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*Research Article*

# Experimental Study of Day-to-Day Route-Choice Behavior: Evaluating the Effect of ATIS Market Penetration

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This paper examines the travelers' day-to-day route-choice behavior with Advanced Traveler Information Systems (ATIS) through laboratory-like experimental method. Five groups of route-choice behavior experiments are designed to simulate actual daily behavior of travelers. In the experiment, subjects are provided with different levels of the complete road network information to simulate the proportion of subjects equipped with ATIS equipment (i.e., ATIS market penetration) and choose the routes repeatedly. The subject's route-choice behavior under different proportions of complete road network information is analyzed, and the strategy of releasing such complete information is determined when the performance of road network system is the best. The Braess network which consists of three routes was used in the experiment and analysis. The results show that the fluctuation of traffic flow runs through the entire experiments, but it tends to converge to user equilibrium. When the market penetration is 75%, both the fluctuation of traffic flow and the tendency of subjects to change routes are the smallest, so the road network system is the most stable. This interesting result indicates that releasing traffic information to all travelers is not the best. Other results show that the travel times of the three routes in the five groups of experiments tend to converge to and finally fluctuate around user-equilibrium travel time. With the increase in ATIS market penetration, the average travel time of subjects in each round tends to increase. The overall trend of the five groups of experiments is that as the number of route switches increases, the average travel time increases. The results also indicate that releasing traffic information to all travelers cannot weaken the Braess Paradox. On the contrary, the more travelers are provided with traffic information, the less likely it will weaken the Braess Paradox.

## 1. Introduction

In recent years, traffic congestion problems have become increasingly serious, especially in large metropolitan areas. Traffic congestion has seriously affected people's normal travel and therefore has attracted extensive attention from governments, the public, and transportation practitioners [1]. With the rapid development of intelligent systems and big traffic data, Advanced Traveler Information Systems (ATIS), as an important part of Intelligent Transportation Systems (ITS), is being considered by many researchers to alleviate traffic congestion problems [2, 3]. Such developments also make the study of travel behavior under the influence of information become one of the hot issues in the field of transportation engineering [4, 5].

The effect of ATIS implementation depends on how the information released by ATIS affects people's travel behavior. There is a great deal of scientific research on travel behavior under the influence of information. Using stated preference/revealed preference (SP/RP) survey methods [6–8] and simulation (simulator and numerical) methods [9–11], researchers found that traveler's personal attributes, traffic information types, accuracy of traffic information, and many other factors can affect traveler route choice [12, 13]. Ben-Elia and Avineri [14] systematically summarized the impact of traffic information on travel behavior (including

mode and route choices) and concluded that information has a beneficial effect on individual travel behavior, but the aggregate impact on travelers' behavior at a network level is still uncertain. There are also some scholars who question the effectiveness of ATIS. Arnott et al. [15] pointed out that the effect of providing incomplete information is worse than that of not providing information. Ben-Akiva et al. [16] analyzed three possible adverse effects of traffic information system: oversaturation, overreaction, and concentration.

In fact, from the perspective of transportation network, travelers will influence each other when they make choices, so their travel choices are interactional. At the same time, due to travelers' habits and learning abilities, their travel choices will also be affected by the results of past choices. With the combined effects of information and travel experience, the daily travel choices of travelers are a day-to-day dynamic process [17, 18]. In the framework of day-to-day dynamics, scholars adopt two types of methods to study the impact of traffic information on traveler's day-to-day route-choice behavior in the network: theoretical modeling/numerical simulation methods and behavioral experimental methods. For the former methods, for example, in the early years, Cascetta and Cantarella [19, 20] proposed a day-to-day and within-day route-choice model and found that traffic information will cause traffic flow to fluctuate continuously, while traveler's personal experience can make traffic flow stable. Kim et al. [21] analyzed the influence of user equilibrium (UE) condition on the evolution of road network traffic flow based on the agent simulation model. The results showed that perfect information and prior information have a great impact on route choice. Cantarella [22] developed a day-to-day dynamic route-choice model under the influence of traffic information. Based on the value of user surplus and its change over time, the effect of traffic information can be evaluated. The results in a toy network indicated that an accurate ITS design based on the impact on total user surplus requires a day-to-day dynamic analysis. Considering the departure time choice of travelers, Liu et al. [23] modeled traveler's day-to-day route-choice behavior under the influence of historical information and real-time information and analyzed the day-to-day dynamic evolution of network traffic flow. They found that the evolution of network traffic flow under historical information and real-time information is similar.

The behavior experimental methods examine the subject's travel choice behavior by constructing different marginal conditions and experimental variables, and then setting up a laboratory-like experiment under hypothetical travel scenarios. Such methods are different from the static methods of SP/RP surveys. Behavior experimental methods can dynamically observe the subjects' travel choice behavior and control the key factors that affect travel choice of subjects. By setting up multiple groups of controlled experiments to investigate the responding behavior of subjects to different traffic management and control strategies, we can evaluate the feasibility and effectiveness of the implementation of traffic management and control strategies [24].

The review of the literature (presented in the next section) shows that several issues in the study of travelers' day-to-day route-choice behavior remain. First, although there is a comprehensive analysis of how information affects travelers, there are some gaps on the impact of ATIS market penetration (referred to throughout as market penetration) on travelers' day-to-day route-choice behavior and the evolution of network traffic flow. Is it better to release traffic information to more travelers? To date, scholars have only conducted research through theoretical modeling and simulation methods [25–27] but have not used behavioral experiments or field data to verify the influence of market penetration on route choice. This issue should be further investigated. Compared with other methods, the day-to-day route-choice behavior experiment can better reproduce the actual trips of travelers and can reflect the subjective factors of the travelers. Therefore, it is necessary to study the influence of market penetration on travelers' day-to-day route-choice behavior based on behavioral experiments. Second, the experimental road network in this paper, Braess road network, is adopted by Rapoport and other scholars [28–32], but they have not studied the impact of market penetration on Braess Paradox phenomenon, which also needs to be studied. Therefore, in view of the preceding aspects, it is necessary to further study travelers' day-to-day route-choice behavior through laboratory-like behavior experiments. It should be noted that the experimental settings of this study are different from those of previous studies and so is the study objective. Therefore, this paper focuses on the following questions:

(1) Does ATIS market penetration influence travelers' day-to-day route-choice behavior using laboratory-like behavior experiments?

(2) Does ATIS market penetration influence Braess Paradox?

(3) Is full market penetration the best?

The remainder of the paper is organized as follows. In the Section 2, related research is reviewed. Section 3 describes the experimental design. Section 4 reports the results of the experiments, and Section 5 discusses the results and compares them with past research. Finally, conclusions are presented in Section 6.

## 2. Literature Review

The characteristics of previous experimental studies are summarized in Table 1 and some studies are highlighted next. Scholars carried out relevant experimental research very early. For example, Iida et al. [33] studied the influence of travel time information on driver's dynamic route-choice behavior by means of experimental analysis and presented two models that used travel experience to predict travel time. Subsequently, they studied the impact of different quality travel time information on traveler's route choice and found that the traveler's willingness to use different quality information is different [34]. Based on behavioral experimental method, Rapoport and his team conducted a series of studies. Rapoport et al. [28] studied the Braess Paradox under variable demand. After a new edge was added to the

Table 1: Summary of relevant literature on experimental studies of travelers' day-to-day route-choice behavior.

| References | No. of subj. | No. of rounds | No. of routes | Experimental conditions[a] | Main contents of analysis[a] |
|---|---|---|---|---|---|
| Iida et al. [33] | 40 | 1: 20, 2: 21 | 2 | Exp. 1: actual TT on the route chosen in the last round<br>Exp. 2: actual and predicted TT on the route chosen in the last round | Traffic flow distribution, actual TT, frequency of route switching, difference between the predicted and actual TT |
| Iida et al. [34] | 35 | 63 | 2 | Exp. 1: NI-HQI-HQI<br>Exp. 2: NI-LQI-HQI<br>Exp. 3: NI-LQI-LQI | Route-choice rate in three periods, effect of actual TT information |
| Rapoport et al. [28] | 240 | 40 | 2, 3 | Number of subjects between OD increased: 10-20-40<br>Number of subjects between OD decreased: 40-20-10 | Traffic flow distribution, mean payoff, route switching rate of three routes in experiment B under different OD conditions |
| Rapoport et al. [29] | 108 | 1: 40, 2: 80 | 2, 3, 5 | Subjects were divided into 6 groups of 18 members each<br>Three groups participated in condition ADD and three others in condition DELETE. | Traffic flow distribution, mean payoff, number of route switches, frequency of route switching |
| Gisches and Rapoport [30] | 180 | 60 | 4, 6 | Subjects were divided into 10 groups of 18 members each. Five groups participated in condition PUBLIC and five others in condition PRIVATE. | Traffic flow distribution, mean payoff, difference of individual route choice, learning behavior |
| Mak et al. [32] | 180 | 40, 20 | 2, 3 | Subjects were divided into 10 groups of 18 members each<br>Five groups participated in condition SIM (40 rounds) and five groups in condition SEQ (20 rounds). | Traffic flow distribution under conditions of simultaneous and sequential route choice, subject's learning behavior |
| Selten et al. [35] | 18 | 200 | 2 | Exp. 1: actual TT of the last chosen route<br>Exp. 2: actual TT of the entire road network in the last round | Traffic flow distribution, number of route switches, cumulative payoff |
| Avineri and Prashker [36] | 24, 23 | 100 | 2 | Sce. 1 (24 subjects): information acquired by subjects only through their own experience<br>Sce. 2 (23 subjects): a priori static TT information provided to subjects | Average distribution of traffic flow, risk type |
| Ben-Elia et al. [37] | 24, 25 | 300 | 2 | Exp. 1 (24 subjects): received real-time and feedback information<br>Exp. 2 (25 subjects): received feedback information | Statistical analysis of the proportions of choices of the faster route |
| Ben-Elia et al. [38] | 36 | 20 | 3 | Three scenarios in each experiment, including safer-fast, risky-fast, and low-risk.<br>Three levels of information accuracy: high, intermediate, and low | Information compliance rate |
| Tanaka et al. [39] | 15 | 60 | 2 | Sce. 1: LAI and without a penalty for late arrival<br>Sce. 2: HAI and without a penalty for late arrival<br>Sce. 3: LAI and a penalty for late arrival<br>Sce. 4: HAI and a penalty for late arrival | Information compliance rate, choice rate of the shortest route |
| Meneguzzer and Olivieri [40] | 30 | 50 | 3 | All participants only knew the TT of the chosen route and the initial free-flow time. | Average flow of three routes, average TT, frequency distribution of individual route switches, personal characteristics of participants |
| Mak et al. [41] | 180 | 50 | 8 | The subjects were divided into 10 groups, five groups participated in condition RCC (provided route information) and five others in condition SCC (provided real-time segment information). | Flow distribution of routes and segments, route switching rate |

Table 1: Continued.

| References | No. of subj. | No. of rounds | No. of routes | Experimental conditions[a] | Main contents of analysis[a] |
|---|---|---|---|---|---|
| Zhao and Huang [42] | 18 | 30 | 2 | Provide feedback information to the subjects: the real and expected travel costs in the preceding round, their own road choice decisions in the preceding round, accumulative payoffs, and number of the current round. | Traffic flow distribution and TT cost of the two routes, proportion of choosing route M, perceived travel cost, and aspiration level of the subjects |
| Wijayaratna et al. [31] | 12 | 20 | 3 | Exp. 1: no online information provided<br>Exp. 2: online information provided at node C regarding the prevailing traffic conditions on link CB | Effect of online real-time information on the paradox |
| Zhang et al. [43] | 25 | 135 | 3 | Subjects acted as commuters traveling, and the size of online travel communities which these subjects belong to increased from 0, 3 to 25 by arithmetic progression. | Effect of social interaction information from friends on the entire traffic system and individuals |
| Klein and Ben-Elia [44] | 90 | 110 | 2 | First 10 rounds: participants were provided TT, arrival time, and payoff in the last round<br>Next 50 rounds: participants were provided the previous experience information, expected TT, and their expected times of arrival<br>Last 50 rounds: participants were provided the previous information and recommended route. | Collective response analysis, individual response analysis, response time analysis |
| Ye et al. [45] | 268 | 26 | 3 | All participants were provided with the TT of all routes in the last round and the initial free-flow time. | Nonlinear effects of flow and cost differences on route switching, participant's path preference, time-varying sensitivity, and day-to-day learning behavior |
| Qi et al. [46] | 64 | 80 | 2 | Same as Selten et al. [35]. | Difference between traffic flow and network equilibrium predictions, difference between the two information conditions, individual response modes |

[a]Exp. = experiment, HAI = high accurate information, HQI = high quality information, LAI = less accurate information, LQI = low quality information, NI = null information, No. = number, Sce. = scenario, Subj. = subjects, and TT = travel time.

two-route network, the travel costs of all subjects decreased when the Origin-Destination (OD) demand was 10, increased when the demand was 20, and did not change significantly when the demand was 40. Based on these results, Rapoport et al. [29] conducted behavioral experiments on the same traffic networks with two and three routes, respectively. The results showed that the flow converged to equilibrium in the two-route network after 40 rounds (trials), while in the three-route network, the route-choice results moved in the direction of equilibrium, but convergence was not reached. Later, Gisches and Rapoport [30] carried out experiments in two networks that have four and six alternative routes, respectively. They examined the impact of public information on traveler route choice and the Braess Paradox phenomenon. Rapoport's network assumed that the impedance of the additional link was zero, which is inconsistent with the actual situation, so it is more reasonable to set a non-zero low impedance value to the link.

Subsequently, Mak et al. [32] slightly improved the traditional Braess Paradox experimental network, which showed both congestion and cost-sharing characteristics. The subjects' simultaneous and sequential route-choice behaviors were analyzed in detail, and the results showed that the sequential route choice increased travel cost. Qi et al. [46] conducted laboratory experiments in a network with two parallel routes under partial and full-information conditions. Individuals whose response modes are featured by a series of conditional probabilities regarding switching behavior naturally cluster into three and four groups under the two conditions, respectively. An in-depth analysis of the behavioral base of each type was discussed. More feedback information was disclosed for the purpose of reducing uncertainty but turned out to reduce the proportion of people who were highly responsive to the new information and who firmly commit themselves to a unique route.

By economic experiment, Selten et al. [35] selected 18 college students as subjects, of which only 9 were able to obtain complete historical information and completed the experiment of route-choice behavior in a network with two parallel routes. In a simple two-link network, where the mean and variance of the travel time of two routes are given, Avineri and Prashker [36] conducted a software platform-based experiment by asking the subjects to choose the route repeatedly. According to the experimental data, the authors

studied the influence of the uncertainty of travel time on the subjects' learning ability. Ben-Elia et al. [37, 38] and Tanaka et al. [39] used a similar experimental method to conduct a series of studies on how information affects subjects' route-choice behavior in a simple two-route network. The similarity of these literature studies [36–39] lies in the assumption that the travel time of each route follows a distribution with a given mean and variance and is independent of traffic flow.

In recent years, under the condition of limited feedback information, Meneguzzer and Olivieri [40] carried out a laboratory-like experiment on route choice and route switching behaviors and calibrated the parameters of the deterministic process model of day-to-day dynamic route choice through experimental data. Mak et al. [41] constructed a day-to-day dynamic route-choice experiment scenario on real-time information of routes and links, enriching the behavioral experimental research on information. Zhao and Huang [42] used laboratory experiments to study the subjects' boundedly rational route-choice behavior under the satisficing rule. Wijayaratna et al. [31] used the classical Braess Paradox road network to verify the existence of the Online Information Paradox through behavioral experiments. Zhang et al. [43] further studied the effects of social interaction information from friends on commuters' day-to-day route-choice decisions. Klein and Ben-Elia [44] proposed the necessary conditions for traveler's cooperative route-choice behavior by behavioral experiments with the information provided by ATIS. Based on a virtual day-to-day route-choice experiment, Ye et al. [45] made use of the latest mobile Internet technologies to examine the existing day-to-day models.

It is clear from the literature review that all previous studies have not involved experiments under different ATIS market penetrations. Therefore, it is the purpose of this paper to address this research gap by accounting for travelers' day-to-day route choice behavior under different ATIS market penetrations in the Braess network using experiments. To the best of the authors' knowledge, the proposed setup, which provides a conceivably more realistic environment to study travelers' day-to-day route choice behavior under ATIS, has not been explored before in previous studies.

## 3. Experimental Design

This section describes the experimental design, including experimental context, variable, and procedure. The data collected from experiment are the basis for the subsequent analysis.

*3.1. Experimental Context.* We designed five groups of day-to-day route-choice behavior experiments. In each group, participants (referred to as subjects) repeatedly chose travel routes in the road network according to their travel experience and the released road network information, which simulated travelers' day-to-day travel.

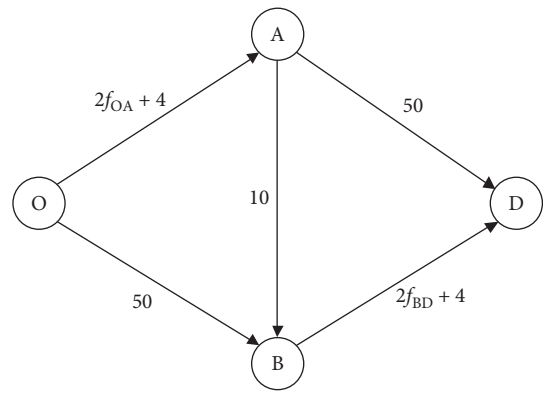



Figure 1: Experimental traffic network.

One hundred undergraduate students were selected as experimental subjects. The subjects are all freshmen in the College of Civil Engineering at Fuzhou University. Each group has 20 subjects. The experimental network is shown in Figure 1. This network which is the classical Braess Paradox network [47] was also used in some experimental studies [28, 29]. All subjects have the same origin (O) and destination (D) and have 3 driving routes (O-A-D, O-B-D, O-A-B-D) to choose. These routes are composed of 5 links (OA, AD, OB, BD, AB). For the purpose of this experiment, the travel time-volume relation is represented by the following linear form:

$$T_{\mathrm{OAD}} = 2f_{\mathrm{OA}} + 54, \tag{1}$$

$$T_{\mathrm{OBD}} = 2f_{\mathrm{BD}} + 54, \tag{2}$$

$$T_{\mathrm{OABD}} = 2\left(f_{\mathrm{OA}} + f_{\mathrm{BD}}\right) + 18, \tag{3}$$

where $T$ is the travel time of the respective route and $f_{\mathrm{OA}}$ and $f_{\mathrm{BD}}$ are traffic volumes of link OA and BD, respectively. Although the road network used in this research is the same as Rapoport et al. [28, 29], which is the Braess network, the impedance functions of the links were changed, especially for the additional link with zero in Rapoport's network.

The subjects were divided into 5 groups of 20 members each. It is assumed that the subjects in each group fully understand the properties of the experimental traffic network, and they are affected neither by the road network familiarity, nor by the road environment or other factors when they choose routes. In order to better simulate the actual commuting trips and improve the enthusiasm of the subjects, a reward mechanism was designed to give subjects some payoffs according to their performance in the experiment. The payoff of each round is expressed in the form of points and is related to the actual travel time of the route chosen by the subject. The calculation method is

$$P = 100 - T, \tag{4}$$

where $P$ is the subject's reward point obtained in one round and $T$ is actual travel time of the route chosen by the subject. The shorter the actual travel time is, the higher the obtained reward is. After the experiment, the subjects exchanged

money according to their points. The shorter the actual travel time is, the higher the payoff is. The same reward mechanism was used in all groups of the experiments. The subjects repeatedly chose travel routes in the experimental network according to road attributes, their travel experience, and the released network information and rewards. Each group of experiments was carried out in 32 rounds (the first two rounds were pre-experiments, the results of which were not used for statistical analysis). Each round represents the traveler's one-day commute trip.

According to the total number of subjects and the link travel time function, the traffic equilibrium assignment could be calculated [48]. When the number of subjects who choose Routes O-A-B-D, O-A-D, and O-B-D is 16, 2, and 2, respectively, the experimental network reaches user equilibrium (UE). At equilibrium, the travel time of all routes is 90 minutes, and the total travel time of the road network is 1800 minutes. When the number of subjects who choose Routes O-A-B-D, O-A-D, and O-B-D is 0, 10, and 10, respectively, the experimental network achieves system optimum (SO). At this time, the travel time of Route O-A-B-D is 58 minutes, the travel times of the other two routes (Routes O-A-D and O-B-D) are both 74 minutes, and the total travel time of the road network is 1480 minutes.

*3.2. Experimental Variable.* As previously mentioned, the purpose of this experiment is to investigate the day-to-day route-choice behavior of travelers under different market penetrations and determine the corresponding market penetration when the system efficiency is the best. Therefore, market penetration is used as the experimental variable in the experiment design. According to the experimental variable, we designed five groups of route-choice experiments, as shown in Table 2.

Consider an ideal situation where travelers receive complete road network information only by ATIS devices in the vehicles. The ATIS center can still control whether to provide information for each traveler, even when all vehicles are equipped with ATIS devices. The market penetration $t$ is defined as the proportion of the subjects who receive complete road network information (i.e., actual travel times of the three routes). In the five groups of experiments, the proportion of subjects who knew the complete road network information is 0%, 25%, 50%, 75%, and 100%, respectively. In other words, the number of subjects in each group with complete network information was 0, 5, 10, 15, and 20; the others only knew the historical information (i.e., actual travel time) of their chosen routes and did not know the actual travel times of the unselected routes.

*3.3. Experimental Procedure.* At the beginning of the experiment, the administrators introduced the experimental context, operation process, and reward mechanism to the subjects in detail. All the experiments of route-choice behavior were carried out in the laboratory and presented in the form of questionnaires. The overall process of the experiment is described in Figure 2.

In each round of the experiment, the administrators collected the experimental questionnaires of the 20 subjects in the previous round and counted the number of subjects who chose the three routes. Using the time-flow function, the actual travel times of the last round of three routes were calculated. Hence, the reward point of each subject in the last round was also calculated. Immediately, the administrators filled in new questionnaires with each subject's number and traffic information. Note that each subject's number is the same from the beginning to the end of the experiment. Among the 20 subjects, $20t$ subjects received the actual travel times and reward points of all the three routes. In contrast, the other $20(1-t)$ subjects only received the actual travel time of the routes chosen by themselves and they were not informed of the travel information of the unselected routes. Then, the administrators distributed the questionnaires with the travel information to the subjects. After receiving the questionnaires, the subjects chose the routes based on the travel information of the previous round and the experimental context and filled the results in the experimental questionnaires.

In this way, 32 rounds were carried out in each group. The first two rounds were pre-experiments to familiarize the subjects with the experimental context and procedure, and therefore the results were not used in the statistical analysis. After the experiment, the subjects were rewarded according to the points obtained in the experiment.

## 4. Analysis of Experimental Results

By sorting out and counting the experimental data of the five groups, this section will analyze the data from the following aspects: traffic volume, travel time, experimental reward, the relationship between the travel time and number of route switches, the impact of market penetration on Braess Paradox, and the subject's route-choice mechanism. This analysis will help to understand the variation of network flow under different market penetration. The statistics and statistical analysis methods used in this section are presented in Appendix.

*4.1. Traffic Volume.* The fluctuation of the number of subjects of the three routes in the five groups of experiments is shown in Figure 3. From the field of traffic engineering, the number of subjects is regarded as traffic volume [40]. As the number of experimental rounds increases, the traffic volume of the road network tends to converge to user equilibrium, but the results in all experiments show that the fluctuation of traffic flow runs through the entire experimental process. By calculation, the flow fluctuation in Group IV (in which $t = 75\%$) is the smallest, and Group V is the closest to the traffic flow of the user equilibrium.

In order to quantitatively describe the flow fluctuation range of the three routes in the five experiments, it is necessary to further calculate the mean and standard deviation of the traffic flow on each route in each group. Assume that the number of subjects who choose a route in the $n^{\text{th}}$ round of experiment is $X$ and the mean and standard

Table 2: Information conditions in the five groups of experiments.

| Group | ATIS market penetration, $t$ (%) | Number of subjects in each group with complete network information |
|---|---|---|
| I | 0 | 0 |
| II | 25 | 5 |
| III | 50 | 10 |
| IV | 75 | 15 |
| V | 100 | 20 |

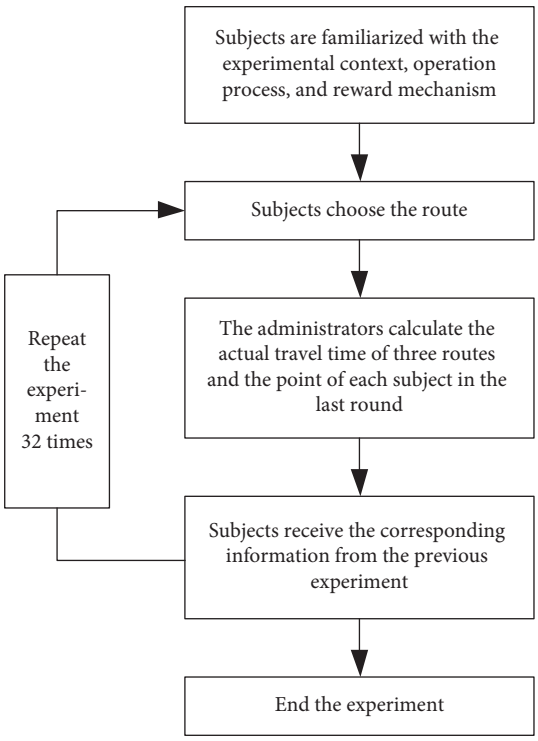



Figure 2: Tasks of experimental scheme.

deviation of traffic volume on the route in each group are denoted by $E(X)$ and $\mathrm{SD}(X)$, respectively. The number of subjects choosing Routes O-A-B-D, O-A-D, and O-B-D when the network reaches user equilibrium is $X^* = 16, 2$, and 2, respectively. The difference between the mean traffic volume on the route and that of network equilibrium can be expressed as $|E(X) - X^*|$. Table 3 shows the mean and standard deviation of traffic volume on the three routes for the five groups of experiments.

As noted in Table 3, from Groups I to IV, taking Route O-A-B-D as an example, we can see that, with the increase in the market penetration, the standard deviation of Route O-A-B-D decreases continuously, and the standard deviation of Group IV is the smallest. Also, the average of standard deviations of the three routes of Group IV is the smallest. This indicates that when $t = 75\%$, the fluctuation of traffic flow is the smallest. Thereafter, when all the subjects in the road network know the complete road network information, the standard deviation of Route O-A-B-D increases, which indicates that excessive openness of the complete road network information will increase the fluctuation of traffic flow and produce certain "side effects." On the other hand, the average of $|E(X) - X^*|$ of the three routes from Groups I to V decreases continuously, and that of Group V is the smallest. This indicates that ATIS can help traffic flow converge to the user equilibrium.

In the five groups of experiments, if the route chosen by a subject in the $n$-th round is different from that in the $(n-1)$-th round, we define it as one-time route switch. Figure 4 shows the distribution of the number of route switches for the five groups. As noted, with the increase in the number of experimental rounds, there are always subjects in the five groups who switch the route, which is consistent with the conclusion that the fluctuation of traffic flow runs through the entire experiment. The number of route switches in Group I ($t = 0\%$) is significantly higher than that in other four groups, which demonstrates that the subjects who know little about the road network information will actively change the current state and search other travel routes to shorten the travel time. This implies that providing complete road network information is beneficial to the stability of the entire road network system because it can help the subject to choose the route and reduce the number of route switches.

In order to further investigate how the number of route switches changes with the increase in the number of rounds, we use Cox-Stuart trend test to verify the results [49].

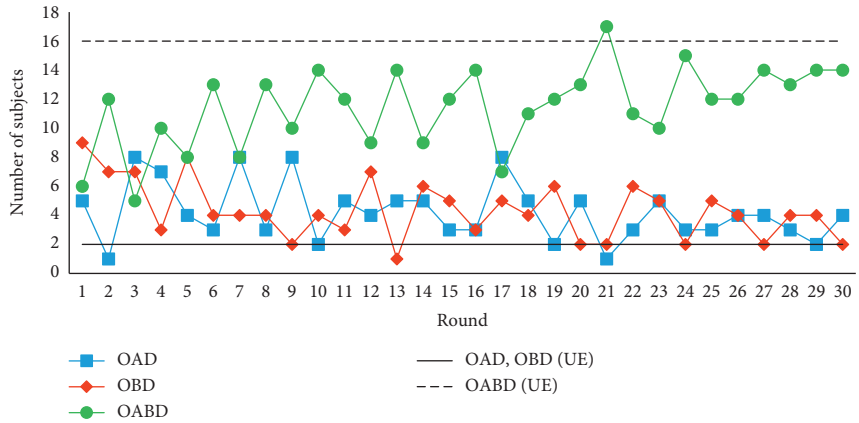
For a significance level $\alpha = 0.05$, the test results are exhibited in Table 4.

The test results show that the number of switches decreases with the increase in the number of rounds in the experiment of Group II ($t = 25\%$), Group IV ($t = 75\%$), and Group V ($t = 100\%$), and the decrease trend in Group IV is the most significant.

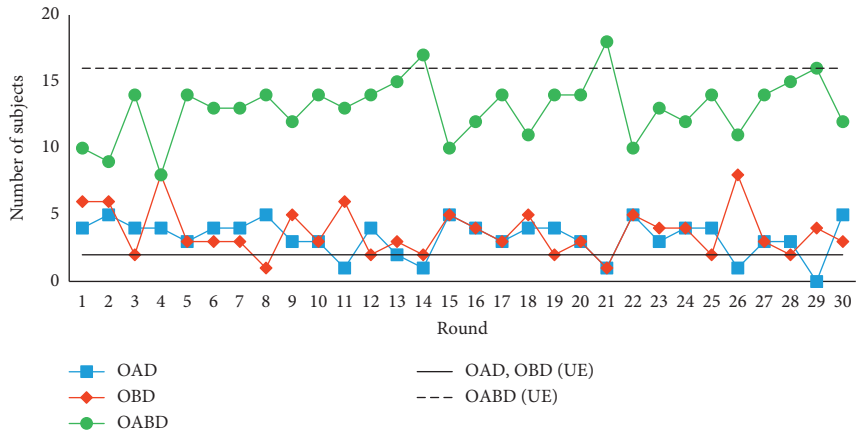
When the significant level is smaller, the test condition becomes more stringent, so the rejection domain of the hypothesis test shrinks. For $\alpha = 0.01$, the test results are shown in Table 5.

As noted, only in Group IV, in which $t = 75\%$, the number of route switches decreases with the increase in the number of rounds, and the decreasing trend of Group IV is highly significant.

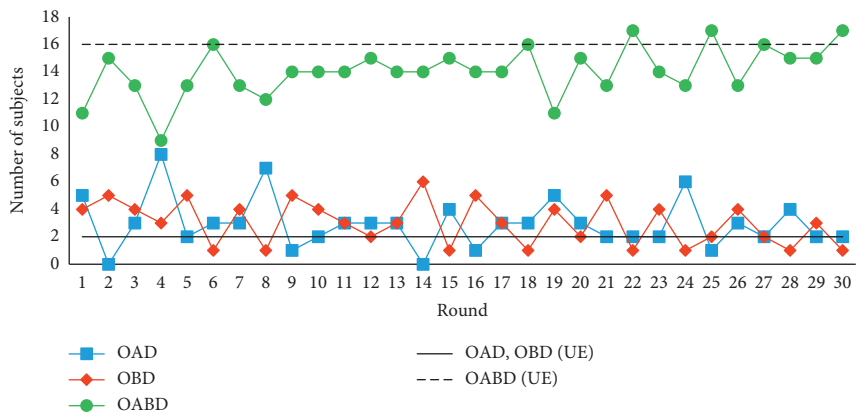
In order to quantitatively analyze the influence of information on the number of route switches in the five groups of experiments, it is necessary to further calculate the mean and standard deviation of the number of switches in each group. Table 6 shows that both the mean and standard deviation of Group IV are the smallest, indicating that when $t = 75\%$, the tendency of subjects to change routes is the smallest, and the road network system is the most stable.




(a)




(b)




(c)

Figure 3: Continued.

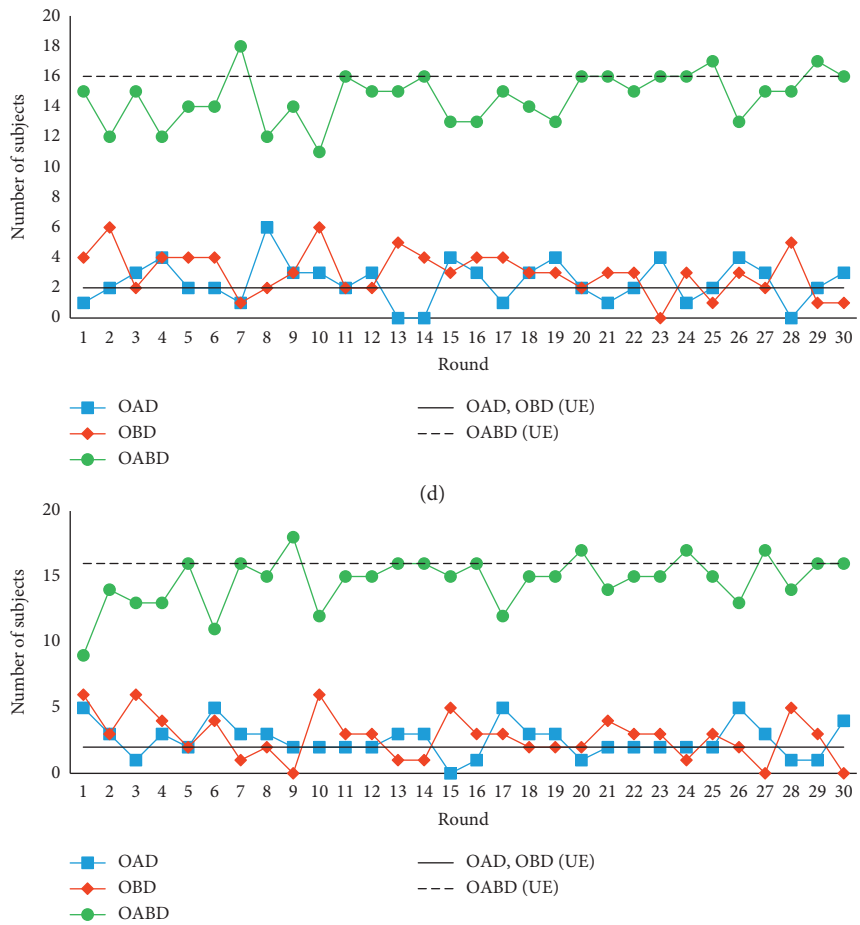



Figure 3: Flow fluctuation of three routes in five groups of experiments. (a) Group I, (b) Group II, (c) Group III, (d) Group IV, and (e) Group V.

Table 3: Mean and standard deviation of traffic volume on each route in each group of experiments.

| Group (market penetration, $t$) | $E(X)$ | $\lvert E(X) - X^* \rvert$ | SD$(X)$ |
|---|---|---|---|
| (a) Route O-A-B-D | | | |
| I (0%) | 11.47 | 4.53 | 2.75 |
| II (25%) | 13.00 | 3.00 | 2.22 |
| III (50%) | 14.07 | 1.93 | 1.81 |
| IV (75%) | 14.63 | 1.37 | 1.66 |
| V (100%) | 14.70 | 1.30 | 1.92 |
| (b) Route O-A-D | | | |
| I (0%) | 4.20 | 2.20 | 1.97 |
| II (25%) | 3.30 | 1.30 | 1.35 |
| III (50%) | 2.93 | 0.93 | 1.81 |
| IV (75%) | 2.37 | 0.37 | 1.38 |
| V (100%) | 2.53 | 0.53 | 1.28 |
| (c) Route O-B-D | | | |
| I (0%) | 4.33 | 2.33 | 1.97 |
| II (25%) | 3.70 | 1.70 | 1.79 |
| III (50%) | 3.00 | 1.00 | 1.55 |
| IV (75%) | 3.00 | 1.00 | 1.46 |
| V (100%) | 2.77 | 0.77 | 1.69 |

*4.2. Travel Time.* As previously described, when the experimental network reaches user equilibrium, the travel time of the three routes is 90 minutes. Figure 5 shows the fluctuation of travel time on each route in the five groups of experiments. As the number of experimental rounds increases, the travel times of all routes in the five groups of experiments tend to converge to that of user equilibrium and eventually fluctuate around the equilibrium point.

In order to quantitatively describe the range of flow fluctuation of the three routes in the five experiments, it is necessary to further calculate the mean and standard deviation of the travel time on each route in each group. Let the travel time of the subjects who chose a route in the $n$-th round experiment be denoted by $Y$ and the mean and standard deviation of travel time on the route in each group be denoted by $E(Y)$ and SD$(Y)$, respectively. The travel time of the subjects who chose each route is 90 minutes at equilibrium (i.e., $Y^* = 90$). The difference between the average travel time on each route and that of network equilibrium was expressed as $\lvert E(Y) - Y^* \rvert$. Table 7 shows the

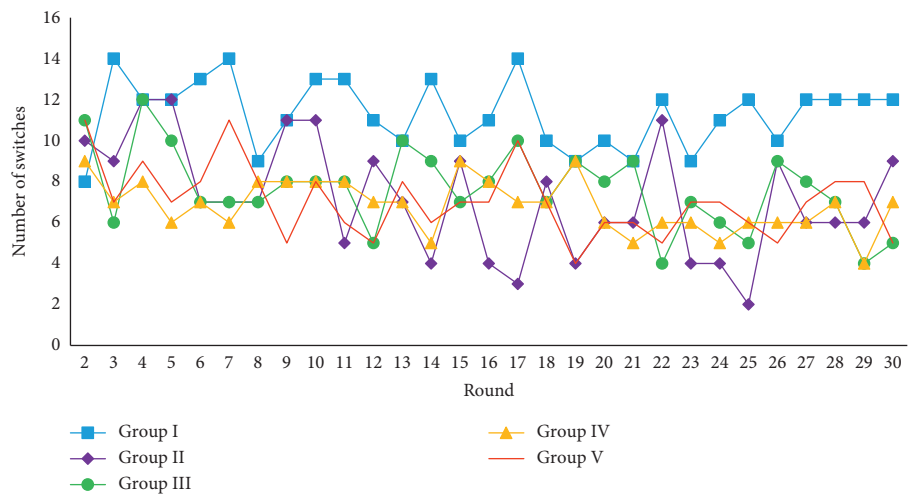



Figure 4: Distribution of number of route switches.

Table 4: Cox-Stuart trend test ($\alpha = 0.05$).

| Group | Test statistics | Trend |
|---|---|---|
| I | $p(K \leq 4) = 0.1334 > \alpha$ | No |
| II | $p(K \leq 3) = 0.0287 < \alpha$ | Decrease |
| III | $p(K \leq 4) = 0.0898 > \alpha$ | No |
| IV | $p(K \leq 1) = 0.0073 < \alpha$ | Decrease |
| V | $p(K \leq 3) = 0.0461 < \alpha$ | Decrease |

Table 5: Cox–Stuart trend test ($\alpha = 0.01$).

| Group | Test statistics | Trend |
|---|---|---|
| I | $p(K \leq 4) = 0.1334 > \alpha$ | No |
| II | $p(K \leq 3) = 0.0287 > \alpha$ | No |
| III | $p(K \leq 4) = 0.0898 > \alpha$ | No |
| IV | $p(K \leq 1) = 0.0073 < \alpha$ | Decrease |
| V | $p(K \leq 3) = 0.0461 > \alpha$ | No |

Table 6: Mean and standard deviation of the number of switches in each group of experiments.

| Group | Mean | Standard deviation |
|---|---|---|
| I | 11.31 | 1.64 |
| II | 7.17 | 2.77 |
| III | 7.62 | 1.95 |
| IV | 6.83 | 1.26 |
| V | 7.03 | 1.71 |

mean and standard deviation of travel time on the three routes in the five groups.

From Table 7, taking Route O-A-B-D as an example, with the increase in market penetration, the average travel time of Route O-A-B-D is increasing and is getting closer to that of user equilibrium. While the standard deviation of travel time on Route O-A-B-D decreases first and then increases, and the standard deviation of Group IV is the smallest. Also, the average of the standard deviations of the three routes of Group IV is the smallest. This is consistent with the conclusion of traffic flow fluctuation analysis: when $t = 75\%$, the fluctuation of the entire experimental network is the smallest.

Next, the average travel time of subjects in each round was calculated for the purpose of analyzing the performance of the entire experimental network. Figure 6 shows the average travel time distribution of the subjects in each group of experiments. As noted, as the number of rounds increases, the average travel time always fluctuates around the equilibrium point, but the overall trend is closer to the equilibrium point.

In order to quantitatively analyze the influence of information on the performance of the road network, the mean and standard deviation of travel time of all subjects in each group were calculated, as shown in Table 8.

As noted from Table 8, the mean of travel time increases as the market penetration increases. The average travel time of Group I is the smallest, which indicates that the overall benefit of the road network system is the highest when $t = 0\%$. From Group I to Group V, with the increase in market penetration, the standard deviation does not change significantly. Although the overall average travel time is increasing, the range of change, between 83.65 and 88.20 minutes, is not very large. Therefore, it is necessary to make a quantitative statistical test on the difference between the average travel times of the five groups of experiments, and to determine whether the average travel times in all groups are different.

To examine the difference of average travel time between groups, the multi-sample hierarchical test (Kruskal–Wallis $H$ Test) is used to determine the impact of different market penetrations on network performance. This test method is a nonparametric test method based on the sum of ranks [50]. Let the significance level $\alpha$ be 0.05. For the number of samples $k = 5$, the critical value is $\chi^2_{0.95}(4) = 9.49$, and the test statistic is $H = 37.08 > \chi^2_{0.95}(4) = 9.49$, so the distributions of the average travel time in all groups are not all the same. With the increase in market penetration, the average travel time of subjects in each round has an increasing trend.

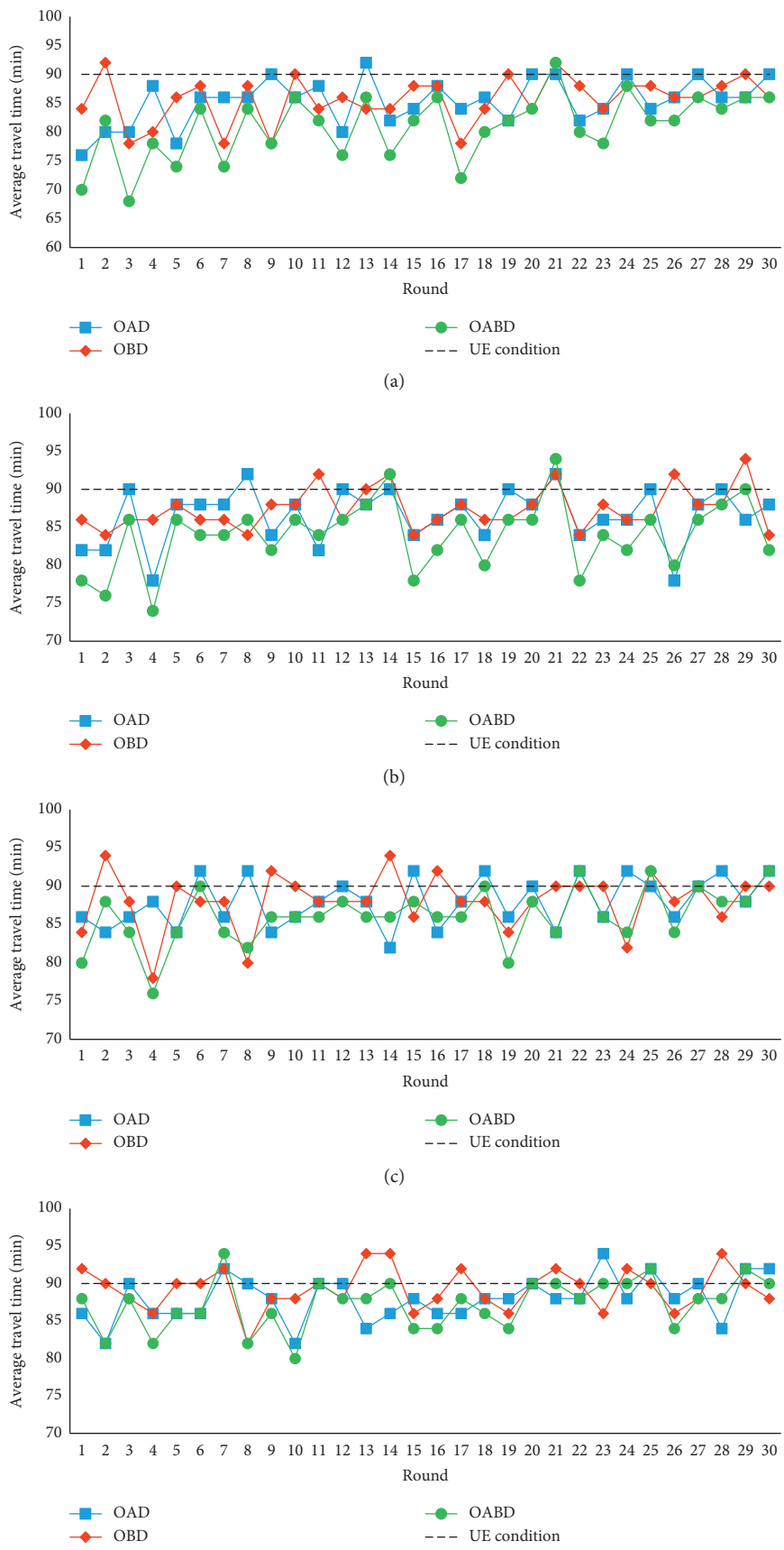
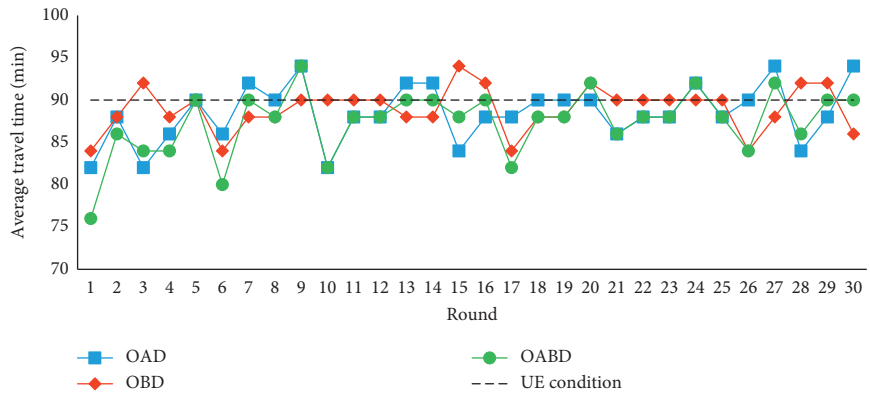



Figure 5: Continued.




(e)

Figure 5: Fluctuation of actual travel time in five groups of experiments. (a) Group I, (b) Group II, (c) Group III, (d) Group IV, and (e) Group V.

Table 7: Mean and standard deviation of travel time on each route in each group of experiments.

| Group (market penetration, $t$) | $E(Y)$ | $\lvert E(Y) - Y^* \rvert$ | $SD(Y)$ |
|---|---|---|---|
| (a) Route O-A-B-D | | | |
| I (0%) | 80.93 | 9.07 | 5.51 |
| II (25%) | 84.00 | 6.00 | 4.44 |
| III (50%) | 86.13 | 3.87 | 3.61 |
| IV (75%) | 87.27 | 2.73 | 3.33 |
| V (100%) | 87.40 | 2.60 | 3.83 |
| (b) Route O-A-D | | | |
| I (0%) | 85.33 | 4.67 | 3.94 |
| II (25%) | 86.60 | 3.40 | 3.58 |
| III (50%) | 88.00 | 2.00 | 3.10 |
| IV (75%) | 88.00 | 2.00 | 2.92 |
| V (100%) | 88.47 | 1.53 | 3.37 |
| (c) Route O-B-D | | | |
| I (0%) | 85.60 | 4.40 | 3.95 |
| II (25%) | 87.40 | 2.60 | 2.69 |
| III (50%) | 88.13 | 1.87 | 3.61 |
| IV (75%) | 89.27 | 0.73 | 2.76 |
| V (100%) | 88.93 | 1.07 | 2.57 |

From the preceding test, the average travel times of the five groups are not all the same, so it is necessary to find out which two groups are different. Based on Mann–Whitney $U$ Test [50], the hypothesis test results between two groups of five experiments are shown in Table 9. The table demonstrates that when $t$ is less than 50%, there is a significant difference in the overall average travel time, but when $t$ exceeds 50%, the overall average travel time has no significant difference. This interesting result reveals that after the number of people who know the complete network information reaches a certain proportion, the continuous increase in information provision is not conducive to the improvement of the performance of the road network system. Therefore, providing complete network information to all travelers cannot achieve system optimization.

*4.3. Experimental Reward.* In order to better simulate the actual commuting trips and improve the enthusiasm of the subjects, we designed a reward mechanism to give subjects some payoffs according to their performance in the experiment. The reward of each round is expressed in the form of points, as equation (4). This mechanism can positively reflect the pros and cons of the subjects' route choice strategies. Figure 7 shows the average experimental point distribution of the subjects in each round. As noted, with the increase in the number of experimental rounds, the average experimental points of the subjects in the five groups decrease slightly, but the decrease is not obvious. Also, the average experimental point of Group I, in which $t = 0\%$, is higher than those of the other four groups.

In order to analyze the effect of information on the experimental rewards of subjects, the mean and standard deviation of points in five groups were calculated. From Table 10, we can see that, with the increase in market penetration, the average points of subjects decrease, while the standard deviation does not change significantly. This implies that the higher the level of complete road network information disclosure is, the lower the experimental reward of the subject is. Therefore, the increase in information provision is unfavorable to the experimental returns of the subjects. The mean of the points is opposite to that of travel time and the standard deviation is similar because the reward is a linear function of travel time. This can also verify the correctness of the travel time analysis.

*4.4. Relationship between Travel Time and Number of Route Switches.* Based on the previous analysis, the relationship between the number of route switches and travel time is further investigated. In the day-to-day route-choice behavior experiment, the reason why the subjects frequently change their travel route may be that they are not satisfied with the travel time of the current route and try to shorten the travel time by changing the route. Figure 8 shows the relationship between the average travel time and the number of switches. The horizontal variable is the number of switches of 20 subjects in each group, and the vertical variable is the average travel time of each subject in 30 rounds. The overall trend is that the higher the number of route switches is, the

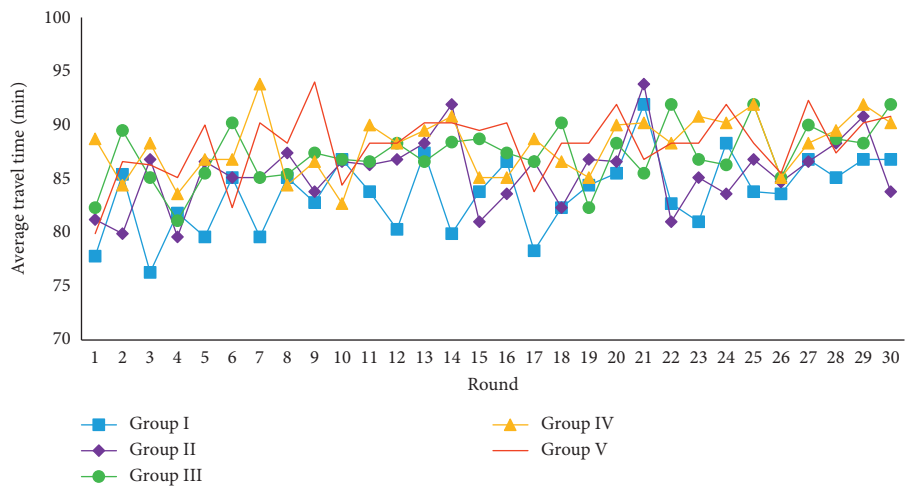



Figure 6: Average travel time distribution of the subjects in each round.

Table 8: Mean and standard deviation of travel time in each group of experiments.

| Group | Mean | Standard deviation |
|---|---|---|
| I | 83.65 | 3.44 |
| II | 85.56 | 3.27 |
| III | 87.27 | 2.69 |
| IV | 88.06 | 2.72 |
| V | 88.20 | 3.02 |

Table 9: Statistical results of Mann–Whitney $U$ Test.

| Group pair | $Z$ | $-Z_{(1-0.05)}$ | Statistical difference |
|---|---|---|---|
| Groups I and II | −1.863 | −1.64 | Yes |
| Groups II and III | −2.321 | | Yes |
| Groups III and IV | −0.946 | | No |
| Groups IV and V | −0.296 | | No |

longer the average travel time is. Because of the obvious correlation between the two variables, regression analysis is used to fit a linear function between the two variables. Assume that the number of route switches is $x$, the average travel time is $y$, and the functional form is

$$y = ax + b, \tag{5}$$

where $a$ and $b$ are coefficients. The linear regression fitting parameters of the five groups of experiments are shown in Table 11.

From Figure 8, the regression parameter $a$ is greater than 0, which indicates that the more the subjects change routes, the more they lose. Furthermore, with the increase in market penetration, regression parameter $a$ shows a decreasing trend, indicating that the average travel time increment caused by each route switch is decreasing. This implies that the increase in complete network information provision can reduce the negative effect of route switching. However, the regression parameter $b$ is increasing, which indicates that the average travel time of the subject becomes longer when the subject does not change his/her route. If we exchange the independent variable $x$ and the dependent variable $y$, another implication can be seen from the figure. The parameter $a$ is greater than 0, indicating that travelers with higher travel time would switch more. Although the casual relationship between travel time and number of route switches is hard to determine, the positive correlation between the two variables is determined. Hence, it is also possible that the two variables influence each other.

From the goodness of fit, the fitting effects of the first two groups are poor because the correlation coefficients $R^2$ are small, and the distribution of some points deviates from the regression line greatly. The correlation coefficients of the latter three groups are larger, and the fitting effects are better than those of the first two groups. Among them, the goodness of fit $R^2$ of Group IV is the largest, which shows that when $t = 75\%$, the phenomenon that the average travel time increases with the increase in the number of route switches is the most obvious. From the analysis in Subsection 4.1, the trend that the number of switches decreases with the increase in the number of rounds is highly significant in Group IV, and the mean and standard deviation of the number of switches in this group are smaller than those in the other groups. It can be understood that a market penetration of 75% makes the subjects realize that route switching is not conducive to shortening the travel time, so they try not to change the routes as much as possible. In short, for a small number of subjects, increasing the number of route switches may shorten the travel time, but for most of the subjects, the increase is not beneficial to reducing the travel time. For the entire road network system, the trend is that the more the subjects switch routes, the longer the average travel time is.

*4.5. Influence of ATIS Market Penetration on Braess Paradox.* The Braess Paradox refers to the phenomenon that when travelers choose their own route independently, adding additional link to the network will lead to the decrease of the overall operation level of the entire road network [28–30, 32, 47]. If the Link AB of the experimental road

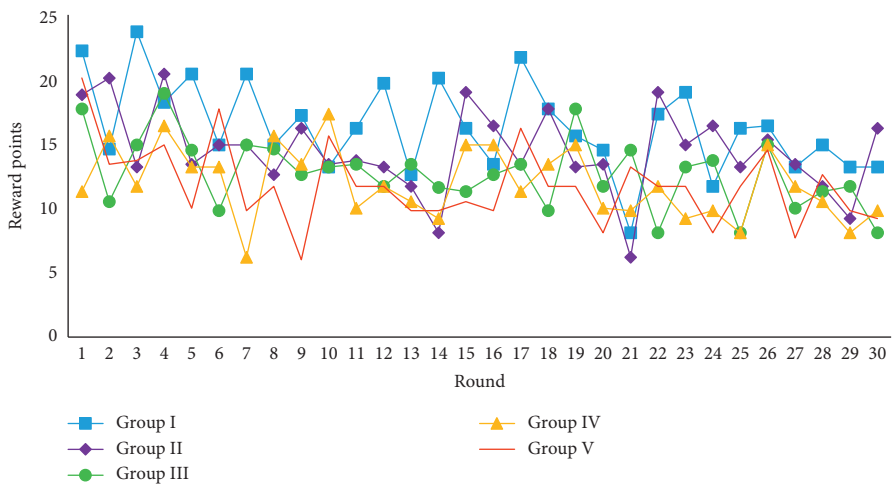



Figure 7: Average experimental point distribution of the subjects in each round.

Table 10: Mean and standard deviation of points in each group of experiments.

| Group | Mean | Standard deviation |
|---|---|---|
| I | 16.35 | 3.44 |
| II | 14.44 | 3.27 |
| III | 12.73 | 2.69 |
| IV | 11.94 | 2.72 |
| V | 11.80 | 3.02 |

network is closed and only two routes are left, then the traffic flows of Routes O-A-D and O-B-D under UE and SO conditions are both 10, and the total travel time of the road network is 1480 minutes. On the other hand, in the experimental network, in which Link AB exists, when the number of subjects who choose Routes O-A-B-D, O-A-D, and O-B-D is 16, 2, and 2, respectively, the experimental network reaches UE. At this state, the total travel time of the road network is 1800 minutes. When the number of subjects who choose Routes O-A-B-D, O-A-D, and O-B-D is 0, 10, and 10, respectively, the experimental network achieves SO. At this state, the total travel time of the road network is 1480 minutes.

Note that adding a link (Link AB) in the road network increases the total travel time of the road network under the UE condition. In other words, the traffic congestion does not decrease but increases, so the Braess Paradox exists in the experimental network. However, it should be noted that there is no Braess Paradox phenomenon under the SO condition. If all subjects do not choose Route O-A-B-D, the UE solution will move towards SO solution and the Braess Paradox of the experimental network will be eliminated. In that case, the total travel time will be reduced, and the congestion situation will be improved, so the performance of road network system will be greatly improved.

Five groups of experiments on route-choice behavior with different market penetrations were conducted for one purpose of investigating the impact of travel information on the Braess Paradox phenomenon. Table 12 shows that, with the increase in market penetration, the average traffic flow of Route O-A-B-D is also increasing, indicating that more and more subjects choose Route O-A-B-D, which leads to the increase in the total travel time of the road network. It reflects that providing complete road network information is not conducive to weakening the Braess Paradox phenomenon. The larger the market penetration is, the closer the experimental road network tends to the UE state, but the more it deviates from the SO state. From the perspective of traffic management and control, it is unfavorable to improve the performance of the entire road network system, which also confirms the conclusions of Subsection 4.2 from another perspective. If the released information can induce the subjects to choose the Route O-A-D or O-B-D instead of Route O-A-B-D and make the proportion of the subjects who choose Routes O-A-D and O-B-D roughly equal, it can greatly weaken the Braess Paradox and help to improve the travel efficiency of the entire road network system.

*4.6. Route-Choice Mechanism of Subjects.* The preceding experimental results are analyzed from an aggregate perspective. In this subsection, the route-choice mechanism of the subjects is studied from an individual perspective. In order to ensure that all the subjects participate in the route-choice experiment under the same condition and to study the subjects' acceptance of complete road network information, the data of Group V, in which $t = 100\%$ and the number of subjects is 20, were used to investigate the route choice mechanism. By analyzing the results of 30 rounds for each subject in Group V, the route choice mechanism of the subjects can be divided into three categories, as follows:

Mechanism 1: winners stay and losers change. For each subject, beginning with the second round of experiments, a comparison of the route choice result between one round and that of the previous round is used as the criterion of Mechanism 1. According to the network information provided, when a subject chooses the shortest route in the last round of the experiment, he/

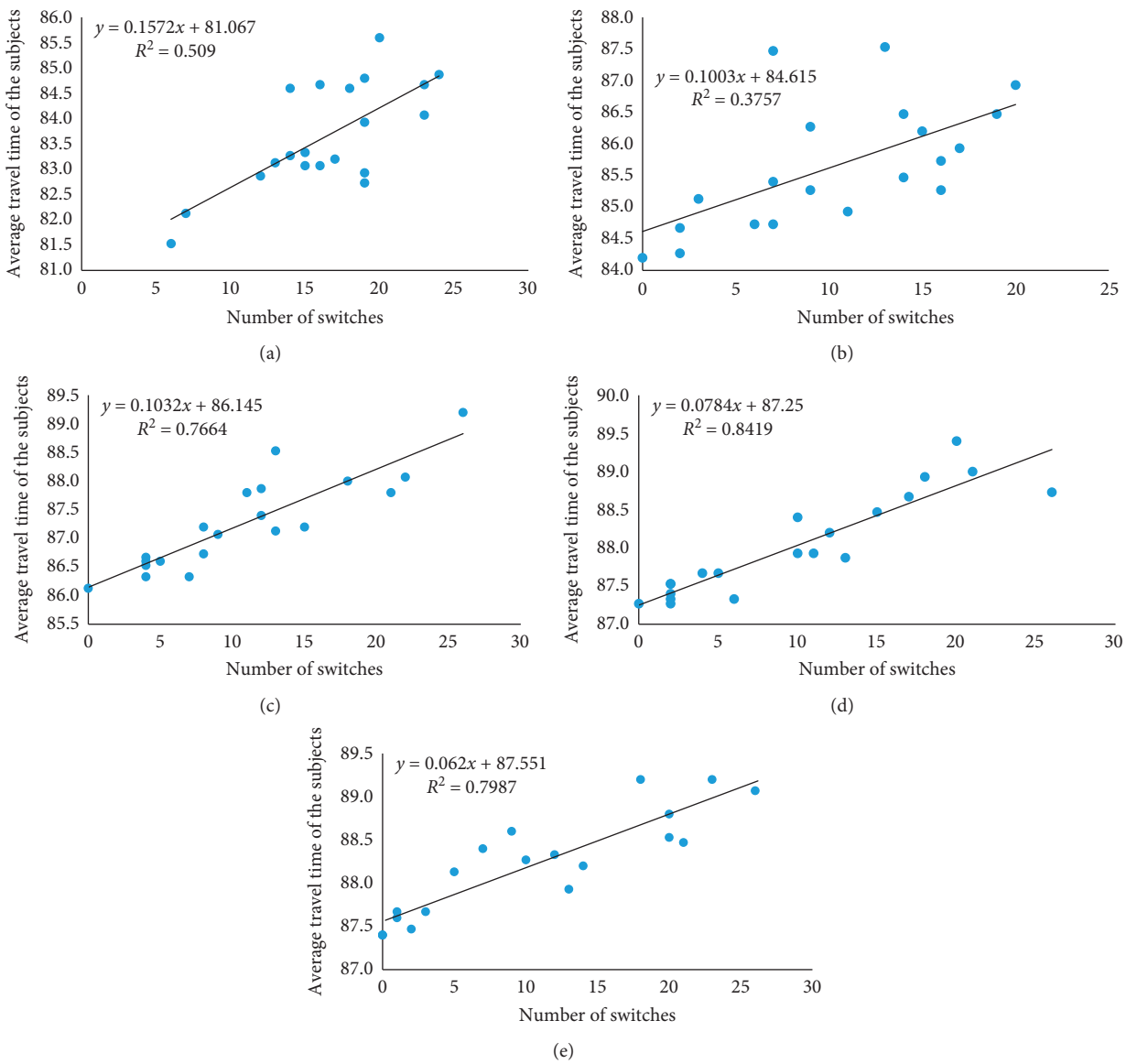



Figure 8: The relationship between the average travel time and the number of switches in five groups of experiments. (a) Group I, (b) Group II, (c) Group III, (d) Group IV, and (e) Group V.

Table 11: Linear regression fitting parameters of the five groups of experiments.

| Group | $a$ | $b$ | Coefficient of determination, $R^2$ |
|---|---|---|---|
| I | 0.1572 | 81.0670 | 0.5090 |
| II | 0.1003 | 84.6150 | 0.3757 |
| III | 0.1032 | 86.1450 | 0.7664 |
| IV | 0.0784 | 87.2500 | 0.8419 |
| V | 0.0620 | 87.5510 | 0.7987 |

Table 12: Mean of traffic flow on Route O-A-B-D and total travel time in each group of experiments.

| Group | Mean traffic flow of route O-A-B-D | Total travel time (min) |
|---|---|---|
| I | 11.5 | 1673 |
| II | 13.0 | 1711 |
| III | 14.1 | 1745 |
| IV | 14.6 | 1761 |
| V | 14.7 | 1764 |

she will use the "stay" strategy: do not change the route in this round. On the contrary, if the route chosen by a subject in the last round is not the shortest, then the subject will adopt the "change" strategy to change his/her route in the current round.

Mechanism 2: winners change and losers stay. Like Mechanism 1, this mechanism requires comparing the route choice result of one round with that of the previous round. If the subjects choose the shortest path in the last round, then they will adopt the "change"

Table 13: Route-choice mechanism for subjects.

| Subject number | Level of conformity (%) | Type of mechanism |
|---|---|---|
| 1 | — | 3 |
| 2 | 82.8 | 2 |
| 3 | 82.8 | 2 |
| 4 | — | 3 |
| 5 | 82.8 | 1 |
| 6 | 82.8 | 1 |
| 7 | 86.2 | 1 |
| 8 | 86.2 | 2 |
| 9 | 82.8 | 2 |
| 10 | 82.8 | 2 |
| 11 | — | 3 |
| 12 | 82.8 | 2 |
| 13 | 72.4 | 1 |
| 14 | — | 3 |
| 15 | — | 3 |
| 16 | 79.3 | 2 |
| 17 | — | 3 |
| 18 | 72.4 | 2 |
| 19 | 82.8 | 2 |
| 20 | — | 3 |

strategy in the current round; otherwise, the subjects will adopt the "stay" strategy.

Mechanism 3: randomness: due to human's subjective initiative and uncontrollable factors, some of the subjects do not use a fixed mechanism or strategy to choose routes. Instead, they randomly choose routes according to their personal preferences, choice habits, and perception of the experimental context, leading to an irregular choice.

According to the definition of the preceding three types of route-choice mechanism, the choice mechanism of each subject in Group V is shown in Table 13.

It should be pointed out that no one chooses route completely according to Mechanism 1 or 2. If a subject adopts Mechanism 1 or 2 in most of the rounds (i.e., more than 70% of all rounds), we consider he/she adopts Mechanism 1 or 2 in the entire experiment. The column "level of conformity" in Table 13 is the percentage of the rounds that meets the definition of Mechanism 1 or 2. According to Table 13, 4 subjects adopted Mechanism 1 (winners stay and losers change), indicating that the four subjects basically adopted a positive thinking to choose routes. The shortest route chosen in the previous round would be retained in this round, while the non-shortest route chosen in the previous experiment would be changed to find the shortest one. Nine subjects adopted Mechanism 2, which showed that these subjects adopted a reverse thinking when they chose routes. They believed that the shortest route in the last round may attract more subjects to choose in this round, so they changed the route to find the shortest route, while the non-shortest route selected in the last round continued to be chosen in this round. The number of subjects who adopted Mechanism 2 "winners change and losers stay" is the largest, which indicates that most of the subjects had careful consideration before choosing routes. The remaining seven subjects adopted Mechanism 3. Although the choice results of these subjects also conformed to the first two mechanisms in some rounds, the overall proportion of 30 rounds was not high and the choices of most rounds were relatively random. The reason why they chose the route randomly may be that they considered the complete road network information provided, or their preference for a certain route, or even an idea before the route choice. Therefore, the results of the route choice and switching did not present an obvious regular pattern.

## 5. Discussion

According to the research by Rapoport et al. [28, 29], the authors initially compared the basic road network of two routes with the enhanced road network of three routes and found that adding one link will lead to the increase in travel cost and deleting one link will reduce the travel cost. This is the experimental verification of the Braess Paradox. However, different OD demand in the road network will lead to different changes in the travel costs of the subjects [28]. Subsequently, the authors carried out comparative experiments in the augmented network with three routes and five routes, respectively. They made a detailed analysis from the following aspects: traffic volume distribution, average payoff, number of route switches, route switching rate, and individual differences of the subjects. It was confirmed that Braess Paradox exists in different road network topologies [29]. On this basis, Gisches and Rapoport [30] further enriched the road network structure and conducted comparative experiments on the basic road network with four routes and the augmented road network with six routes. They preliminarily investigated the influence of different information conditions on the subjects' route-choice behavior. In recent years, Wijayaratna et al. [31] carried out an experimental study on "Online Information Paradox" and found that providing information will increase the travel costs of the subjects, but will reduce the volatility of travel cost in the non-information scenarios, indicating that information can improve the reliability of the road network system. Mak et al. [32] slightly improved the traditional Braess Paradox experimental network. The network exhibited both congestion and cost-sharing characteristics and made a thorough analysis of the subjects' simultaneous and successive route-choice behaviors. The results showed that the successive route choice aggravated travel costs.

Based on the literature review, we can note that there is a difference in the experimental setting of this paper and previous studies. In this paper, the market penetration was controlled in the experiment. Only part of the subjects can obtain the information of all the routes, while others only knew the information of the route they chose. Previous studies have investigated the effect of public and private information on Braess Paradox [30, 31]. In fact, the public and private information correspond to the situation that $t = 100\%$ and 0%, respectively. In addition, the present study investigated the situations where $t = 25\%$, 50%, and 75%. Therefore, the influence of market penetration on subjects' day-to-day route-choice behavior and on Braess Paradox was analyzed.

Moreover, the subjects' route-choice mechanism was also analyzed, which is an aspect not addressed in previous studies.

Although this study is different from previous studies in the design of road impedance and the setting of information conditions, some of the conclusions are similar, as follows: (1) traffic volume eventually fluctuates near the UE equilibrium, but does not always reach equilibrium, and (2) information is not beneficial to weakening Braess Paradox [31].

In addition, some results of this paper are similar to those of the research conducted using theoretical modeling and simulation approaches. Through a numerical example, Han et al. [27] pointed out that when the ATIS market penetration takes some middle values (neither 0 nor 1), the evolution of network traffic flow is stable. In Subsection 4.1 of this paper, we find that the minimum fluctuation occurs when the ATIS market penetration is 75%, which is consistent with the previous results. Yang [25] showed that in a traffic network ATIS may not necessarily reduce total travel time, depending on the travelers' familiarity with the network. When the travelers' uncertainty of travel time is high, the total travel time will first decrease and then increase as ATIS penetration increases. When the travelers' uncertainty of travel time is low, the total travel time will increase as ATIS penetration increases. However, our research shows that the total travel time of the system increases with the increase of ATIS penetration. Therefore, the conclusion of this paper is consistent with the situation that travelers in Yang's study are more familiar with the traffic network. In fact, our experimental network is relatively simple. The first two rounds were pre-experiments to familiarize the subjects with the experimental context and procedure, and the results were not used in the statistical analysis. The subjects were familiar with the experimental network. So our conclusion is credible.

Some results of this paper are different from previous results. Huang and Li [26] concluded that although the average travel disutility of users varies differently across user classes, when the market penetration takes some middle values average travel disutility is the smallest. However, the average travel time of Group I in our experiments is the smallest. The different findings may be due to the differences between the experimental subjects. The users in the traffic network in Huang and Li's [26] study are different across different value of time, while participants in our experiment are college students, and their time values are little different. This difference suggests that we should do further behavioral experiments in the future. We can do experiments on subjects with different time values to investigate whether the conclusions are different from this study. Similarly, in some other literatures, there are some conclusions which are inconsistent with those of this paper. The reason is also due to the difference between simulation conditions and the experimental settings of the present study. For example, Emmerink et al. [51] drew a conclusion that, in many cases, when the ATIS penetration exceeds 20%, the total travel time is longer than that when there is no information; otherwise, the travel time is shorter than that without information. Obviously, this conclusion is different from that of our paper. The reason for the difference is that the simulation scene design and our experimental conditions are different. Emmerink et al. [51] consider travelers' departure time choice, and in the simulation experiment, pre-trip, post-trip, and en-route information are all given to travelers. Consequently, from past studies, the laboratory-like experiments of the day-to-day route choice behavior need to be further studied due to different experimental conditions.

## 6. Conclusions

To investigate how the ATIS market penetration influences the day-to-day route-choice behavior, this paper has designed a laboratory-like experiment, often used in behavioral economics. Based on this study, the following comments are offered:

(1) The fluctuation of traffic flow runs through the entire experiment, but tends to converge to user equilibrium. When $t = 75\%$, the fluctuation in the experimental system is the smallest, the mean and standard deviation of the number of route switches are also the smallest, and the trend of decrease is obvious. Thus, under this information condition, the tendency of subjects to change routes is the smallest, and the road network system is the most stable.

(2) Three types of route-choice mechanism can be used to characterize the results of subjects' route choice. From the macro level, the travel times of the three routes in the five groups of the experiments tend to converge to that of user equilibrium and finally fluctuate around the equilibrium. At the micro level, as the market penetration increases, the average travel time of subjects in each round tends to increase. Meanwhile, the correlation between the number of route switches and the average travel time is positive.

(3) Providing complete road network information is not conducive to weakening the Braess Paradox phenomenon. The larger the market penetration, the closer the experimental road network to the UE state, but the more it deviates from the SO state. Thus, complete road network information is unfavorable for the performance of the entire road network system.

(4) It should be pointed out that the number of subjects used in the experimental design was greater than that used in most previous experimental studies. The number of rounds was also greater than that used in some studies. Future research could explore the effect of many rounds as well as other factors that affect the experimental context.

(5) Some comments on ATIS market penetration are worth noting. In each group of the experiment, the market penetration was predetermined. If a subject had an ATIS device, he/she would receive the complete traffic information. Therefore, an assumption that ATIS market penetration is the proportion of travelers who receive complete traffic information is introduced in the experimental design. However, in reality, they may not be the same. Some people driving a car without an ATIS device

may acquire information through advertising or other means. A few people may not use the ATIS device or do not consider traffic information although they have ATIS devices. In this study, we only focus on how travel information affects route-choice behavior. More precisely, we focus on how the proportion of travelers who receive the complete traffic information affects travelers' day-to-day route-choice behavior. The way how travelers obtain travel information is not our focus. Hence, this project represents a fundamental research and its implementation in practice should be explored. For example, to implement this research finding regarding optimal market penetration $t = 75\%$, how to accurately control the proportion of people who receive the complete traffic information needs to be solved in practice.

## Appendix

### Statistical Analysis Methods

Let $X_1, X_2, \ldots, X_n$ be a series of values of the variable $X$. In the paper, the following two statistics are used:

(1) Mean

$$E(X) = \frac{X_1 + X_2 + \cdots + X_n}{n}. \tag{A.1}$$

The mean, $E(X)$, is a measure of the central tendency of the series.

(2) Standard deviation

$$\mathrm{SD}(X) = \sqrt{\frac{\sum_{i=1}^{n}(X_i - E(X))}{n-1}}. \tag{A.2}$$

The standard deviation, $\mathrm{SD}(X)$, is a measure of dispersion of the series.

The statistical analysis methods used in Section 4 are nonparametric hypothesis test and regression analysis. The specific methods are stated as follows:

(1) Cox–Stuart trend test [49]

The purpose of this method is to test whether there is an increasing or decreasing trend in the series, and its theoretical basis is sign test.

The series are grouped into pairs $(X_1, X_{1+c})$, $(X_2, X_{2+c})$, $\ldots$, $(X_{n-c}, X_n)$, where $c = n/2$, if $n$ is even, and $c = (n+1)/2$, if $n$ is odd, and the middle random variable is excluded from the analysis if $n$ is odd.

The difference between the two elements in each pair $D_i = X_i - X_{i+c}$ is used to measure the increase or decrease. Let $S_+$ and $S_-$ be the positive and negative number of $D_i$, respectively. When there are many plus signs (i.e., when $S_+$ is very large or $S_-$ is very small), it tends to decrease. When $S_-$ is very large, it tends to increase. In this paper, the decrease trend is tested. The null hypothesis $H_0$ and the alternative hypothesis $H_1$ are as follows:

$H_0$: no tendency to decrease exists in the series
$H_1$: the series is characterized by a tendency to decrease

Theoretically, $K$ is the test statistic and the probability is computed as

$$p(K \le S_-) = \left(\frac{1}{2}\right)^{n_l} \sum_{i=0}^{k} C_{n}^{i} \le \alpha, \tag{A.3}$$

where $\alpha$ is confidence level. If $p < \alpha$, then $H_0$ is rejected. This indicates that the series tend to decrease.

(2) Mann–Whitney $U$ Test [50].

The Mann–Whitney $U$ test is used to test for difference between two independent samples, which is the nonparametric alternative to the $T$-test for independent samples. Instead of comparing means of the two samples, as in the case of the $T$-test, the Mann–Whitney $U$ test actually compares medians. It converts the scores on the continuous variable to ranks across the two samples and then evaluates whether the ranks for the two samples differ significantly. In this test, the null hypothesis $H_0$ and the alternative hypothesis $H_1$ are as follows:

$H_0$: there is no difference between two independent samples
$H_1$: there is difference between the two samples

The first step in this test is to combine the scores from Sample 1 ($n_1$) and Sample 2 ($n_2$) and then to rank the combined list of scores from 1 for the smallest score to $n_1 + n_2$ for the largest score. Tied ranks are given the average of the ranks they would have if they were adjacent but not tied. To determine which alternative is true, the ranks assigned to each sample are summed to get $R_1$ (the sum of ranks for Sample 1) and $R_2$ (the sum of ranks for Sample 2). These sums are then used to calculate the $U$ values for the two samples:

$$U_1 = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1, \tag{A.4}$$

$$U_2 = n_1 n_2 + \frac{n_2(n_2+1)}{2} - R_2, \tag{A.5}$$

where $n_i$ ($I = 1, 2$) is the size of sample and $R_i$ ($i = 1, 2$) is the sum of the ranks for sample. The smaller of these two values, $U_1$ or $U_2$, becomes the Mann–Whitney $U$ test statistic $U$.

The statistic $U$ is used to compare with the critical value $U_\alpha$ for a particular significance level $\alpha$ (check the Mann–Whitney table). If $U < U_\alpha$, the null hypothesis $H_0$ is rejected and the alternative hypothesis $H_1$ is accepted. It indicates that there is a difference between the two samples. In particular, when one of the two

sample sizes ($n_1$ or $n_2$) is greater than 20, the distribution of the test statistic $U$ approaches a normal distribution, and so the $U$ value can be transformed into a $Z$ value, as follows:

$$Z = \frac{U - (n_1 n_2/2)}{\sqrt{(n_1 n_2 (n_1 + n_2 + 1)/12)}}. \quad (A.6)$$

When $Z < -Z_{(1-\alpha)}$, the null hypothesis is rejected, that is, the two populations do not have the same distribution.

(3) Kruskal–Wallis $H$ test [50].

The Kruskal–Wallis $H$ test is used to analyze the difference among $k$ populations, where $k$ is greater than 2. This rank-sums form of test is an extension of the two-sample Mann–Whitney $U$ test. In the Kruskal–Wallis H test, the independent variable is called the *factor*, and the categories of the factor are called *treatments*. The null hypothesis $H_0$ and the alternative hypothesis $H_1$ are as follows:

$H_0$: the $k$ independent treatment-samples with sizes $n_1, n_2, \ldots, n_k$ come from the same population or that all sampled populations have the same distribution

$H_1$: at least one treatment comes from a population that is different from others

The first step in the Kruskal–Wallis $H$ test is to combine the observations from the $k$ treatments and to rank the combined list from 1 for the smallest to $N$ for the largest, where $N$ is the total number of observations in all $k$ treatments ($N = \sum_{i=1}^{k} n_i$). The rank sum for each treatment, symbolized $R_i$, is then calculated. The next step after getting the sums of ranks is to calculate a test statistic $H$ as follows:

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1), \quad (A.7)$$

where $N$ is the total number of observations, $n_i$ is the number of observations in treatment $i$, and $R_i^2$ is the squared sum of the ranks for treatment $i$.

The value of $H$ indicates the distribution of ranks among the $k$ treatments, and the larger the value, the greater the differences in ranks. Evaluation of the test statistic $H$ depends on the number of treatments ($k$) and the number of observations within each treatment ($n$). If $k > 3$ or $n > 5$, the sampling distribution of $H$ is approximately a chi-square distribution with $(k-1)$ degrees of freedom (where $k$ is the number of treatments), so the chi-square distribution can be used for testing. When the value of $H$ is larger than expected (at a particular significance level), the null hypothesis $H_0$ is rejected, which means that the populations do not have the same distribution.

(4) Regression analysis.

In statistics, regression analysis refers to a statistical analysis method to determine the quantitative relationship between two or more variables. The idea is to determine the causal relationship between variables by specifying dependent and independent variables, establish a regression model, estimate the parameters of the model according to the observed data, and then evaluate whether the regression model can fit the observed data well.

## Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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