AVs. The aforementioned studies concluded that the adoption of AVs could reduce travel time and thus eliminate traffic congestion, but ignored the interaction between travelers' choice behavior and traffic flow distribution. Predicting traffic distribution in mixed traffic flow is a sophisticated issue because the public acceptance of AVs and social interaction among travelers may affect traveler behavior. This study attempts to shed light on this field by setting up an economic experiment to understand travel mode choice behavior and predict the penetration rate of AVs and flow distribution under mixed traffic.

Experimental methods are applied to understand travelers' choice behavior and study traffic equilibrium, especially in daily commuting. In an economic experiment, Selten et al. (2007) studied route choice behavior between a main road and a side road. Travelers repeatedly made their decisions and received feedback based on their chosen route. The results showed that the traffic distribution tends to be close to the predicted equilibrium. Ben-Elia et al. (2008), Ben-Elia and Shiftan (2010), Ben-Elia et al. (2013a,

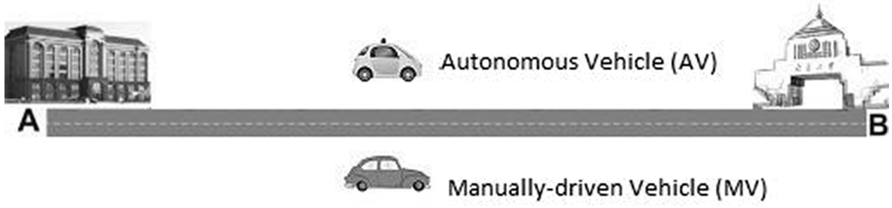

Fig. 1. The experimental scenario where travelers commute on a mixed traffic road, and they choose between two modes: AV or MV.

2013b) conducted a series of experiments on route choices. They found that travelers with more information were prone to be risk-seeking, and they reduced the trials for exploration in the first few rounds. Lu et al. (2011) set up experiments to test the role of information in the travel decision-making process. Real-time information helps travelers make choices before departure, whereas providing information feedback afterwards increases travelers' risk-seeking behaviors. In the traffic network experiment designed by Rapoport et al. (2014), each participant represented a fleet of vehicles to analyze their route-choice behavior. Mak et al. (2015) observed that the distributions quickly converged to equilibrium in a sophisticated network, with the group provided with real-time information tending to be more stable. They also noted that in repeated rounds, switching routes had a negative impact on payoffs. According to experimental data collected by Wijayaratna et al. (2017), providing more en-route information on roads had a negative impact on the travel time of travelers, which is termed "online information paradox." Liu et al. (2015) and Mak et al. (2018) conducted mode choice experiments for public transportation networks, assuming positive externalities wherein users' costs decrease as the number of cost-sharing travelers increases. It is clear that the experimental method is an effective empirical tool to investigate travel choice behavior and is particularly useful for evaluating policy influence in scenarios that are difficult to control variables in practice.

A social dilemma is a situation in which non-cooperative decisions of all rational individuals leave them worse off than if all of them had cooperated (Dawes, 1980). Focusing on traffic flow analysis, Yamauchi et al. (2009) and Nakata et al. (2010) found that social dilemmas occur when two lanes merge into one. Following their study, Tanimoto et al. (2014a,b), Tanimoto and Nakamura (2016) also observed social dilemma structures in lane-changing and route-choice problems and inferred that this dilemma can be used to analyze traffic flow. Risto and Martens (2012) discussed the dilemma of using connected cruise control (CCC), wherein free-ride drivers would benefit from other CCC users. They suggested that reducing perceived cost and increasing perceived benefit may solve this problem. In terms of the effect of AVs on traffic flow, Tanimoto et al. (2020), Tanimoto and An (2019) established cellular automata models and proved that traffic flux would decrease if AV users refused to cooperate. Previous studies have shown that social dilemma structures are broadly observed in traffic flow analyses. In this research, we observe travelers' mode choice behavior using a social dilemma scenario in which AVs and MVs co-exist in traffic systems, and solve the dilemma by eliminating perceived cost indifference.

Social interaction in repeated games plays an important role in the study of human behavior. In the field of evolutionary game theory, dynamic learning explains the process of social interaction. Participants update their strategy according to the feedback information about the payoffs in the previous steps. Tanimoto (2015, 2019) considered the dynamics of traffic flow to be similar to a multi-player dilemma game, and applied evolutionary game theory to traffic flow analysis and route choice problems. Mak et al. (2015) proposed a Markov adaptive learning model to determine the behavioral factors that affect the convergence of route choice. Iwamura et al. (2020) applied evolutionary game theory to tackle the dynamics of a social dilemma game. Moreover, irrational behavior in social dilemmas can be explained by social preferences. Fehr and Schmidt (1999) thought that the presence of inequality aversion leads to the failure of cooperation in dilemma games. Rabin (1993) incorporated fairness into a game theory model to understand the fairness equilibrium outcomes. Charness and Rabin (2002) proposed a social preference model that considers social welfare. Based on the aforementioned models, this study proposes a learning model that considers inequality to reproduce the decision-making process in travel mode choices.

3. Experimental design

3.1. Experiment scenario

The experimental scenario settings are as follows (Fig. 1): At the beginning of each round, a group of N travelers ($N = 15$) was asked to choose travel modes between two alternatives: manually-driven vehicles (MVs) and autonomous vehicles (AVs). MVs are private cars owned by travelers, whereas AVs share autonomous taxis operated by companies. Travel costs depend on their choices and the proportion of AV travelers on the road. The expressions of the cost function are provided in the experiment instructions. Players are bounded rational and thus less willing to cooperate in last few rounds in finitely repeated games, which is the so-called "end-game effect" (Normann & Wallace, 2012; Selten & Stoecker, 1986). To avoid the end-game effect in our experiment, a random stopping rule was applied in which participants made choices for about 60–80 rounds.

Assume that travelers depart at the same time, and there is only one road available for traveling. Thus, travel times are equal for all travelers and depend on the proportion of AVs to MVs. First, we assume that only MVs drive on this road. The travel time on the road was calculated as follows:

$$T = a_{MV} n_{MV} + b \tag{1}$$

Table 2
The Cost of both modes in all situations, where four special states are marked.

Number of AVs	Cost of AV	Cost of MV	Social cost	State
0	75	80	1200	
1	71	75	1121	
2	67	70	1044	
3	63	65	969	
4	59	60	896	
5	55	55	825	Equal
6	51	50	756	
7	47	45	689	
8	43	40	624	
9	39	35	561	Pareto-inferior NE
10	35	30	500	Pareto-superior NE
11	31	25	441	
12	27	20	384	Social Optimum
13	27	20	391	
14	27	20	398	
15	27	20	405	

where n_{MV} is the number of MVs, a_{MV} is a constant coefficient, and b represents the free-flow travel time.

As mentioned in the literature review, there will be less congestion in the presence of AVs. In the mixed traffic of AVs and MVs, the travel time is expressed as:

$$T = \begin{cases} a_{MV}n_{MV} - a_{AV}n_{AV} + b & \text{if } a_{MV}n_{MV} - a_{AV}n_{AV} \geqslant 0 \\ b & \text{if } a_{MV}n_{MV} - a_{AV}n_{AV} < 0 \end{cases} \tag{2}$$

where n_{AV} is the number of AVs, $n_{MV} + n_{AV} = N$. The constant a_{AV} represents the marginal effect of AV on reducing congestion. When $a_{MV}n_{MV}$ - $a_{AV}n_{AV}$ is negative, all vehicles run at a free-flow speed and the travel time equals to b.

The travel cost of MV users is defined as:

$$c_{MV} = T = \begin{cases} a_{MV}n_{MV} - a_{AV}n_{AV} + b & \text{if } a_{MV}n_{MV} - a_{AV}n_{AV} \geqslant 0 \\ b & \text{if } a_{MV}n_{MV} - a_{AV}n_{AV} < 0 \end{cases} \tag{3}$$

Travelers choosing AVs could undertake other activities while driving, so the value of travel time is expected to be lower than that of MVs (Steck et al., 2018, de Almeida Correia et al., 2019). However, AV travelers must pay for each trip because AVs are operated as driverless taxis. The travel cost of an AV is defined as:

$$c_{AV} = \alpha + \beta T = \begin{cases} \beta(a_{MV}n_{MV} - a_{AV}n_{AV}) + \alpha + \beta b & \text{if } a_{MV}n_{MV} - a_{AV}n_{AV} \geqslant 0 \\ \alpha + \beta b & \text{if } a_{MV}n_{MV} - a_{AV}n_{AV} < 0 \end{cases} \tag{4}$$

where α denotes the relative monetary cost of the AV compared to that of the MV, which is caused by the money paid for companies. β denotes the discount for the value of time; $0 < \beta < 1$.

We assume that $a_{MV} = 4$, $a_{AV} = 1$, $b = 20$, $\alpha = 11$, and $\beta = 0.8$, so that a social dilemma emerges in the mixed traffic of MVs and AVs. The travel costs for all possible outcomes of the experiment are listed in Table 2. At the beginning of each round, the traveler received 100 initial tokens. At the end of the experiment, 40 out of 60–80 rounds were randomly selected for payment. We did not pay for the outcome from every decision made to avoid wealth effects (Charness et al., 2016).

3.2. Equilibrium predictions

Assuming that other travelers remain constant in their strategies, the benefits that a traveler acquired by deviating from an AV to an MV can be calculated by the following formula:

$$\Delta c_{AM} = -n_{AV} + 10 \tag{5}$$

The participant has an incentive to deviate unilaterally from the current strategy if the $n_{AV} > 10$. Similarly, a traveler deviating from an MV to an AV gains an incentive to

$$\Delta c_{MA} = n_{AV} - 9 \tag{6}$$

Suppose others do not change their strategies, then an MV traveler switches to AV if $n_{AV} < 9$.

When $9 \leqslant n_{AV} \leqslant 10$, none of the travelers have an incentive to deviate from the current choice, which is the so-called Nash equilibrium. Therefore, there are two Nash equilibrium points (see Table 2). The first one was named Pareto-inferior NE, where nine participants chose AVs at a cost of 39 and six participants chose MVs at a cost of 35. The second one was named Pareto-superior NE, where ten participants chose AVs at a cost of 35 and five participants chose MVs at a cost of 30. Note that there are fifteen participants who choose between two alternatives; then, there are $15!/(9!6!) = 5005$ combinations of strategies in Pareto-inferior NE. Similarly,

Table 3
Treatment designs.

	Partial information (PI)	Full information (FI)
Standard mechanism	PI in standard mechanism	FI in standard mechanism
Reward mechanism	PI in reward mechanism	FI in reward mechanism

there are 3,003 combinations of strategies for the Pareto-superior NE. The experiment also has a mixed strategy Nash equilibrium (mixed NE), where all travelers choose AVs with a probability of $P = 0.6$ and MVs with a probability of $P = 0.4$. The expected number of AV travelers was nine (=15 × 0.6).

This mode choice experiment was modeled as a symmetric game with asymmetric equilibria. In equilibrium, the travel cost of AV travelers is higher than that of MV travelers, although they do not have any incentive to change travel modes. If the number of AV travelers is less than nine, a traveler has an incentive to deviate from choosing an MV to choosing an AV. The strategy of switching is a collective behavior of cooperation that brings benefits to individuals and other participants, but other AV travelers can obtain better value than the traveler who changes from AV to MV. For example, suppose there are seven travelers choosing AVs at a cost of 47 and eight travelers choosing at a cost of 45. A traveler choosing an AV will not deviate from the current travel mode because all travelers will receive a higher cost from their switching behavior. However, an MV traveler can reduce their costs from 45 to 43 by switching to an AV. Meanwhile, the costs of other AV travelers are reduced from 47 to 43, and the costs of other MV travelers are reduced from 45 to 40. The travel costs of MV travelers are lower than the new travel costs of the travelers who switched.

The social cost in the experiment is calculated by:

$$c_{SOCIAL} = \begin{cases} n_{AV}^2 - 80n_{AV} + 1200 & \text{if } n_{AV} \leqslant 12 \\ 7n_{AV} + 300 & \text{if } n_{AV} > 12 \end{cases} \tag{7}$$

Thus, if $n_{AV} \leqslant 12$, a traveler switching from an MV to AV would reduce social costs. A social optimum is achieved when there are 12 AV travelers. However, it is difficult to achieve a socially optimum result. When $10 \leqslant n_{AV} \leqslant 12$, there is a conflict between individual and social interests. A traveler changing from an MV to an AV unilaterally increases travel cost, while all other travelers benefit from the changing behavior. Social costs also decrease. However, if two travelers switch from MVs to AVs at the same time, their travel costs can still be lower than before switching. However, the reciprocity mechanism is difficult to establish without communication among travelers.

3.3. Treatment designs

A 2 × 2 mixed design was used in this study (Table 3). Information was set as a between-group factor (partial vs. full information). At the end of each round, feedback on travel costs was privately presented to the participants on the computer screen. In partial information (PI), the costs of the chosen modes were provided. The costs of both modes were provided in full information (FI).

A reward mechanism is introduced to incentivize more travelers to choose AVs. In the standard mechanism, participants were paid according to their payoff in the payment rounds (40 randomly selected rounds). In the reward mechanism, participants who choose an AV for more than half of the payment rounds can receive a reward of eight tokens per round. For example, if a traveler chooses an AV for 26 rounds and an MV for 14 rounds, the traveler could receive a reward of 26 × 8 = 208 tokens. In the reward mechanism, choosing an AV is always the dominant strategy. The order effects can be removed by reverse counterbalancing. Thus, the reward mechanism was set as a within-group design.

4. The experiment

4.1. Subjects

A total of 180 undergraduate students were recruited from Tianjin University to conduct these experiments. They were randomly assigned to 12 groups of 15 individuals each. Six groups took part in the PI treatments, and the remaining six groups participated in the FI treatments. Referring to previous studies such as Selten et al. (2007), Rapoport et al. (2014), and Liu et al. (2015), the sample size and number of sessions in this experiment are sufficiently large. For each treatment, three groups took the standard mechanism session first and then took the reward mechanism session, while the other three groups took the two sessions in reverse order, which can eliminate the order's effect on the mechanism. Payment is converted into RMB at a ratio of 120:1. Participants received 50.56 yuan on average, including a 5-yuan show-up fee. The experiment lasted 60–90 min, with an average of 75 min per session.

4.2. Procedure

The experiment was conducted in a conference room at the Tianjin University. In each session, a total of 15 participants were recruited as a group and randomly assigned to the seats in the lab. The participants did not know each other before the experiment, so the anonymity condition was fulfilled. Computers in the laboratory were separated by partition boards. Each participant sat in front of a computer and could only see their own computer screen. At the beginning of the experiment, participants received experimental

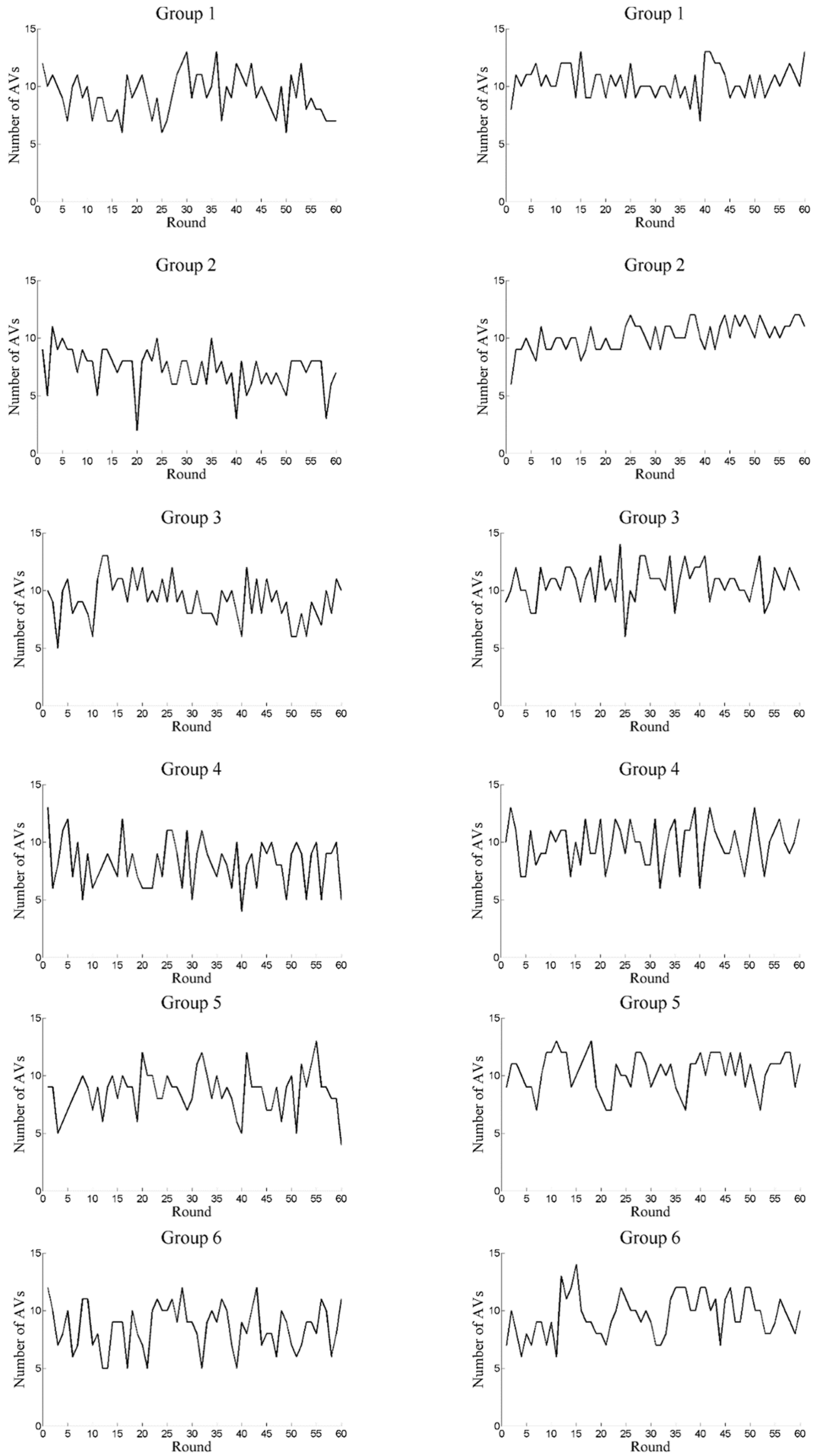

Fig. 2. The number of AVs in partial information treatments (left column: the standard mechanism; right column: the reward mechanism).

instructions that described the experimental scene and the tasks in detail. Three simple examples are provided to help them understand better. When all participants had read and clearly understood the instructions, they were allowed to practice on a computer for five rounds. Scores were not recorded in the practice rounds because the purpose was to ensure that all participants understood the

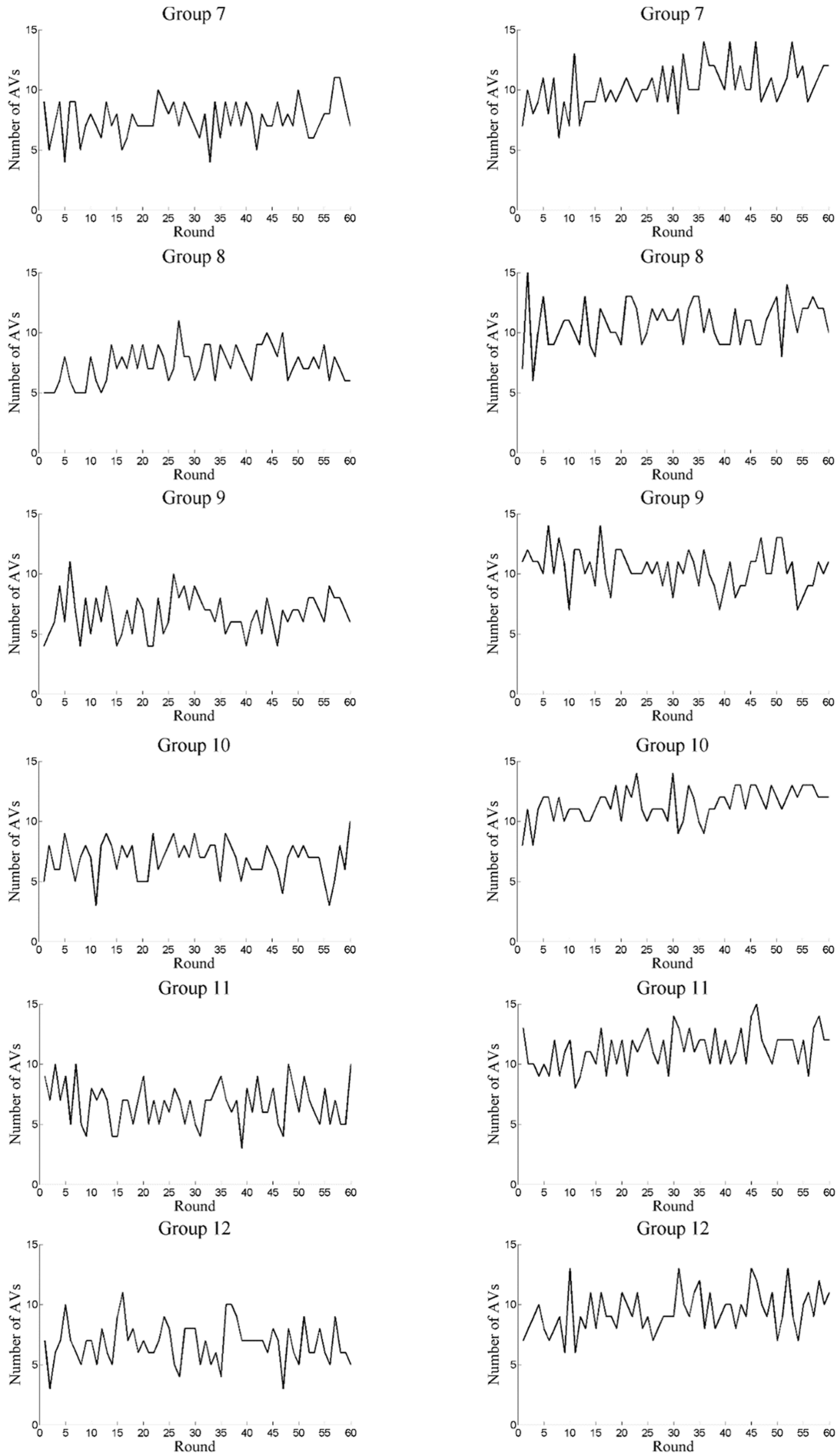

Fig. 3. The numbers of AVs in full information treatments (left column: the standard mechanism; right column: the reward mechanism).

experimental procedure. Communication was not allowed during the experimental process, and the questions were answered privately. The participants made choices repeatedly until the session was terminated by the assistant. At the end of each session, a computer program was used to select 40 rounds of payment.

Table 4
DF test results for the unit root.

	PI in Standard	PI in Reward	FI in Standard	FI in Reward
Num. of AVs	−1.12 (0.13) **	−0.81 (0.13) **	−0.99 (0.13) **	−1.15 (0.13) **
Trend	−0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.03 (0.01) **
Constant	9.83 (1.14) **	7.95 (1.23) **	6.73 (0.92) **	11.43 (1.28) **

*p < 0.05.
** p < 0.01.

Table 5
Linear regression.

Num. of AV	Coef. (St.Err.)	P-value	[95% Conf	Interval]
Info.**	−1.52 (0.34)	0.00	−2.22	−0.82
Reward**	1.67 (0.34)	0.00	0.97	2.37
Info. × Reward**	1.95 (0.48)	0.00	0.95	2.94
Constant**	8.51 (0.24)	0.00	8.01	9.00

** p < 0.01, * p < 0.05.

5. Results

5.1. Preliminary observations

Figs. 2 and 3 show the number of AVs in each round for the FI and PI treatments, respectively. It was indicated that the number of AVs did not converge in any session, but continued to fluctuate within a certain range. Thus, we assume that the distributions do not tend to converge, even in the long term, but would rather fluctuate. Table 4 shows the Dickey–Fuller (DF) test results for the number of AVs in each treatment. In three out of four treatments, the results demonstrated that the number of AVs remained stationary over multiple rounds, except for FI in the reward mechanism. In FI in the reward mechanism, the number of AVs increased as the experiment progressed, so this number might continue to increase if the experiment continued.

The average number of AVs varied among the treatments. In PI, on an average there were 8.51 and 10.18 AVs in the standard mechanism and reward mechanism, separately. In the standard mechanism, the number of AVs was less than the Pareto-inferior Nash equilibrium, but the difference was not significant (Wilcoxon test, $p = 0.116$). In FI treatments, the number of AVs were 6.99 and 10.60 in the standard mechanism and reward mechanism, respectively. In the standard mechanism, the number of AV travelers was different for all four special states (Wilcoxon test, $p = 0.028$).

The mixed-strategy Nash equilibrium is not a good predictor of travelers' behavior. According to the mixed-strategy Nash equilibrium, the probability that a traveler chooses an AV is 0.6 in each round, and the probability that a traveler switches to the other travel mode is 0.48. In FI in the standard mechanism, the frequency of a traveler's choice of an AV is significantly different from 0.6 (Wilcoxon test, $p < 0.01$), while the frequency of switching is significantly different from 0.48 (Wilcoxon test, $p < 0.01$). In PI in the standard mechanism, although the frequency of choosing an AV is not significantly different from 0.6 (Wilcoxon test, $p = 0.051$), the frequency of switching is significantly different from 0.48 (Wilcoxon test, $p < 0.01$). Therefore, travelers did not employ mixed strategies in their individual mode-choice behavior.

Linear regression was used to compare differences among treatments. The average number of AVs in each session was taken as the dependent variable. Information (Info = 0: partial information, Info = 1: full information), mechanism (reward = 0: standard mechanism, reward = 1: reward mechanism), and interaction of information and rewards are independent variables. The regression results are shown in Table 5. All three treatments were significantly different from baseline (PI in the standard mechanism). The number of AVs decreased by 1.52 in FI. In the standard mechanism, the number of AVs grew with more feedback information. In the reward mechanism, the number of AVs increased, both in the partial information and full information treatments, while this number increased to a greater extent in the full information treatment. Moreover, we found an increasing trend in FI in the reward mechanism through the DF test, so there might be more AV travelers if the experiment was to continue.

5.2. Role of information

The experiment showcases the online information paradox that the provision of information deteriorates road network performance compared to the situation where information is not provided (Wijayaratna et al., 2017). In a standard mechanism, when provided with full information, travelers are reluctant to take AVs. In contrast, in a reward mechanism, more information induces travelers to use AVs. We assume that the different impacts of information are caused by the inequality in costs.

5.2.1. Inequality

Suppose that travelers are not self-interested and partially consider the costs of others. Then, travelers might be willing to choose MVs more, even if they did not earn the most. Based on this assumption, we propose a perceived cost formula to consider the inequality

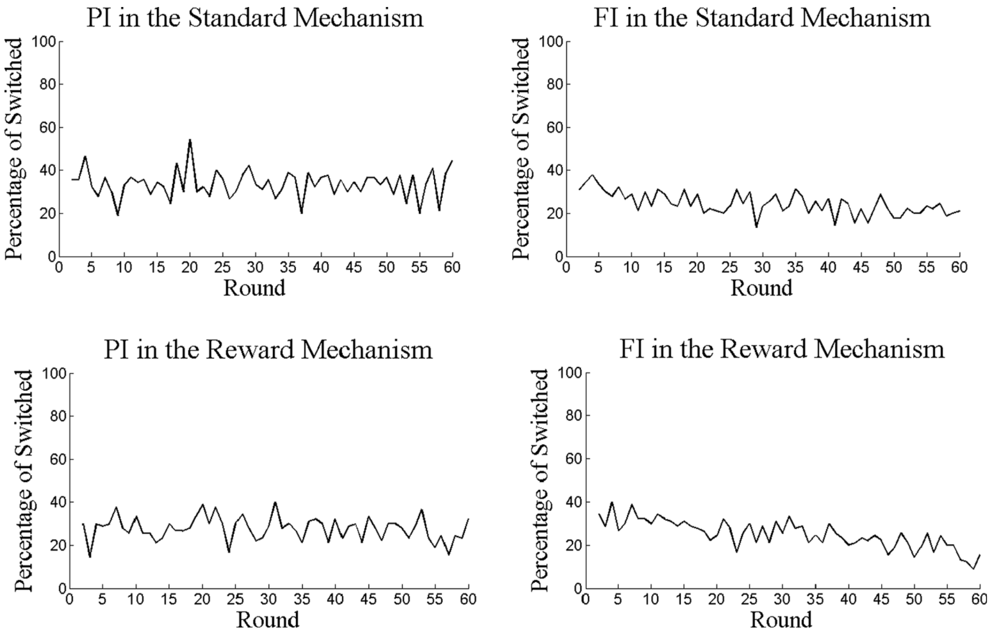

Fig. 4. The percentage of switched choices over the rounds (calculated by the average of six sessions).

Table 6
Linear regression of the percentage of travelers that switched (calculated by an average of six sessions).

	PI in Standard	PI in Reward	FI in Standard	FI in Reward
Round	0.00 (0.87)	0.00 (0.29)	−0.00 (0.00) **	−0.00 (0.00) **
Constant	0.34 (0.00) **	0.29 (0.00) **	0.30 (0.00) **	0.34 (0.00) **
R-squared	0.00	0.02	0.36	0.61

** $p < 0.01$, * $p < 0.05$

$$PC_i = c_i + \theta max(c_i - c_{-i}, 0) \tag{8}$$

A traveler not only considers the cost of his choice, but also considers the difference between his chosen cost and the unchosen cost. The cost of a traveler's choice i in a round is denoted as c_i, while the cost of the unchosen choice is denoted as c_{-i}. Thus, θ ($\theta \geq 0$) is the coefficient of the disadvantageous inequality. A traveler will perceive a higher cost than the actual cost if his/her cost is higher than that of others. According to inequality aversion theory, players prefer advantages over disadvantages (Simonson & Tversky, 1992; Fehr & Schmidt, 1999; Rohde, 2010), so we did not take advantage of inequality in the model.

In the standard mechanism, the cost difference between the two modes may induce an inequality. It seems that the provision of more information strengthens the perceptions of inequality, which damages both individual and social benefits. In the reward mechanism, choosing an AV is always the dominant strategy regardless of θ. This may explain why more travelers take AVs as a reward mechanism. However, the experimental results show that fewer travelers choose AVs compared to the predicted equilibrium. A possible explanation is that some travelers did not realize that choosing an AV is the dominant strategy. Information can help travelers gain better knowledge of costs, so there was an increased number of AVs in the full information treatment.

5.2.2. Switching behavior

Another role of information is to improve system reliability, that is, to decrease the switching frequency with the experiment. Fig. 4 displays the average percentage of travelers who switched their choices over the rounds. In both FI treatments, there was a decrease in trends over the rounds. The percentage in the PI treatments remained stationary over the rounds, although it fluctuated. Using the rounds as an independent variable, the linear regression model demonstrated that the percentage of switch significantly decreased over rounds in the FI treatments, while no trend was observed in the PI treatments (Table 6). It appears that the provision of information on both modes can help the system become more stable.

In the standard mechanism, an average of 33 percent of travelers switched during each round under PI treatment. This number decreased significantly for the FI treatment, with 28 percent of travelers switching on average (Mann-Whitney test, $p < 0.01$), suggesting that the provision of information helps travelers with their choices. However, in the reward mechanism, in each round, 25 percent of travelers switched choices, both for the PI and FI treatments. However, there was no significant difference (Mann–Whitney test, $p = 0.31$). A possible reason is that travelers do not need a tradeoff between payoff and inequality in a reward mechanism.

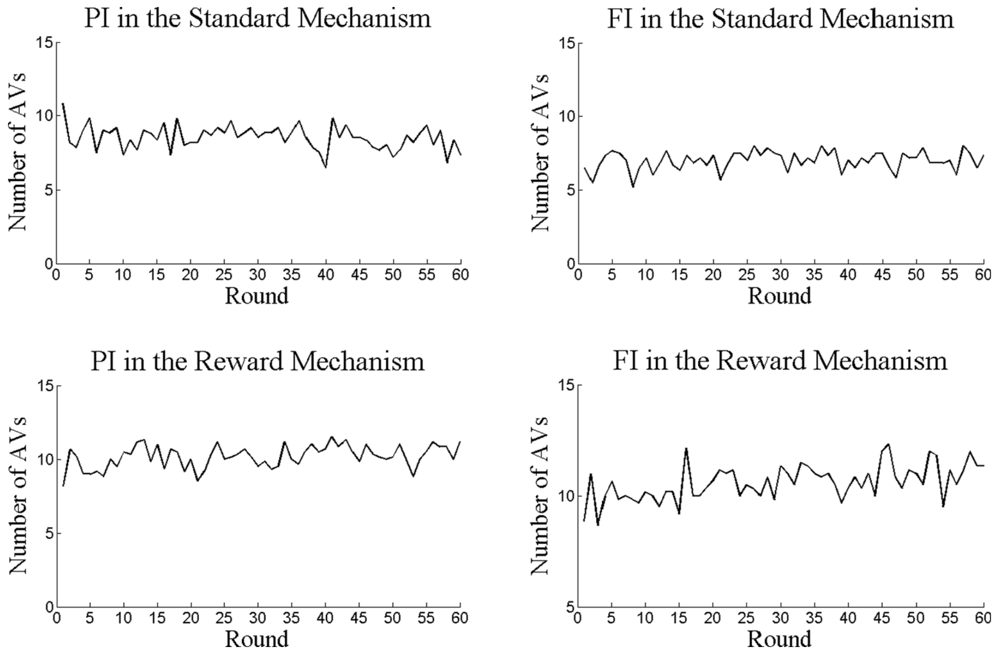

Fig. 5. Number of AVs over rounds (calculated by the average of six sessions).

In summary, more information led to fewer trials and errors. This consequently accelerated the convergence to equilibrium through less switching behavior. The effect of information was more significant in the standard mechanism, possibly because there was an inequality between the two modes.

5.3. Effectiveness of the reward mechanism

Dilemma strength quantifies the potential pitfalls in 2 × 2 social dilemmas (Tanimoto & Sagara, 2007; Wang et al., 2015; Ito and Tanimoto, 2018). Social Efficiency Deficit (SED) is a multiplayer version of the dilemma strength that is used to measure deviation from a situation where travelers cooperate to achieve minimum social cost. In this section, we introduce the concept of SED to evaluate the effectiveness of the reward mechanism. SED is defined as the gap between the Nash equilibrium and the socially efficient outcome (Arefin et al., 2019; Kabir and Tanimoto, 2019):

$$SED = ASC^{NE} - ASC^{SO}$$

where ASC^{NE} and ASC^{SO} denote the average social costs at the Nash equilibrium and social optimum, respectively. A large SED indicates that a socially efficient outcome can hardly be achieved, and $SED = 0$ implies that Nash equilibrium is socially optimal.

In the standard mechanism, the average social cost is 530.5 at Nash equilibrium and 384 at social optimum. The $SED = 146.5$ is positive, which reveals the existence of a social dilemma. In the reward mechanism, a subsidy of eight tokens is paid to each round traveler who chooses the AV. Thus, choosing an AV is a strictly dominant strategy, and $ASC^{NE} = ASC^{SO} = 405$. SED will shift from 146.5 to 0, which presents no social dilemma in the reward mechanism and social optimal results can be reached, and the amount of total reward is 120. An increase in reward on payments leads to a considerable decrease in social costs.

Next, we evaluated the effectiveness of the reward in the experimental results. In PI in the standard mechanism, there are an average of 8.51 AV travelers and 6.49 MV travelers, resulting in a total social cost of 591.62 tokens. By means of the reward, the number of AVs increased by 1.67, while the total social cost was reduced to 489.23 tokens. The average reward was 76.80 tokens per session per round, which is 75.01 percent (=76.80/102.39) of the social cost reduction, so the reward mechanism is effective. Compared to FI in the standard mechanism, the number of AVs in FI in the reward mechanism increased by 3.61, and the total social cost was reduced by 226.96 tokens. The average reward was 79.37 tokens in each round, which is 34.98 percent (=79.37/226.96) of the social cost reduction. In the FI treatment, the reward is also effective and can significantly improve the social benefits. In general, the reward mechanism is always effective because a small reward would lead to a significant decrease in social costs. The reward mechanism is more effective in the FI treatment, probably because there are fewer AVs in the standard mechanism.

5.4. Interaction of information and mechanism

Fig. 5 displays the number of AVs over the rounds, averaged by session. The largest number of AV travelers was observed in FI in the reward mechanism treatment, with an increasing trend over rounds (see Table 5). The interaction between information and

Table 7
Calibration coefficient of the MAL model in PI and FI treatments.

	Partial information	Full information
Observation	5400	5400
λ_0	8.15	17.46
θ	0	1.48
λ	0.08	0.06

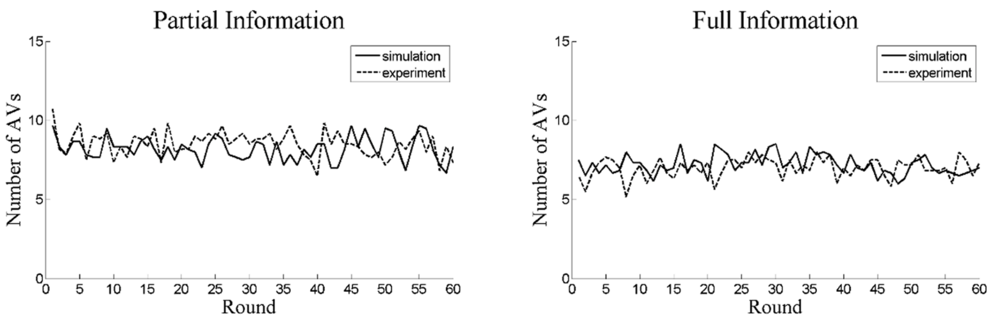

Fig. 6. Compare the number of AVs between learning model simulations and experimental data. The number of AVs is calculated by sessions.

mechanisms is the most effective treatment. In FI in the standard mechanism, the number of AVs decreased because of cost inequality, which implies that provision of information deteriorates social benefits. In PI in the reward mechanism, some travelers might not be aware that AVs are the dominant strategies. When both full information and the reward mechanism are applied, the cost inequality is eliminated, and the provision of information improves social benefits. Consequently, travelers could be induced to take AVs.

5.5. Learning model

Referring to Mak et al. (2015), a learning model is proposed to account for the disadvantageous inequity aversion behavior in travel mode under mixed traffic of AVs and MVs. Travelers make decisions based on the attraction of alternatives, and attractions are updated by the interaction among travelers.

We assume that travelers update their attractions in round t ($t = 2,3,\ldots,n$) based on their state in the prior round. In other words, their choices and feedback information in round t-1. Therefore, a traveler's decision-making process can be regarded as a Markov process. The perceived cost (Equation (8)) was applied to measure utility. $U_{i,t}$ is denoted as the utility when a traveler chooses i in round t. Utility is calculated as follows:

$$U_{i,t} = \pi_0 - PC_{i,t} = \pi_0 - [c_{i,t} + \theta max(c_{i,t} - c_{-i,t}, 0)] \tag{9}$$

where π_0 is the initial token that a traveler gets at the beginning of each round, and $\pi_0 = 100$ in our setting. $PC_{i,t}$ is the perceived cost that occurs when the traveler chooses i in round t. Attraction of travel mode i in round t is estimated as

$$A_{i,t} = \begin{cases} \lambda_0 + U_{i,t} & \text{if } i = R_{t-1} \\ U_{i,t} & \text{if } i \neq R_{t-1} \end{cases} \tag{10}$$

R_{t-1} represents the choice in round t-1. If alternative t is the actual choice for the traveler in the prior round, then the attraction for i equals the sum of the utility of alternative i and the inertia. If i is not the chosen mode in the prior round, then the attraction is equal to the utility. $\lambda_0 \geq 0$ is interpreted as inertia. A multinomial logit function is used to calculate the probability of a traveler choosing mode i in round t:

$$P(R_t = i) = e^{\lambda A_{i,t}} / \sum_k e^{\lambda A_{i,t}} \tag{11}$$

The maximum likelihood estimation was used to calibrate the parameters of the model. Table 7 presents the estimated results. λ_0 in the FI treatment demonstrates that inertia has a greater influence when providing more information to travelers. This also means that the system is more stable when it provides more information. Cost difference did not affect travelers' behavior in the PI treatment. However, the value of θ in the FI treatment is 1.49, which demonstrates that travelers consider inequality to a large extent when given more information.

In a simulation setting, 15 travelers interacted for 60 rounds, and each of the two treatments was simulated six times. The setting was the same as that in the experiment. Travelers receive feedback in a prior round and update their attraction to both travel modes using Equation (10). Therefore, travelers choose travel modes with a probability of P according to the multinomial logit function (Equation (11)). When all travelers made their decisions, the travel cost was calculated, and everyone received their feedback

Table 8
Simulation results in PI and FI treatments.

			1	2	3	4	5	6	AVE	P-value
Number of AVs	PI	Experiment	9.25	7.3	9.18	8.2	8.58	8.55	8.51	0.33
		Simulation	7.85	8.38	8.2	8.25	8.33	8.18	8.2	
	FI	Experiment	7.57	7.33	6.67	6.87	6.7	6.77	6.98	0.23
		Simulation	7.12	7.43	7.07	7.47	7.05	7.1	7.21	
Percentage that Switched	PI	Experiment	0.32	0.29	0.31	0.41	0.34	0.34	0.33	0.80
		Simulation	0.35	0.33	0.34	0.35	0.37	0.30	0.34	
	FI	Experiment	0.21	0.17	0.28	0.26	0.29	0.26	0.25	0.68
		Simulation	0.24	0.23	0.24	0.23	0.21	0.27	0.24	

information. The probability for the first round was obtained from the average frequency of the first round of the experiment. Fig. 6 compares the average number of AVs for each round between the simulations and experiments. The simulation results fluctuated and did not reach equilibrium, which is similar to the experimental results.

Table 8 lists the results from the simulation and the experiment. There were no significant differences between the statistics obtained from the simulation and the experimental data (t test, $p > 0.01$ for all results). Our learning model can reproduce the experimental results.

6. Conclusion

In this study, we constructed a road framework based on mixed traffic with AVs and MVs. Travelers were recruited to make decisions on their travel mode for 60–80 rounds. On the one hand, more AVs can improve road capacity and reduce travel costs for all vehicles. On the other hand, AV travelers have lower perceived time costs but a higher relative monetary cost compared to MV travelers. There is a conflict between individual and social payoffs. Two variables were considered in the experiment: information and mechanism. The main conclusions of this study are as follows.

The experiment shows that more than half of the travelers chose AVs. The result was close to the Nash equilibrium but did not reach the social optimum. Social preferences show that travelers are inequality averse. When feedback costs for both modes were provided, they also focused on the cost difference between the two travel modes. Perceived cost is proposed, which considers inequality. The equilibrium calculated by perceived cost better explains the results.

In the reward mechanism, AV is a dominant strategy. Eliminating cost inequality through a reward mechanism can incentivize more AV travelers. The extent of the AV subsidy lowers the social cost, which implies that the reward mechanism is effective. However, a small number of travelers still chose MVs. This may be because some travelers may not realize that choosing AVs is the dominant strategy.

Information contributes to traveler behavior in two ways. First, information increases the traveler's perception of inequality. In the FI treatment, fewer travelers chose AVs because travelers can intuitively see the cost difference between the two travel modes on the computer screen as feedback information, thereby paying more attention to the inequality. Additionally, information can help the system become more stable. Travelers in the FI treatments switched less frequently in the experiment.

Learning model simulations were used to reproduce the decision-making processes of travelers. The results show that the main factors affecting travelers' decisions are inertia, experience, and inequality. Inertia is the most important factor, as travelers tend to keep their prior round choices unchanged, unless the cost is too high or if there is a strong sense of disadvantageous inequality. The model reveals that disadvantageous inequality aversion may have a detrimental effect on traffic flow and social benefits under the mixed traffic of MVs and AVs.

To the best of our knowledge, this is the first study to investigate the effects of AVs using economic experiments. We demonstrated that while AVs can improve road capacity, they are more expensive than MVs. Eliminating traffic congestion will benefit all vehicles, but AV travelers incur higher costs compared to MV travelers, which may induce a feeling of inequality. Thus, AV companies may face the challenge of establishing the appeal of AVs for travelers when entering the market. Subsidies that eliminate cost inequality can induce travelers to take AVs and make the traffic system more efficient. Such a policy can perform well in the short term, but to solve the problem fundamentally, it is still necessary to develop technology to reduce the costs of AVs.

Our experiment shows that when more information was provided, a higher perception of inequality was induced, which resulted in losses of both individual and social benefits. However, when subsidies that eliminate cost inequality are provided, more information helps travelers make better decisions. The impact of information on social welfare may vary in different situations; thus, whether information should be provided depends on the situation. This is important for policy development and transportation planning.

Further investigations need to be conducted in future studies. For example, the contradiction between the experimental results and mixed Nash equilibrium and heterogeneity among participants could also be explored. Moreover, the single-road scenario setting could be extended to a large road network to predict travel behavior in a more sophisticated situation.

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CRediT authorship contribution statement

Qianran Zhang: Investigation, Writing – original draft. **Shoufeng Ma:** Supervision, Funding acquisition. **Junfang Tian:** Conceptualization, Methodology. **John M. Rose:** Writing – review & editing. **Ning Jia:** Software, Data curation.

Declaration of Competing Interest

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

Appendix A. . Instruction for PI in standard mechanism (translated into English)

Instructions

Welcome and thank you for your participation. This experiment involves multiple participants. You and your group mates will be presented with a series of choices. At the end of the experiment, you will receive a payment based on your payoff, which depends on the decisions you make, as well as the decisions of other participants.

Please note that during the experiment, communication with other participants is not allowed. If you communicate with others in any shape or form, the experiment will be terminated immediately, and no payment will be made. If you have any questions, raise your hand, and we will come to assist you in private. Thank you for your cooperation.

Please read the experimental instructions carefully. You are free to revisit the instructions at any time during the experiment. This is an interactive experiment, so you might have to wait after making your choice until all the participants have made their choices, and only then you may move on to the next round.

Description

Altogether, 15 persons participate in a group. You are assumed to travel from the origin to the destination over a given period. Each of you will have to choose a travel mode for this trip: whether to take a manually-driven vehicle (MV) or an autonomous vehicle (AV). The choice task will be repeated several times. The payoffs in each round are independent of the other rounds. In other words, your choice made in the current round will not have any effect on the payoffs in previous or subsequent choices.

Payment:

At the beginning of each round, each participant received an initial score of 100 tokens. If all participants have made their choices, travel costs and payoffs will be displayed on a computer screen. The payoff in each round is calculated as follows:

Payoff in current round = initial score – cost in current round

Informed feedback includes your own history choices and costs. The selection process will be repeated and terminated randomly in 60–80 rounds. At the end of the experiment, 40 rounds will be randomly selected, and the cumulative payoffs in these rounds will be paid. The payment that you earned will be converted to RMB at a ratio of 120:1.

Cost:

1. Travel time:

The travel time of each participant is calculated in the same way and depends on the total number of AV travelers and MV travelers in your group:

a) Travel time increases as the number of AV travelers increase;
b) Travel time decreases as the number of MV travelers increase;
c) When the number of AV travelers is large enough, travel time does not decrease as the number of MV travelers increases.

The travel time contains a fixed constant of 20, which is determined by the road characteristics.

In summary, the travel time is calculated as follows:

$$T = \max(4 \times \mathrm{n}_1 - \mathrm{n}_2, 0) + 20$$

2. Cost of manually-driven vehicles (MVs):

If you choose a manually-driven vehicle, your travel cost equals the travel time:

$$c_{MV} = T$$

3. Cost of autonomous vehicles (AVs):

If you choose an autonomous vehicle, your perceived travel time is reduced because the AV is not driven by yourself, and you can perform other tasks during the trip.

Table A1
Examples of travel costs in the experimental scenario.

Number of travelers	Travel time T	Cost of AVs c_{AV}	Cost of MVs c_{MV}
15 MVs, 0 AVs	80	–	80
7 MVs, 8 AVs			
0 MVs, 15 AVs	20	28	–

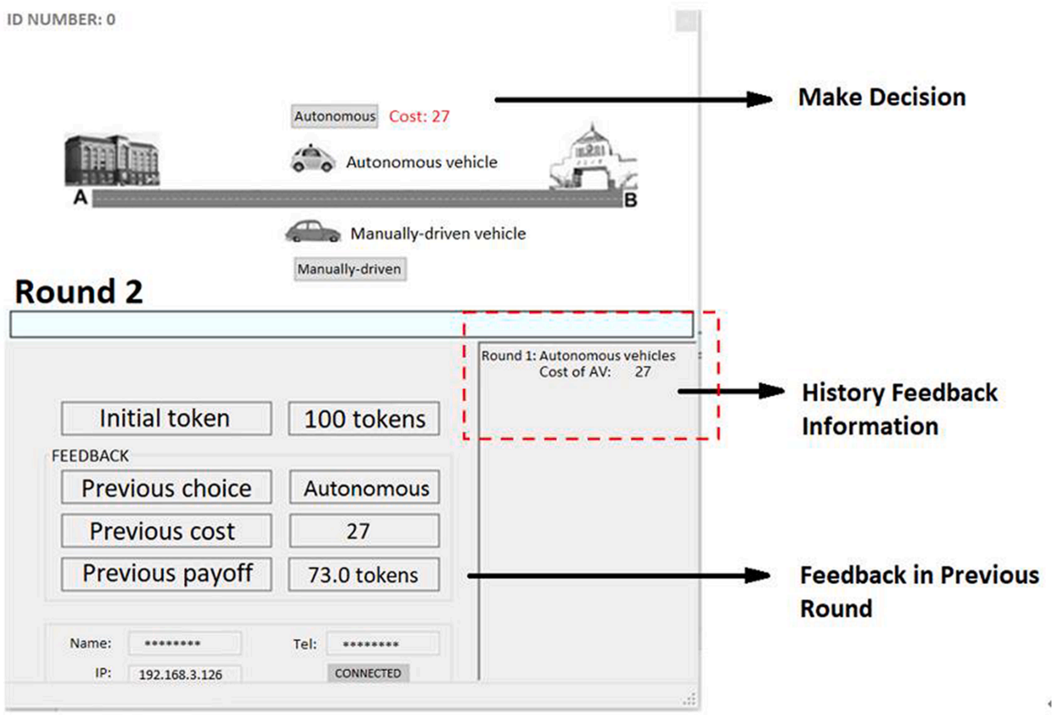

Fig. A1. Screen on participants' computer terminal in the PI treatment. Feedback information includes the costs of the travel mode chosen by the participant.

However, the maintenance cost of AVs is relatively higher than that of MVs, so there is an extra constant in the expression. Travel cost of AV is calculated as follows:

$$c_{AV} = 12.25 + 7/9 \times T$$

The payoff for each round is calculated according to the above formula.

Example

The following example will help you gain an understanding of the calculation of the payoff. Please read the example and write down the calculations (see Table A1.).

1. If the experimental result is 15 MVs, then the travel time will be 80, the cost of MV travelers will be 80, and their payoffs will be initial tokens – 80.
2. If the experimental result is 7 MVs and 8 AVs, then the travel time will be , the cost of MV travelers will be , their payoffs will be ; the cost of AV travelers will be , and their payoffs will be .
3. If the experimental result is 15 AVs, then the travel time will be 20, the cost of MV travelers will be 28, and their payoffs will be initial tokens–28.

Appendix 2. . Screens for FI and PI treatment in the experiment.

See Figs. A1 and A2

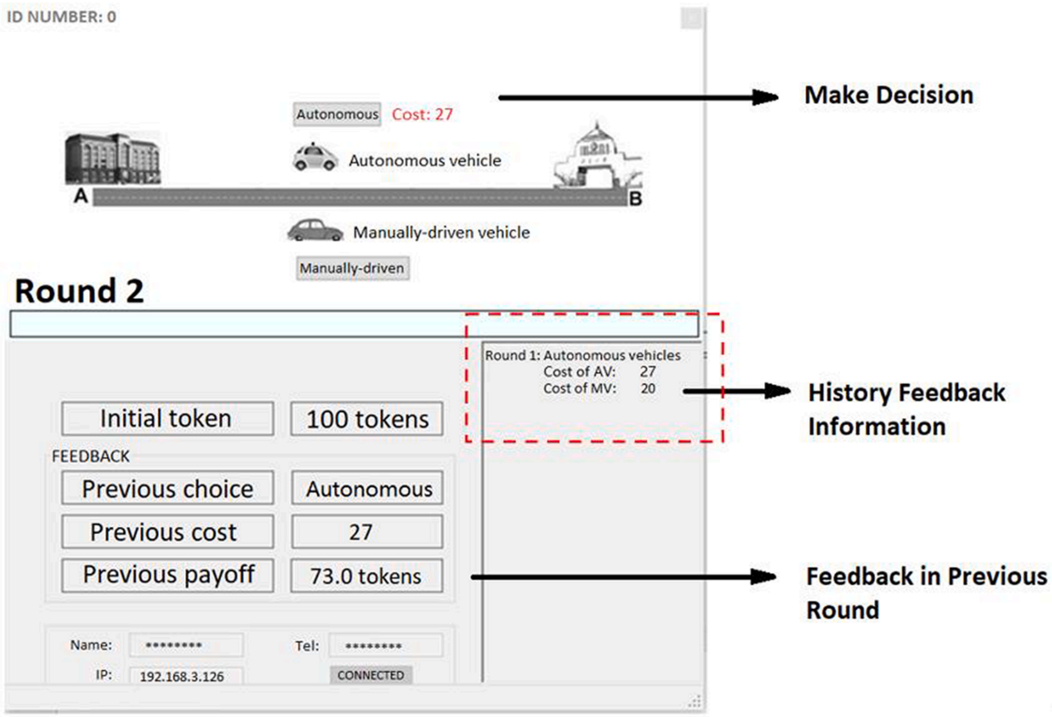

Fig. A2. Screen on participants' computer terminal in the FI treatment. Feedback information includes the costs of both travel modes.

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