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Study on the influence of road capacity and information feedback on urban traffic system equilibrium state

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ABSTRACT

This paper presents an experimental study on the equilibrium state transition of a traffic system under road capacity changes. The experiments were based on a discrete bottleneck model. Four groups of experiments are conducted under two types of information feedback conditions. The experimental results show that it needs a long time for traffic system to approach a stable state when road capacity is reduced. However, players can adjust their decision-making rapidly and system can approach a stable state in a short time when road capacity is increased. The individuals' choice behavior is analyzed in detail, and the analysis results show that an individual's payoff will decrease if he/she frequently changes travel decisions. The Mann–Whitney U tests show information feedback has no significant influence on both the collective behavior of system and the players' choice behavior. A reinforcement learning model is used to verify the experimental results, and the simulation results are in good agreement with the experimental results. The research can provide some theoretical references for urban traffic management.

1. Introduction

There are many uncertainties in a real transportation system, for example traffic accidents, vehicle failures, adverse weather conditions, and road construction. Uncertainties can be investigated by changing road capacity; for instance, if a traffic accident occurs, road capacity will be reduced, but it will be restored after the traffic accident is handled. With the rapid development of information technology, information on traffic conditions can be obtained easily before traveling so that travelers can accordingly change their travel route, travel mode, or departure time to mitigate travel uncertainties.

In recent years, great attention has been paid to travel choice behavior analysis in order to determine the main factors affecting an individual's decision and traffic system equilibrium [1–7]. Rapoport et al. [8,9] studied the influence of pre-trip information on a route-choice decision under stochastic travel conditions, and the results showed that under uncorrelated conditions, the mean payoff was higher with the information feedback than without it. However, the information had no significant effect on the experimental results under the correlated condition. In all cases, the system could achieve user equilibrium. To investigate the influence of information on the route-choice behavior under uncertain conditions,

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Table 1
Distribution of road capacity and information feedback in four groups of experiments.

Group	Capacity s and the corresponding rounds	Information
1	$s = 8$ in rounds 1–30; $s = 7$ in rounds 31–80; $s = 10$ in rounds 81–130	Self-information
2	$s = 8$ in rounds 1–40; $s = 7$ in rounds 41–80; $s = 8$ in rounds 81–120	Self-information
3	$s = 7$ in rounds 1–40; $s = 8$ in rounds 41–80; $s = 7$ in rounds 81–120	Self-information
4	$s = 7$ in rounds 1–40; $s = 8$ in rounds 41–80; $s = 7$ in rounds 81–120	Global-information

Lu et al. [10] conducted a series of experiments on information and incident scenarios. Their results showed that the mean flow of routes was close to the equilibrium in the information scenario but significantly diverged from it in the incident scenario. The proportion of individual decision changes was obviously higher in the incident scenario than in the information scenario, which indicated that information had a certain effect on individuals' choice behavior. The mean travel time and its standard deviation were both smaller in the information scenario than in the incident scenario, which implied that information was useful under uncertain traffic conditions.

Ben-Elia and Avineri [11] showed in their review paper that information could be useful for individual travelers under uncertain conditions, but the impacts of traffic information on collective behavior remained unclear. Numerous studies have demonstrated that the information influence is related to many factors, including the transportation network topology and information type [11–13]. In certain cases, a large amount of information might lead to the information paradox [14,15].

Rapoport et al. [16] also studied individual queuing behavior under constant and variable service capacity and found that the collective behavior could achieve equilibrium under the fixed capacity, whereas it diverged from equilibrium under the variable capacity. Innocenti et al. [17] investigated the travel mode (driving a car or taking public transport) choice behavior of individuals under uncertain travel time, and the experimental results showed that most individuals had a preference for choosing a car, regardless of relatively high uncertainty, and that traffic information had little effect on their choice behavior.

As mentioned previously, many experimental studies on travel choice behavior have been conducted, but there is still insufficient research on the departure time choice behavior under uncertain conditions. To address this shortcoming, this paper studies individuals' departure time choice behavior based on a discrete bottleneck model [18,19] under uncertain condition where road capacity will change twice during individual travel. The objective of this study is twofold: for departure time travel choice, to determine how the traffic system state changes with road capacity and to investigate whether the traffic information has an impact on the system state change and individuals' choice under uncertain condition.

The rest of this paper is organized as follows. Section 2 describes the experimental design. Section 3 discusses the experimental results from the aspects of collective and individual behaviors. Section 4 proposes a reinforcement learning model and presents the simulation results. Finally, Section 5 concludes the paper and presents future work directions.

2. Experimental design

The experiment is performed using a discrete bottleneck model, in which a fixed number of identical commuters travel from the origin to the destination along a single road. On the road, there is a potential bottleneck with a fixed road capacity s. If traffic flow rate exceeds s, the bottleneck will be activated, and a queue will be formed. The travel time from the origin to the destination is calculated as $T(t) = T^f + T^v(t)$, where T^f denotes the fixed travel time, $T^v(t)$ is a variable travel time due to congestion, and t represents the departure time from the origin. Without loss of generality, we set $T^f = 0$. Suppose $q(t)$ be the queue length, then $T^v(t) = q(t)/s$, where $q(t) = \max\{q(t-1) + n(t) - s, 0\}$. Here $q(t-1)$ is the queue length at departure time $(t-1)$, and $n(t)$ is the number of commuters who choose departure time t. Given that the working time is t^*, according to the bottleneck model, if a commuter leaves the origin at time t, his/her travel cost is calculated as follows:

$$C(t) = \alpha T^v(t) + \beta \max\{0, t^* - t - T^v(t)\} + \gamma \max\{0, t + T^v(t) - t^*\} \quad (1)$$

where the first term on the right side denotes the travel time cost, the second term denotes the early-arrival cost, and the third term is the late-arrival cost; cost coefficients α, β, and γ satisfy the condition of $\gamma > \alpha > \beta$. In the experiment, they were set $\alpha = 2$, $\beta = 1$, and $\gamma = 3$.

In the experiment, 136 subjects were recruited, and they were all undergraduate students. The numbers of male and female participants were approximately equal. All subjects were divided into four groups, each of which included 34 participants. Each group participated in a single experiment that lasted approximately 90 min and included 30 min of experimental explanation (refer to Appendix A). One experiment included three sessions wherein the capacity was changed twice. The capacity values and the corresponding experimental rounds are given in Table 1. When the capacity changed, the subjects could see text messages about the capacity change (decrease or increase) on the experimental interface. Three groups participated in the self-information scenario experiment, and the remaining group participated in the global information scenario experiment. In the self-information scenario, on the experimental interface screen,

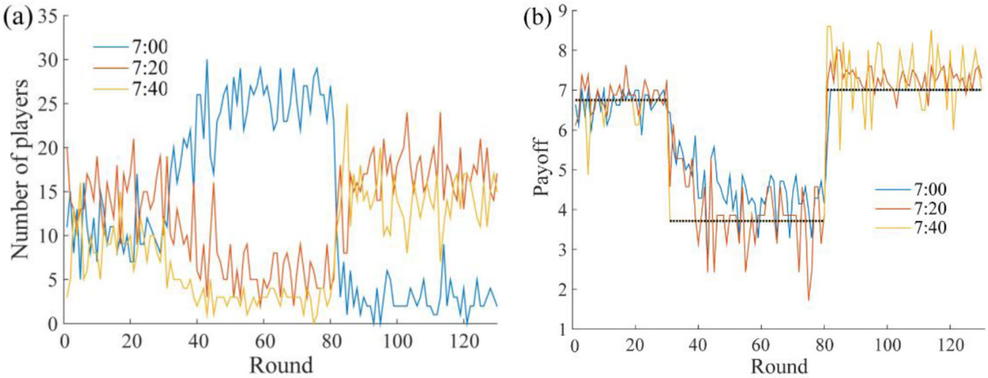

Fig. 1. Comparison of the experimental results of Group 1 and the UE prediction. (a) The number of players and (b) the payoff of each departure time.

Table 2
The theoretical UE prediction under different road capacity conditions, and mean number of players and mean payoffs for each departure time of Group 1.

	Capacity	Player	Payoff
Theoretical UE prediction	8	(10, 16, 8)	(6.75, 6.75, 6.75)
	7	(28.4, 2.8, 2.8)	(3.71, 3.71, 3.71)
	10	(2, 20, 12)	(7, 7, 7)
Experimental results	8	(10.4, 14.6, 9)	(6.68, 6.85, 6.63)
	7	(23.88, 7.02, 3.1)	(4.51, 3.92, 3.71)
	10	(3.4, 16.6, 14)	(6.97, 7.3, 7.32)

a subject could only see his/her own departure time, travel time, arrival time, early- or late-arrival time, and the corresponding cost. In the global information scenario, the information about all departure times was fed back, including arrival time and travel cost (refer to Appendix Figure 1 in Appendix B). The experimental platform was built using Python software. All subjects were anonymous and obtained travel information through computers connected to the local area network.

In all groups, the start of the working time was set to 8:00 a.m., and in each round, each subject can choose one departure time from 7:00 a.m., 7:20 a.m., and 7:40 a.m. to leave the origin. Subjects' payoff in one round was computed by subtracting travel cost $C(t)$ from the 10 game points. The total payoff were accumulated across all rounds and converted to money at a fixed rate (refer to Appendix A).

3. Experimental results

This section analyzes the experimental results from the aspects of collective and individual behaviors. Also, the state system transition process is analyzed under variable road capacity.

3.1. Collective behavior

The definition of user equilibrium (UE) and social optimum (SO) given in [5] is used in this study. The changing trends of the number of players and the payoff at each departure time of Group 1 are shown in Fig. 1, where the dotted lines denote the theoretical UE prediction. The detailed data are given in Table 2. In the first session, the capacity s was set to eight, and the players made choices randomly at the beginning of the experiment. From the second round, all players could make choice according the travel information showed in the experimental interface. The experimental result was not significantly different from the theoretical UE prediction according to the t-test for the payoff (p-value $= 0.384$).

In the second session, the capacity s was reduced to seven, and the number of players and payoff moved slowly toward the theoretical UE prediction and fluctuated near it after approximately 20 rounds (see also Table 3). The t-test rejected the null hypothesis of no difference between the experimental result and the UE prediction at the significance level of 5% (p-value < 0.05). As shown in Table 2, the mean number of players choosing the departure time of 7:00 a.m. was 15.95% lower than the UE prediction. Most of the players chose the departure time of 7:20 a.m., which caused the experimental result to be 150.71% higher than the UE prediction. This was the main reason why the experimental result could not reach the UE prediction.

In the third session, the capacity was increased to 10; players could respond quickly to the capacity change, and the collective behaviors were close to the UE prediction by a short time of adjustment (see also the second line in Table 3,

Table 3
The mean experimental payoff in 12 blocks of 10 rounds each and the UE prediction in each treatment.

Group	Round											
	1–10	11–20	21–30	31–40	41–50	51–60	61–70	71–80	81–90	91–100	101–110	111–120
1	6.63	6.78	6.75	4.62	4.00	3.81	4.01	3.82	7.31	7.15	7.16	7.17
	UE prediction: 6.75				UE prediction: 3.71				UE prediction: 7.00			
2	6.60	6.64	6.65	6.59	4.89	4.20	3.89	3.81	6.60	6.69	6.78	6.64
	UE prediction: 6.75				UE prediction: 3.71				UE prediction: 6.75			
3	4.32	4.18	3.94	3.78	6.63	6.63	6.63	6.66	4.25	3.93	3.87	3.67
	UE prediction: 3.71				UE prediction: 6.75				UE prediction: 3.71			
4	4.25	4.18	3.79	4.19	6.51	6.49	6.72	6.69	4.08	3.86	4	3.61
	UE prediction: 3.71				UE prediction: 6.75				UE prediction: 3.71			

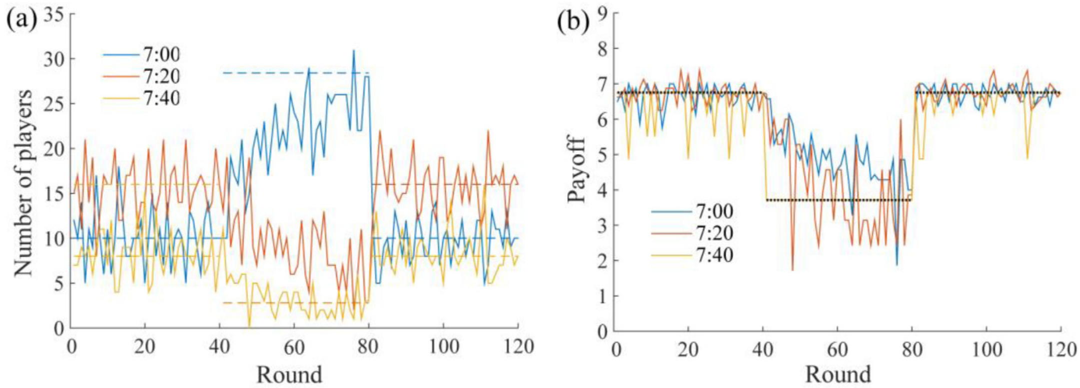

Fig. 2. Comparison of the experimental results of Group 2 and the UE prediction. The fluctuating solid lines are experimental results and the dotted lines denote the UE prediction. (a) The number of players and (b) the payoff of each departure time.

in which the mean payoff of rounds 81–90 is 7.31 and it is close to the UE prediction). However, according to the t-test (p-value < 0.05), the experimental result was significantly different from the UE prediction. The reason for this result could be explained as follows. Based on the data in Table 2, the observed mean payoff at 7:00 a.m. was approximately equal to the UE prediction, but it was 4.29% and 4.57% higher than the UE predictions at 7:20 a.m. and 7:40 a.m., respectively; thus, the experimental results were very close to the UE predictions. However, as shown in Fig. 1, the number of players choosing each departure time fluctuated greatly. The standard deviations of the mean number of players at 7:00 a.m., 7:20 a.m., and 7:40 a.m. were 3.49, 3.52, and 3.34, respectively; thus, the experimental result could not reach the UE prediction because of the large fluctuation.

In the experiment, Group 2 was the control group. The results of Group 2 were used to examine whether the collective behaviors could reach the UE prediction when the capacity was re-set to the original value and whether the travel experience accumulated by players in the first session had an influence on their decision-making in the third session. The detailed parameters of Group 2 are given in Table 1. In the first two sessions, the capacity changing trend and the experimental results of Group 2 were similar to those of Group 1, as shown in Fig. 2 and Table 4; so, this Group 2 focuses on the transition process from the second session to the third session and the collective behavior in the third session.

As shown in Fig. 2, the players could quickly adjust their decision choice when the capacity changed from seven to eight, and the collective behavior could reach the UE prediction in a short time (see also the fourth line in Table 3, in which the mean payoff of rounds 81–90 is 6.60 and it is very close to the UE prediction), which were confirmed by the t-test at the significance level of 5% (p-value $= 0.13$). The results show that the travel experience accumulated by players in previous sessions has no influence on their decision-making in the current session if the road conditions are different. Thus, the equilibrium state of a traffic system and the transition process from one state to another are related only to road capacity.

According to Table 4, the standard deviations of number of players and payoff in the third session were both lower than those in the first session, indicating that players could learn from the previous decision-making experience if the road conditions were the same, even if they had experienced different road conditions in the second session.

For Groups 1 and 2, the road capacity first decreased and then increased. The questions are: what would be the result if the capacity first increased and then decreased? And what would be the transition process of the collective behavior? To answer these questions, the experiment of Group 3 was conducted. The parameters of Group 3 for variable capacity are given in Table 1. The experimental results and the UE predictions are shown in Fig. 3. In the first session, the capacity was set to $s = 7$, and the experiment included 40 rounds. After approximately 20 rounds, the number of players and payoffs

Table 4
The mean number of players and the mean payoffs as well as their standard deviation (signed numbers) for each departure time of Group 2.

Session	Mean player	Mean payoff
One	(10.2, 15.55, 8.25) (±3.14, ±3.09, ±2.62)	(6.67, 6.73, 6.47) (±0.32, ±0.3, ±0.60)
Two	(21.68, 8.98, 3.35) (±4.83, ±3.94, ±2.14)	(4.85, 4.04, 3.71) (±0.84, ±1.32, ±0)
Three	(9.73, 15.86, 8.40) (±2.46, ±2.85, ±2.41)	(6.74, 6.76, 6.53) (±0.25, ±0.27, ±0.52)

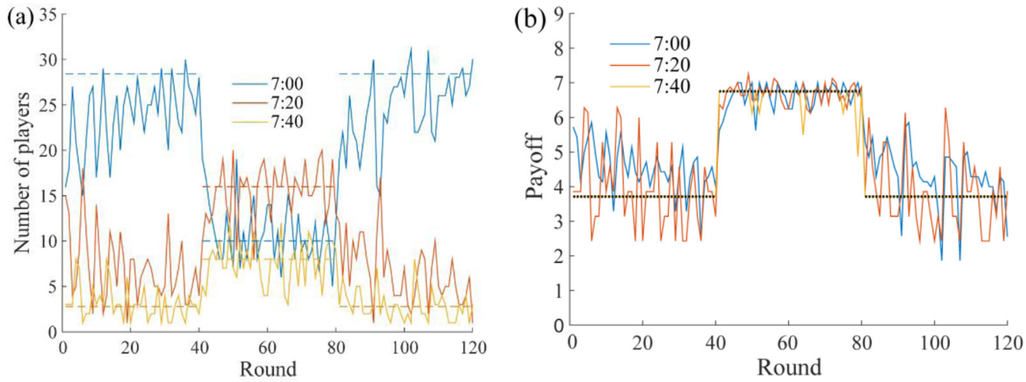

Fig. 3. Comparison of the experimental results of Group 3 and the UE prediction. The fluctuating solid lines are experimental results and the dotted lines denote UE prediction. (a) The number of players and (b) the payoff of each departure time.

for each departure time were both close to the UE predictions; see also the sixth line in Table 3, in which the mean payoff in the first two blocks are 4.32 and 4.18 that are quite different from the UE prediction value 3.71. Furthermore, the t-test confirmed both the number of players and payoffs could not arrive the UE prediction at the significance level of 5% (p-values < 0.01). In the second session, the capacity was increased to eight, and the collective behavior could reach the UE prediction rapidly (see also the sixth line in Table 3, in which the mean payoff of rounds 41–50 is 6.63 that is approximately equal to the UE prediction). The t-test result confirmed that the experimental result was not significantly different from the UE prediction at the significance level of 5% (p-value = 0.16).

In the third session, the capacity was decreased to seven, which was the same as that in the first session. From Fig. 3, it can be seen that the experimental results approached the UE prediction slowly and did not arrive until the end of the session (t-test result p-value < 0.01). The trend of closing to the UE prediction was the similar as in the first session; thus, the road condition of the second session and the players' experiences accumulated in the first session had no significant effect on their decision-making in the third session.

The experiments of Groups 1–3 were all performed under self-information conditions. Group 4 was the control group of Group 3, and it was used to investigate whether information feedback had an effect on travel choice behavior.

The experimental results of Group 4 are shown in Fig. 4, where it can be seen that in the first 40 rounds, the trend of approaching the UE prediction of Group 4 was slightly faster than that of Group 3; see also the first block of lines six and eight in Table 3, in which the mean payoff of Group 4 is closer to the UE prediction. In the first two sessions, the standard deviations of the payoff and the number of players at each departure time of Group 4 were both larger than those of Group 3, which could also be concluded from the large fluctuations in the experimental results. In the third session, the standard deviations of Group 4 were similar to those of Group 3, as shown in Table 5.

Next, the Mann–Whitney U hypothesis test was used to examine whether the information feedback had a significant impact on the players' choices. The test results are presented in Table 6, where it can be seen that all p-values were larger than 0.05, which confirmed the null hypothesis of no difference between Groups 3 and 4 at the significance level of 5%. Thus, the information feedback had no effect on the collective behavior.

To investigate whether the players' decision-making follows a certain rule, the trajectories of players' decision-making were analyzed, and the results are shown in Fig. 5. In Fig. 5, the lines represent the combined trajectories of subjects who selected three departure time points from the first to the last round in each experiment; the red, green, and blue lines denote the trajectories in the first, second, and third sessions, respectively; points indicate the number of players at each departure time; the largest points indicate the theoretical UE predictions, and cross marks indicate the theoretical SO predictions. As shown in Fig. 5, the trajectories were all close to the UE predictions but far away from the SO predictions, which had no fixed evolutionary pattern.

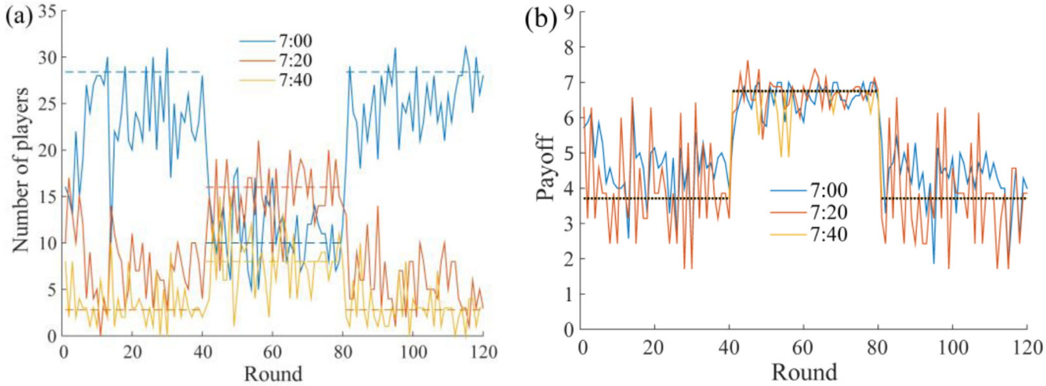

Fig. 4. Comparison of the experimental results of Group 4 and the UE prediction. The fluctuating solid lines are experimental results and the dotted lines denote UE prediction. (a) The number of players and (b) the payoff of each departure time.

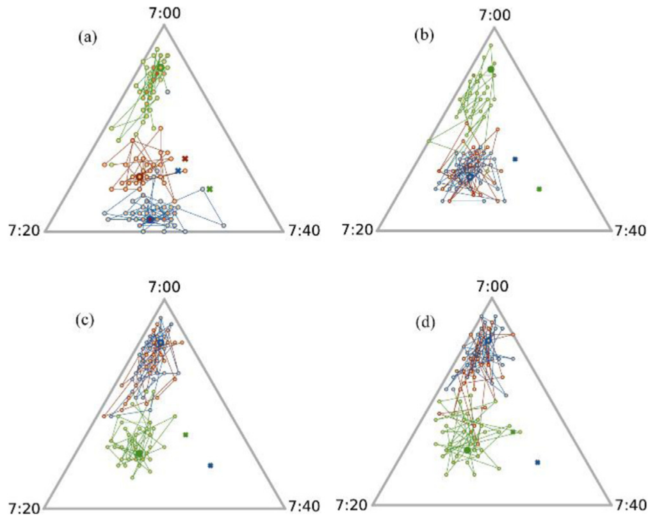

Fig. 5. Trajectories between round and round in our experiments. (a)–(d) denote Group 1–Group 4, respectively.

Table 5
Mean number of players and mean payoffs as well as their standard deviation (signed numbers) for each departure time of Groups 3 and 4.

	Session	Mean player	Mean payoff
Group 3	One	(23.75, 7.08, 3.18) (±3.89, ±3.87, ±1.88)	(4.54, 3.91, 3.71) (±0.69, ±1.18, ±0)
	Two	(10.93, 15.40, 7.68) (±3.32, ±2.97, ±2.42)	(6.61, 6.68, 6.63) (±0.38, ±0.29, ±0.38)
	Three	(24.58, 6.50, 2.93) (±4.00, ±3.46, ±1.7)	(4.32, 3.76, 3.71) (±0.90, ±1.10, ±0)
Group 4	One	(22.93, 7.60, 3.48) (±4.94, ±3.73, ±2.47)	(4.60, 4.00, 3.71) (±0.95, ±1.36, ±0)
	Two	(11.35, 14.83, 7.83) (±3.69, ±3.48, ±3.29)	(6.56, 6.68, 6.58) (±0.41, ±0.43, ±0.47)
	Three	(25.15, 5.90, 2.95) (±3.38, ±3.11, ±2.22)	(4.24, 3.71, 3.71) (±0.82, ±1.31, ±0)

3.2. Individual behavior

To understand the players' travel choice behaviors better, the results are analyzed from the individual behavior perspective.

Table 6
The p-values obtained by Mann–Whitney U test on the number of players at each departure time for Groups 3 and 4.

Departure time	Round 1–40	Round 41–80	Round 81–120
7:00 a.m.	0.481	0.595	0.615
7:20 a.m.	0.414	0.408	0.444
7:40 a.m.	0.837	0.919	0.779

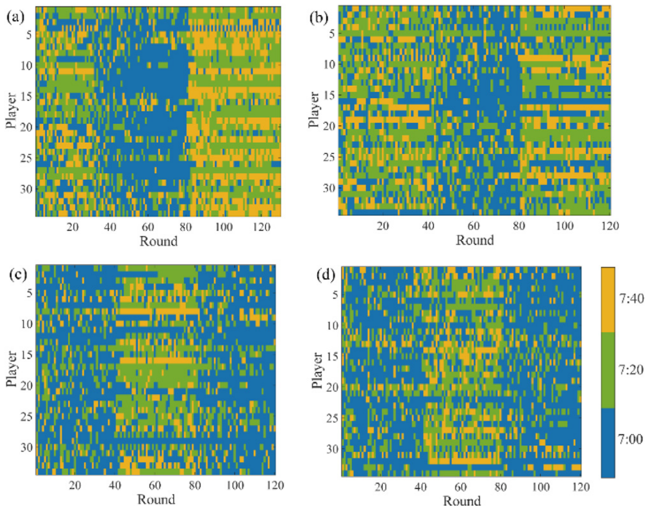

Fig. 6. Evolution of the individual choice behavior during the experiments, (a)–(d) denote Group 1–Group 4, respectively.

The evolution of the individual choice behavior during the experiment is shown in Fig. 6, where the vertical axis denotes the player number, which was set from 1 to 34, and colors indicate players' choices. In Fig. 6, it can be seen that players had no strictly defined decision-making pattern. For instance, in the first and third sessions of Group 1, most decisions of player No. 11 were to choose the departure time of 7:40 a.m., but most decisions of player No. 27 were to choose the departure time of 7:20 a.m.; the decisions of player No. 4 were to choose a departure time between 7:00 a.m. and 7:40 a.m. alternately. In the second session of Group 1, the decision of player No. 25 was constantly changing between 7:00 a.m., 7:20 a.m., and 7:40 a.m., and player No. 26 selected 7:40 a.m. once, 7:20 a.m. twice, and then selected only 7:00 a.m. until the end of the session. The individual choice behaviors in Groups 2–4 are similar as in Group 1 and they are no longer discussed one by one.

In all experiments, each player had his/her own choosing strategy; for instance, after several rounds, some of the players were no longer changing their decision-making, while the others constantly changed their decision-making; so, it could be difficult to classify individual decision-making. This result is similar to real traffic, where every driver has his/her own driving preferences.

Next, the impact of decision-making changing frequency on the individual payoff was analyzed. The relationship between the decision-making changing frequency and the individual mean payoff is shown in Fig. 7, where the dots and circles denote players of different group, and lines represent the results of the least squares fitting. As shown in Fig. 7, the slopes of the linear fits are all negative, and they are -0.78, -0.48, -0.70, and -0.60 for Groups 1–4, respectively. This result indicates that the individual mean payoff will decrease if players frequently change their travel strategies.

The relationship between the decision changing frequency and the individual mean payoff of Groups 3 and 4 is shown in Fig. 7(b), where it can be seen that they are similar. We implemented Mann–Whitney U test (a test of comparison of trends in two sets of independent data) and the result showed p-value $= 0.194$, which confirmed the null hypothesis that the information has no significant effect on the individual choice behavior at the significance level of 5%.

For revealing more information about individual choice behavior, the evolution of individual payoff was checked in Fig. 8, where the vertical axis denotes the player number, which was set from 1 to 34 for each group, and colors indicate players' payoff.

From Fig. 8, it can be seen that the payoff of each player fluctuates with the round whether the player changes his/her travel strategy or not. The main reason is that the travel time $T^{v}(t)$ in the expression of $C(t)$ is related to the queue length at departure time $(t-1)$ and the number of players who depart at time t (see also the first paragraph in Section 2). Since other players would change their travel choice, a player's payoff might change even if he/she did not change travel strategy; that is a player's payoff is not only related to his/her own choice, but also affected by other players' choices.

Furthermore, combining with Figs. 6 and 8, we analyze the relationship between a single play's decision-making and his/her payoff. For instance, in Group 1, most decisions of player No. 4 were to choose a departure time between 7:00 a.m.

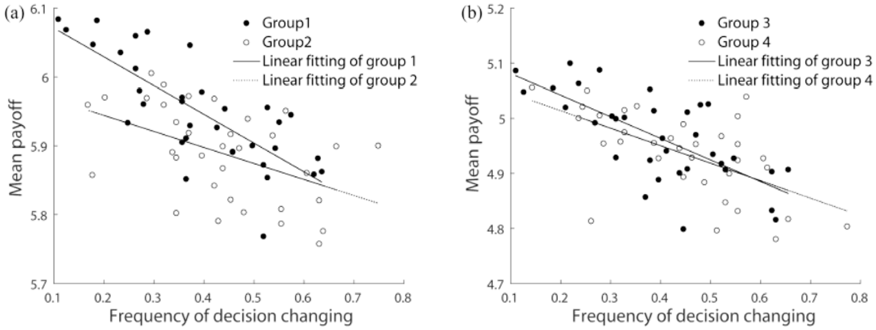

Fig. 7. Relationship between the decision-making changing frequency and the mean payoff of player.

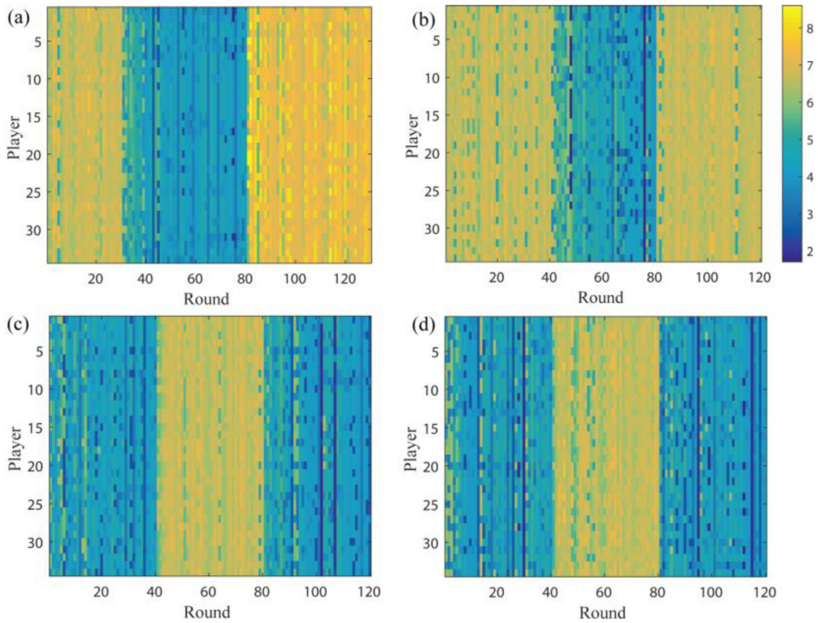

Fig. 8. Evolution of the individual payoff during the experiments, (a)–(d) denote Group 1–Group 4, respectively.

and 7:40 a.m. alternately, and the decision changing frequency of the player is 0.64 in whole experiment; his/her choice was 7:00 a.m. in round 16 and changed to 7:40 a.m. in round 17. For player No. 27, his/her most decisions were to choose the departure time of 7:20 a.m. in first and third sessions and 7:00 in second session, and the decision changing frequency of the player is 0.11 in whole experiment; his/her choice was 7:20 a.m. in rounds both 16 and 17. Thus, from round 16 to round 17, player No. 4 changed strategy, while player No. 27 did not; however, from round 16 to round 17, the payoff of player No. 4 reduced from 7 to 6.75, while the payoff of player No. 27 increased from 6.75 to 7.63. From round 17 to round 18, player No. 4 changed his/her choice from 7:40 to 7:00 and his/her payoff increased from 6.75 to 7; while the decision of player No. 27 remained unchanged and his/her payoff decreased from 7.63 to 6.88. The relationship between other players' strategy and their payoff are similar as player No. 4 and player No. 27, and they are no longer discussed one by one. In summary, payoff of a player may decrease, increase or unchanging whether the player changes strategy or not.

4. Simulation model and results

To obtain a deeper insight into the experimental results, simulations based on the reinforcement learning model were conducted. The specific simulation steps were as follows.

(1) Initial propensity: Assume that all individuals have the same initial propensity for each departure time, which is set to be the same as the payoff of the UE prediction.

Table 7
Parameter's values in the reinforcement learning model.

Parameter	s_j	b_j			θ	θ_1	μ	ν	λ
		7:00	7:20	7:40					
Value	7	20	5	2	0.2	0.02	0.1	0.3	0.45
	8	9	15	7					
	10	1	21	23					

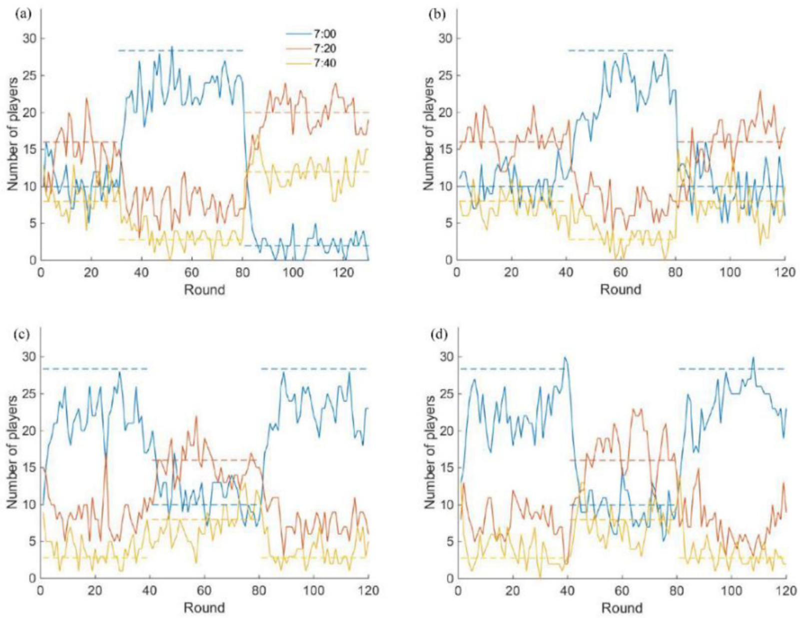

Fig. 9. Simulation results of the mean number of players for each departure time. The fluctuating solid lines are simulation results and the dotted lines denote the UE prediction. (a)–(d) denotes Groups 1–4, respectively.

(2) Update propensities: Suppose that an individual m has chosen departure time t in round i; then, its propensity in round (i + 1) is updated to:

$$\begin{cases} q_m^t\,(i+1) = \theta(u_m^t\,(i) + b_j) + \mu q_m^t\,(i) + \nu s_j \\ q_m^{t'}\,(i+1) = \theta_1(u_m^{t'}\,(i) + b_j) + \mu q_m^{t'}\,(i) + \nu s_j \end{cases} \tag{2}$$

where $q_m^t(i{+}1)$ and $q_m^{t'}(i{+}1)$ denote the propensities of individual m choosing departure times t and t' in round (i+1); $u_m^t(i)$ and $u_m^{t'}(i)$ denote the payoffs of individual m choosing departure times t and t' in round i; b_j is the auxiliary parameter of the payoff under different capacity s_j, where $j = 1, 2, 3$ corresponds to the departure time of 7:00 a.m., 7:20 a.m., and 7:40 a.m., respectively. The parameter of b_j is to stimulate the payoff so that an individual can have a higher propensity to choose the departure time with the higher payoff. Further, θ and θ_1 denote the learning rates, and $\theta_1 = 0$ in the self-information scenarios because an individual does know the payoff of departure time t'; μ is the attenuation factor, which can weaken an individual's propensity in the previous round; ν is the capacity adjustment parameter, which can adjust an individual's propensity under different capacity conditions.

(3) Update probabilities: The probability of choosing departure time t in round $(i + 1)$ is calculated as follows:

$$p_m^t\,(i+1) = \frac{e^{\lambda q_m^t(i+1)}}{\sum_{k=1}^{T} e^{\lambda q_m^k(i+1)}} \tag{3}$$

where λ is a parameter that determines reinforcement sensitivity, and $\lambda > 0$; k is the number of optional departure times, and $k = 1, 2, \ldots, T$.

In the simulation, the reinforcement learning model parameters were set as shown in Table 7. The parameters' values were obtained by the least squares method that was used to calculate the minimum variance between the simulation and experimental results.

The simulation results were in good agreement with the experimental results, as shown in Figs. 9 and 10. In particular, the reinforcement learning model could reproduce the transition from one steady state to another when the capacity changed (increases or decreases). In addition, the model could reproduce the experimental phenomenon that fluctuations

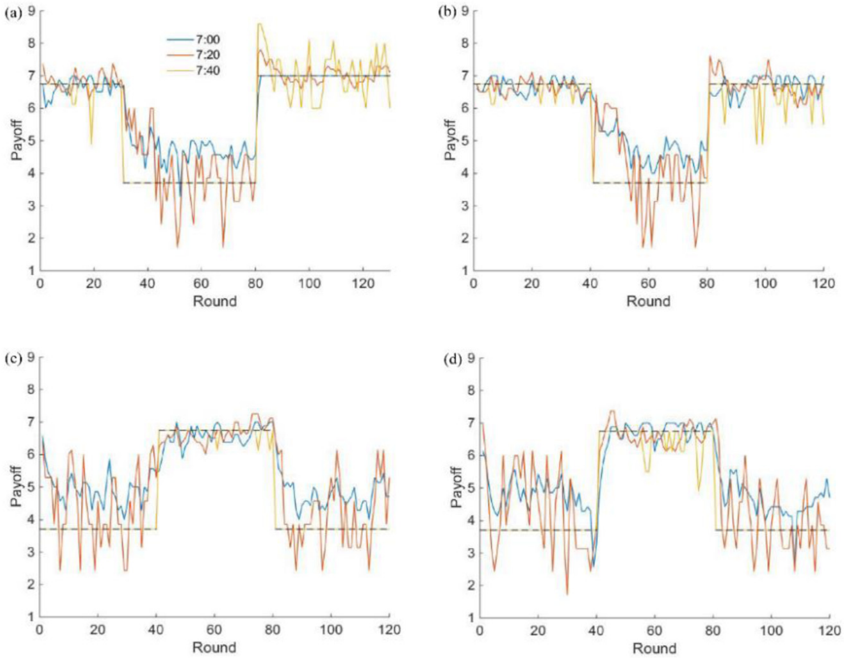

Fig. 10. Simulation results of the mean payoff for each departure time. The fluctuating solid lines are simulation results and the dotted lines denote the UE prediction. (a)–(d) denotes Groups 1–4, respectively.

in the number of players and payoff were slightly larger for Group 4 than for Group 3 (refer to Appendix Table 1 for more details).

In the experiment, the collective behavior could not reach the UE prediction when *s* was 7 or 10. The reinforcement learning model can simulate the experimental result, which indicates that our model is highly adaptable.

5. Conclusion

This paper presents the results of four groups of travel choice behavior experiments under uncertain conditions that road capacity will change twice during individual travel. Different capacity changing orders and different information feedbacks are investigated in the experiments. Based on the experimental data, system's collective equilibrium behavior and individual behavior of players are investigated, and the transition process of the macro traffic characteristics from one stable state to another is analyzed. The results show that the traffic system will take a long time to close to the UE prediction when the capacity decreases, but players can quickly adjust their travel choice and the traffic system can rapidly approach the UE prediction when the capacity increased. This is because that the equilibrium is difficult to reach when the road is congested, while the equilibrium is easy to achieve when traffic is free flow state. Each individual makes a travel decision based on the road information and his/her own accumulated experience. The mean payoff of an individual will be decreased if the individual frequently changes travel decision-making strategy. Information feedback has no significant effect on the individual choice behavior and system's collective equilibrium state. A reinforcement learning model is established to verify the experimental results, and the simulation results show that the model can simulate not only the collective behavior of players but also the transition process of the system from one state to another.

This paper clarifies that road capacity is the main factor that affects the equilibrium state of the transportation system. Management departments can effectively manage transportation by controlling road capacity, and the research can provide a certain theoretical reference for both urban traffic and highway traffic management.

Although a good agreement between the results and predictions is achieved, this study has certain shortcomings. When the capacity was 7 or 10, the experimental results differed from the UE predictions, which may be due to a relatively small number of experimental rounds. To address this shortcoming, in future work, an analysis with a larger number of experimental rounds will be conducted. In addition, in the experiment, the capacity was changed only twice to fixed values during experiment, but in real traffic, the capacity varies more often and randomly; so, the individual travel choice behavior that is closer to the real traffic conditions will be examined in future.

CRediT authorship contribution statement

Xiaoyan Sun: Proposing the ideas, Writing – original draft, Analyzing data. **Wentao Li:** Performing the experiments. **Rui Jiang:** Creation of models, Analyzing data. **Yubing Zhu:** Performing the experiments, Statistical analysis. **Dong Chen:** Statistical analysis.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.physa.2022.126935.

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