Information impacts on route choice and learning behavior in a congested network: An experimental approach

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ABSTRACT

Every individual traveler makes route choices in an inherently uncertain environment, due to random disruptions to the traffic system such as incidents and bad weather, and random behavior of his/her fellow travelers. The premise underlying the development of Advanced Traveler Information Systems (ATIS) that better-informed travelers make better route choices both at the individual and system levels should not be taken as granted but rigorously tested. This paper studies two types of information, namely *en route* real-time information on the occurrence of an incident and *ex post* information on foregone payoffs (FPs), i.e., travel times on non-chosen routes. Data were collected from an interactive experiment, where human subjects made multiple rounds of route choices in a hypothetical network subject to random capacity reductions, and travel times were determined by performance functions of route flows from the previous round. Preliminary results and bootstrap statistical tests are presented. It is indicated that *en route* real-time information increases the network's travel time saving and reliability under the specific setting of the experiment, yet FP information has the opposite impact. The most efficient information structure in terms of travel time saving is a combination of real-time information and no FP information. Furthermore, the availability of real-time information at downstream nodes encourages participants' strategic behavior at the origin. Last but not least, FP information seems to increase risk-seeking behavior, and it encourages route switching without real-time information, but suppresses them with real-time information. These results are potentially valuable for policy evaluations regarding further developments of ATIS.

Keywords: Route choice behavior, real-time information, forgone payoff, interactive experiment, stochastic network, strategic route choice, learning

INTRODUCTION

Every individual traveler makes route choices in an inherently uncertain environment. The sources of uncertainties in a traffic network can be broadly divided into two categories. At one hand, there are unpredictable disturbances to the system that usually result in capacity reductions, such as incidents, vehicle breakdowns, bad weather, special events, and work zones. On the other hand, a more prevalent although probably less disruptive source is his/her fellow travelers' unpredictable behavior, where the collective random individual departure time and route choices result in the random shifting of traffic flows in time and space.

A traveler can reduce the uncertainty in his/her decision-making by acquiring more information. The natural source of information is the traveler's own experience, obtained through explorations of alternative routes over a relatively long time period on regular traffic conditions. However personal experience is likely not enough given the large scale of the decision problem, in terms of the number of alternative routes and the myriad of sources of uncertainties. Information beyond personal experience can come from fellow travelers, and more recently, advanced traveler information systems (ATIS) that makes use of the fast developing sensor, telecommunication and computing technologies. Information provided by an ATIS can be divided into three categories: historical, prevailing, and predictive (*1*). For example, Google Maps provide archived average traffic conditions by time-of-the-day and day-of-the-week, which could help travelers reduce the uncertainties from unknown alternatives. Google Maps also provides information on prevailing conditions that are useful to travelers who are already familiar with the area and need to know, for example, whether there are constructions on his/her usual route today. Predictive information concerns the traffic conditions in the near future, which have to be calculated by prediction models and not as widely available as the other two types. Prevailing and predictive information could potentially reduce the uncertainties from disruptive disturbances and day-to-day demand fluctuations.

In this paper, we focus on the impacts of two types of information, namely the *en route* real-time information on the occurrence of an incident (prevailing) and the *ex post* information on foregone payoffs (FPs), which are the travel times on un-chosen alternative routes (historical). We study the impacts at both the individual and system levels. Specially, we are interested in the following three questions:

1) How does FP information affect a traveler's route choice learning process?
2) Does a traveler make strategic route choices, i.e., planning ahead for real-time information downstream?
3) How does real-time information affect the performance of a traffic system subject to random capacity reductions?

The rest of the paper is organized as follows. Related research is reviewed in the next section underlying the contribution of this paper. The methodologies are then presented including the experimental setup and analysis procedures. Preliminary results based on bootstrap statistics are discussed in the following section. Finally we conclude with major findings and future research directions.

LITERATURE OVERVIEW

In this section, we provide a literature overview along the lines of the aforementioned three research questions. The review is limited to empirical research with stated preference (SP), experimental and/or revealed preference (RP) data. Theoretical modeling and simulation studies are out of the scope.

Decision makers can learn (over time) from their own experience i.e. feedback information from their actual choices. Experience leads to reinforced learning but, at the same time, it is also a function of sampling available information on the basis of the past experience. Psychologists have been long aware of the "payoff variability effect" which suggests increasing the level of variability in the decision environment inhibits reinforced learning. It occurs when the decision maker receives no specific information describing the possible outcomes of choice and has to rely on feedback from past experience (see e.g., *2*). Descriptive information that provides a more complete picture of the decision environment could potentially affect the learning process, however, the resulting behavior varies. Several studies *(e.g. 3, 4)* assert that travelers will tend to exhibit risk aversion when faced with static pre-trip travel time information. Combining both experiential and descriptive information in the experiment setup, (*5,6*) have shown that descriptive information expedites travelers' learning but may also encourage them to exhibit risk prone behavior. The exception is the study by *(7)* involving travelers' interaction in a competitive game setting. They show that travelers with access to FP information have less capricious behavior (in terms of route switching). *(8)* also shows people perform best under the most elaborate information scenario, though the benefit of *ex post* information decreasing over time.

The literature saw a large body of studies on diversion or compliance under real-time information, e.g., at a variable message sign (VMS). See *(9)(10)* for two recent reviews on this topic. However, the modeled adaptation behavior is basically reactive – meaning that the traveler's decisions before arriving at a VMS do not consider the fact that the VMS will provide updated traffic conditions in the future. In reality, travelers might decide to acquire information as long as there is a reasonable prospect of reward from it *(11)*. Therefore the fact that a branch of the network has VMS installed could make it more attractive even before the traveler arriving at the VMS location. A strategic traveler, in this case, is one that considers the availability of information in all later decision stages, not just the current one. *(12)* and (13) verified that a significant portion of subjects made strategic route choices, using PC- and driving-simulator-based experiments respectively. However, these studies were static in nature and did not account for experiential or FP information.

A main drawback of all the aforementioned individual-based studies is that travel times were usually obtained from underlying probability distributions that were not affected by the travelers' choices. Thus, the inherent link occurring on congested networks (recurring and non-recurring) between travelers' route choices and travel times is missing in the current literature. (*14) (15) (16) (7) (17) (18)(19)* carried out route choice experiments in congested networks where travel times are determined by subjects' route choices through either travel performance functions or traffic simulations. However, their networks were deterministic and the day-to-day variations in travel times resulted purely from travelers' departure time and/or route choice variations, not disturbances that brought forth random capacity reductions. In the domain of RP data, (*20*) showed that by broadcasting expected travel times, VMSs can improve the network performance. However, such studies do not have detailed data on individual learning processes.

As such, it is the purpose of this paper to overcome some of the drawbacks of previous work by accounting for individual strategic route choices and learning processes and the resulting system-wide outcomes in an experimental setting involving random disturbances and an array of information types: en route real-time, experiential through feedback and FP. To the best of the authors' knowledge, this setup, which provides a conceivably more realistic environment to study route choice behavior under uncertainty, has never been explored before in the travel behavior literature.

METHODOLOGY

Experimental set up and design

In this research we adopted the network structure from *(12)*, which allows strategic routing behavior and also provides *en route* real-time information relating to incidents. A web-based non-cooperative interactive route choice experiment was carried out on a congested hypothetical network with occurring random incidents. Figure 1 presents a screen shot of the experiment lay out containing three possible routes from origin to destination, whereby Park Avenue is a stochastic link with random incidents; other links all have deterministic link performance functions.

There are in total four scenarios with two control variables, real-time and FP information. The real-time information relates to an incident indicator via a VMS located just before the second branch, which tells drivers whether there is an incident on Park Avenue. This information, however, is not available at any other node and only those passing the VMS are exposed to it. A scenario without the real-time information is named an incident case, while that with the real-time information is named an information case. Note that random incidents exist in any of the cases. The FP information gives travelers the *ex post* travel times on their non-chosen alternatives after each choice trial, and otherwise, only the chosen alternative's travel time (i.e. experiential information) was given. One session of the experiment consisted of two cases, incident and information, both with FP. Another session of experiment consisted of the incident and information cases under the without (w/o) FP situation. Twelve participants were allocated randomly between the two sessions respectively with six participants each. In both sessions, participants first took the incident case and then information case. Participants took a break and received another round of instructions before a new scenario began to minimize the carryover effect. Each combined experiment consisted of sixty trial days in the incident case followed by sixty trial days in the information case.

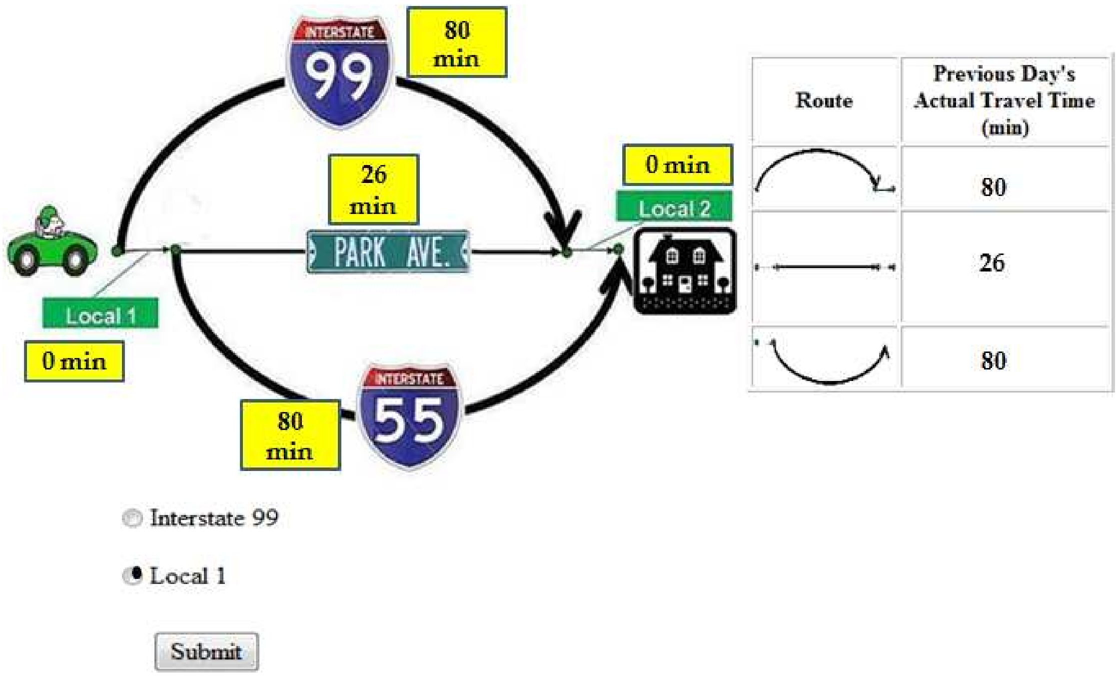


FIGURE 1 Screen shot of Initial Experiment's Presentation

Following the recruiting method of *(5)(6)(7)(17)*, which conducted human subject experiments using university students for transportation or economic research, most of our participants were students from the University of Massachusetts Amherst. In our two experiment sessions, there are a total of twelve subjects, including six undergraduates, four graduates, one professor and one from outside of the university. Each had to be at least eighteen years old and hold a valid U.S. driver's license with at least one year of driving experience. Our research is of an exploratory nature that deals with human mental processes, and thus we adopted the common approach in cognitive and behavioral studies where major breakthroughs were generally first made in experiments conducted with university students and later further verified in field studies *(21)*. Future studies involving more diversified population groups are required if conclusions from the exploratory phase are to be generalized to the general population.

The payment is $30 for each participant regardless of the performance during the experiment. Our primary goal is to let the subjects apply their real life experience in making the route choices. We try to avoid creating a sense of 'winning' during their trip making as in reality travelers are not competing for monetary rewards. Moreover, providing a performance-based incentive in a non-cooperative setting with a rather limited number of participants may induce them to try to maximize personal gains by influencing equilibrium conditions, which they would not be doing in reality where the ability of one driver to influence traffic conditions is negligible. Therefore, the fixed payment is a compensation for them to take part in the experiment. Secondly, if performance-based incentives are given, it is implicitly assumed that the same value of time applies to every participant, which is not always the case and might bring unnecessary complications. Moreover, there is no solid proof that people would have the same risk attitude towards monetary gains (or losses) and travel time savings (or losses) and we are cautious in equating these two. Additionally, existing literature reveals *(22)* that monetary incentives are neither necessary nor sufficient to ensure subjects' cooperativeness, thoughtfulness, or truthfulness.

Before experiment, participants were instructed to complete a set of trips from work to home on a day-to-day basis, and informed regarding the characteristic of each road in the network. The free flow travel time on each road was shown on the map and the corresponding congested coefficient was also explained during the instructions, whereby inter-state highways have the lowest congested coefficient, local roads have the largest and the shortcut arterial Park Avenue has the value in between. Participants were informed that incidents could occur on Park Avenue with a probability of 0.25, which may results in significant congestion. However, the exact cost functions were not revealed to them. The numbers in the yellow boxes were the links' actual travel times on the previous day. In day 1, those numbers reflected free flow link travel times. A table provided participants with the previous day's actual route travel times. Note that, in the without FP case, only the information of the route traveled in the last day was shown. Participants were required to make a choice at each of the two nodes by determining which link to take next. Note that at the first step, if I-99 was chosen no other choice was made and the trip was continued by taking Local 2 to the destination. Routes were chosen by clicking the appropriate radio button and then the "submit" button to confirm. At the end of each trial-day, all participants' route choices were recorded and the resulting actual travel time for each alternative route was calculated by plugging the number of choices into the link performance functions. The actual link and route travel times was presented at the beginning of the next day.

Equilibrium design

The link travel time depends on the numbers of participants choosing the link.

We use the following notation:

a :	name of link
i :	index of path (routing policy)
x_a :	flow on link a
f_i :	flow on path (routing policy) i
$C_a(x_a)$:	link travel time as a function of flow on link a
e_i :	(mean) travel time of path (routing policy) i

The travel time (in minutes) on a given link is a function of the link flow specified as follows:

$C_{\text{I-99}}(x_{\text{I-99}}) = 80 + x_{\text{I-99}}$, $C_{\text{I-55}}(x_{\text{I-55}}) = 80 + x_{\text{I-55}}$, $C_{\text{local1}}(x_{\text{local1}}) = 4x_{\text{local1}}$,

$C_{\text{local2}}(x_{\text{local2}}) = 4x_{\text{local2}}$,

$C_{\text{Park\_ave}}(x_{\text{park\_ave}}) = 26 + 3x_{\text{park\_ave}}$, with probability 0.75 (normal condition)

$26 + 55x_{\text{park\_ave}}$, with probability 0.25 (incident condition)

The three paths are defined as follows:

Path 1: I-99-Local 2,
Path 2: Local 1-Park Avenue.-Local 2
Path 3: Local 1-I-55.

We use a routing policy to describe the strategic route choice, which will be manifested as paths under different network conditions. For example, one routing policy (Routing Policy 4) can be defined as: "first take Local 1, and if the incident has occurred, take I-55, otherwise take Park Avenue and then Local 2". It will be manifested as Path 2 under the normal condition and Path 3 under the incident condition. A path can be viewed as a specialized routing policy, e.g., Path 2 can be described as follows: "take 'Local 1' at the origin, and take 'Park Avenue' no matter what the VMS shows". Notwithstanding, such adaptive strategies exist only under the information case. This is because real-time information provided at the second branch allows meaningful route changes, which helps participants update their route choice in response to incident information. However, in the incident case, no such cognitive mechanism exists to improve their choices. Therefore, only three fixed paths are available to a participant.

Route choice behavior can be compared to the theoretical results under the assumption of user equilibrium principles. Under the incident case the resulting user equilibrium condition will be generalized as such that all used paths have equal and minimum mean travel times. The equilibrium solution's flows are: $f_1 = f_3 = 1.784$, $f_2 = 2.432$, with the corresponding path travel times are: $e_1 = e_2 = e_3 = 98.65$.

In contrast under the information case, we hypothesize routing-policy-based user equilibrium where all used routing policies have equal and minimum mean travel times. There are five possible routing policies in the network. Routing Policy 1 through 3 are Paths 1 through 3, and Routing Policy 4 is the one just discussed. Routing Policy 5 is the opposite of Routing Policy 4, i.e. "first take Local 1, and if the incident has occurred, take Park Avenue and then Local 2, otherwise take I-55". Routing Policy 5 is conceivably inefficient. The equilibrium solution's flows are: $f1 = f3 = f5 = 0, f2 = 1, f4 = 5$. We can verify that under these routing policy flows, the network is in equilibrium such that Routing Policies 2 and 4 have equal and minimum mean travel times of 96.25 minutes.

Bootstrap statistical tests

Since the decisions of the participants are inherently dependent upon each other, in a sense each scenario provides just observations from one "compound subject" formed by six element subjects. Moreover since the same group participated in both the incident and information cases (i.e. repeated measurements), these are also dependent. These complications restricted us from doing conventional statistical testing using a random sample of subjects (both parametric and nonparametric).

Even though there is in a sense only one "compound subject" for each scenario, the observations were obtained from a day-to-day random learning process. In order to draw valid conclusions for the two specific "compound subjects", we need to carry out statistical testing that accounts for the random process over the sixty trial days. Instead of making hypothesis over a random sample of subjects, all of our null hypotheses regarding no-difference are between two random processes using bootstrap techniques *(23).* These include the following variables: average travel times, route shares and route switches. Bootstrap simulation is an approximate method to derive statistics by re-sampling from the original data - the approximation lies on the fact that the original data is treated as the true empirical distribution.

The block bootstrap method is used due to the data dependencies from day to day *(20)*. Blocks are re-sampled with block lengths having a geometric distribution with a mean of 5, the number of weekdays in a week. We conduct the bootstrap of the time series 10,000 times and obtain 10,000 new time series, each with a length of sixty days. We can then calculate the sample average from each bootstrap sample, which can be viewed as one realization of the distribution of the sample average. The p-value for a null hypothesis of equal mean between the two random processes can be obtained by counting the frequency at which the difference between each pair of sample average realizations from the two random processes is greater than or equal to the difference between the original sample averages. Note that the "compound subject" remained intact and the re-sampling applied only to the day-to-day process.

RESULTS

Route Shares

Table 1 summarizes the average route shares over the first and second thirty-day period and all sixty days respectively, in each of the four scenarios. It can be seen that none of the scenarios reached the theoretical equilibrium within the span of sixty days. Note that, the equilibriums here refer to those we calculated in the equilibrium design, which are based on a simplified traffic assignment model by assuming a minimum and equal mean travel time on each used path/routing policy. Route shares in the information case with FP, are the closest to the equilibrium pattern, and comparing the first and last thirty trials, we can also observe that route shares are approaching the network equilibrium. This is because the information case with FP has the lowest level of uncertainty among all scenarios, which makes it easier to get to the equilibrium. Based on our previous assumptions, the equilibriums in the incident and information cases are quite different, as there are only three paths in the incident case, compared to five routing policies in the information case where real-time information is provided at the branch allowing for a detour from prospective incidents. Such incident information does in fact affect the individual behavior pattern, where more participants tend to choose the stochastic branch at the origin node and the stochastic shortcut at the intermediate node in the information case than in the incident case, regardless of FP, which indicates that travelers would take strategic responses to the information *en route*. Table 2 summarizes the complete statistic results in route shares, network travel time and switches, and it shows that there are significant differences on road shares between the information and incident cases (with or without FP) at the level of 1% (one-sided). However, according to conventional route choice models, this difference should only exist at the intermediate node, where travelers are assumed to react on the spot to *en route* information rather than plan strategically. Thus, the strategic advantage of the provided information can be recognized as in the static study of *(12)(13)*.

Iterations	Path 1				Path 2				Path 3			
	With FP		W/o FP		With FP		W/o FP		With FP		W/o FP	
	W/o Info	Info	W/o Info	Info	W/o Info	Info	W/o Info	Info	W/o Info	Info	W/o Info	Info
0-30	1.70	0.40	1.57	1.17	2.97	4.23	2.63	3.33	1.33	1.37	1.80	1.50
30-60	1.60	0.33	1.37	1.10	2.90	4.57	3.20	3.53	1.50	1.10	1.43	1.37
Overall	1.65	0.37	1.47	1.13	2.93	4.40	2.92	3.43	1.42	1.23	1.62	1.43

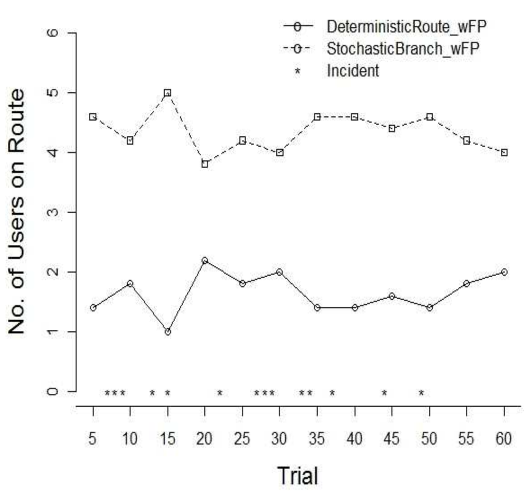
TABLE 1 Average Route Shares in the Four Scenarios

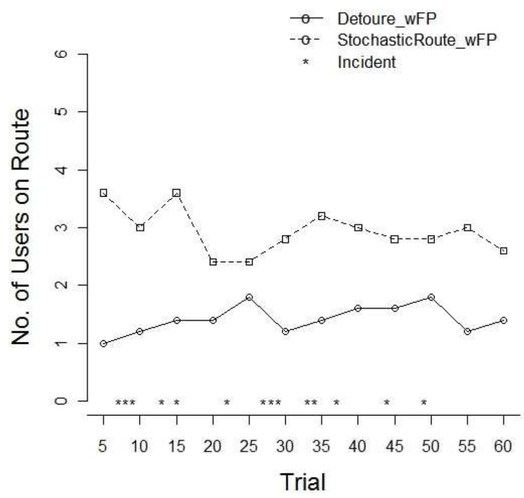
Performance Measure	**Real-Time Information?** / **FP Information?**	With FP	Without FP	Between Subjects P-value (one-sided)
Travel Time (min)	Without real-time information	116	105.3	> 5%
	With real-time information	96.8	92.7	1.32%
	P-value (one-sided)	0.08%	0.67%	
Route Shares at the Origin (Users on Path 1)	Without real-time information	1.65	1.46	> 5%
	With real-time information	0.37	1.13	0%
	P-value (one-sided)	0%	0.69%	
Route Shares at the Branch (Users on Path 2)	Without real-time information	2.93	2.92	> 5%
	With real-time information	4.4	3.43	0.16%
	P-value (one-sided)	0%	2.87%	
Number of Switches per Day at the Origin	Without real-time information	2.43	2.05	3.75%
	With real-time information	0.7	2.01	0%
	P-value (one-sided)	0%	> 5%	
Number of Switches per Day at the Branch	Without real-time information	1.47	1.25	> 5%
	With real-time information	1.9	1.45	2.5%
	P-value (one-sided)	1.47%	> 5%	
		Within Subjects		

TABLE 2 Bootstrap Statistic Test Results

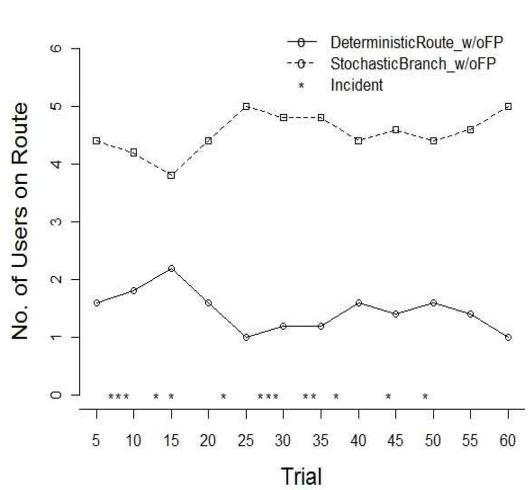
As for the impacts of FP, average route shares with FP are closer to the designed equilibrium than those without FP, in both incident and information cases, which indicates that providing FP helps push the network towards user equilibrium to some extent. However, for the information scenario, participants in the FP case seem to be more risk-seeking than those in the without FP sessions whereby more people choose the stochastic shortcut through Park Avenue. Participants in the without FP group are more inclined to choose Path 1, which is the deterministic route. According to the bootstrap statistical test, there is a significant difference between the average route shares with and without FP at the origin at the level of 1% (one-sided). Moreover, the percentage of participants at the intermediate node who choose the deterministic detour is also higher in the without FP cases than with FP. The bootstrap statistic result shows a significant difference at the level of 5% (one sided). This can be explained that without FP, participants become more sensitive when stuck in traffic, whereas the deterministic route/detour is not too bad. Thus providing travel time information on all alternative routes could potentially motivate more competition and risk-seeking behavior as suggested by *(5,6)*. Conversely, no such observation exists in the incident scenario. The bootstrap test fails to find a significant difference in the shares at origin and intermediate node between the case with and without FP. This may be due to the increase in the level of uncertainty, which may offset the impact of FP.

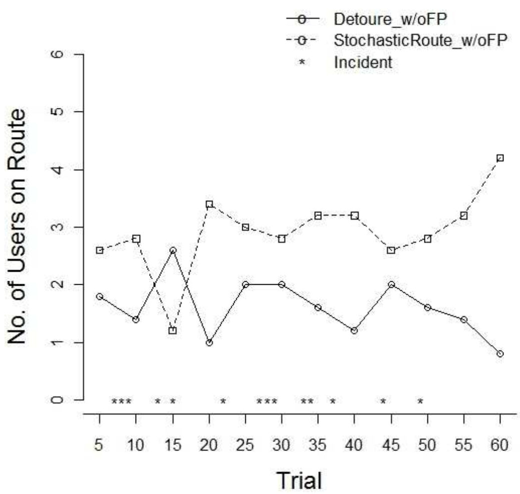
To find out how the network system performs over time, we plot in Figures 2 the average route shares for every five trials at the origin and intermediate nodes in both incident and information cases respectively. In Figure 2(1), shares are more stable over time with FP than without FP in the incident case. This is probably related to an expedited learning rate with a complete feedback on all possible alternatives. The same trend can be observed in Figure 2(2) for the information case. Comparing the charts in Figures 2(1) and 2(2) with the same index, we find that shares in the information case are generally more stable compared to the incident case. This indicates that real-time incident information can improve the system's reliability.





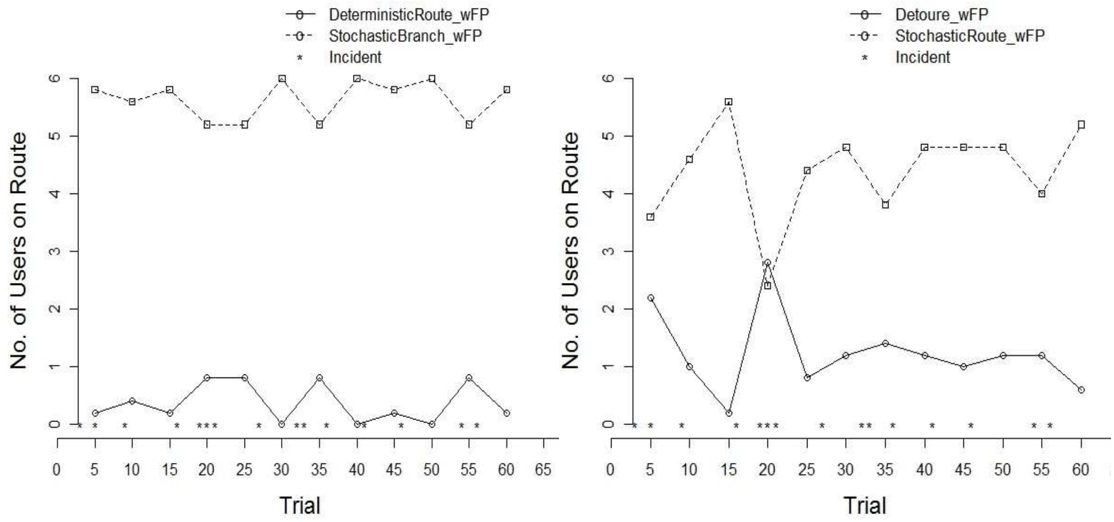
(a) Route Shares at Origin Incident case with FPs **(b) Route Shares at Stochastic Branch Incident case with FPs**



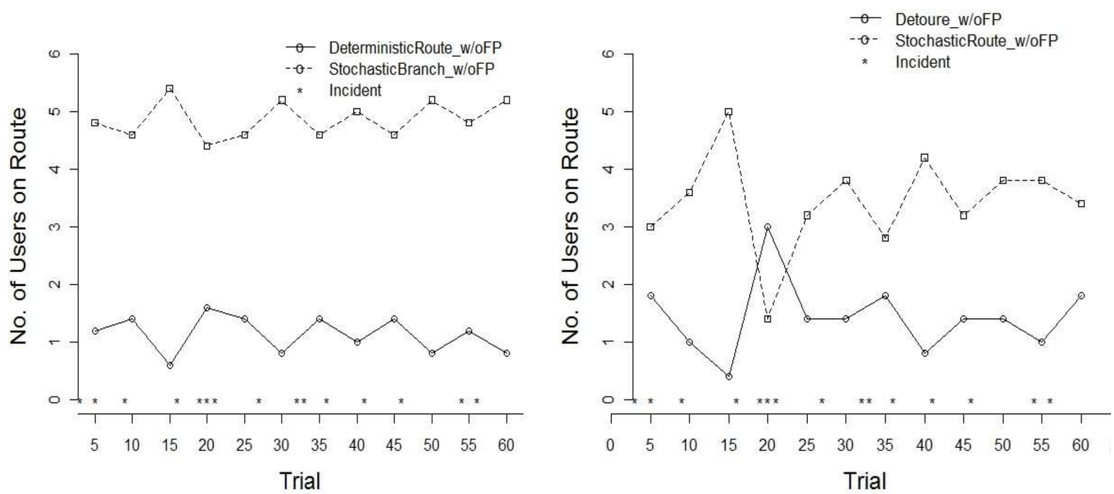


(c) Route Shares at Origin Incident case w/o FPs **(d)Route Shares at Stochastic Branch Incident case w/o FPs**

(1) Route Shares at Two Decision Nodes in Incident Case with and without FP



(a) Route Shares at Origin Information case with FPs (b) Route Shares at Stochastic Branch Information case with FPs



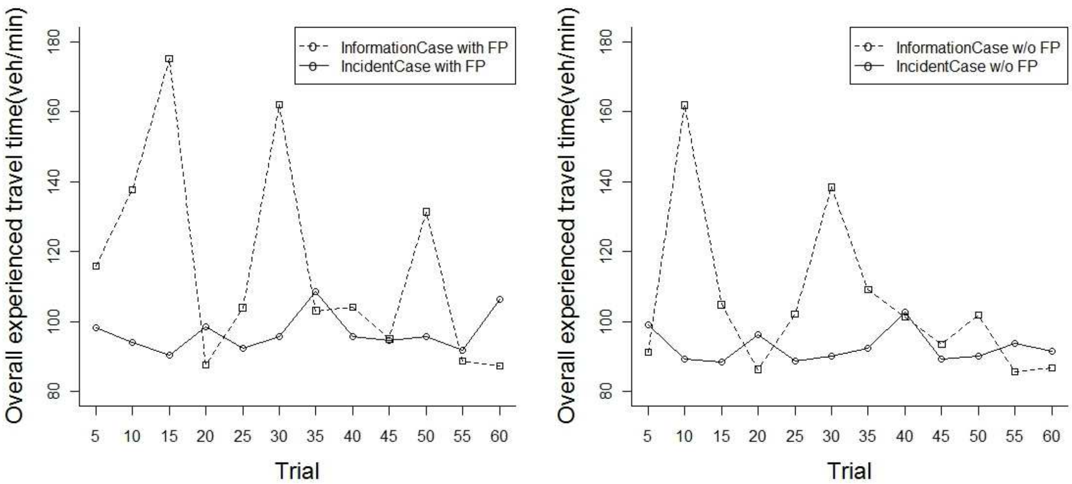
(c) Route Shares at Origin Information case w/o FPs (d) Route Shares at Stochastic Branch Information case w/o FPs

(2) Route Shares at Two Decision Nodes in Information Case with and without FP

FIGURE 2 Route Shares at Two Decision Nodes

Network Travel Time

The overall network travel time is presented in Figure 3, taking the average over every five trials. Overall network travel time is the average experienced travel time accounting for all participants' choices. Both Figure 3(a) and 3(b) show that average travel times are higher and have larger volatility in the incident cases than in the information cases. This result indicates that real-time incident information increases the efficiency and reliability of the network's performance. We also employed the bootstrap statistics to check the significance of average travel time differences when providing incident information. In both with and without FP cases, both differences are significant at the level of 1% (one-sided). Although in our designed user equilibrium, the difference of mean travel times between the incident and information cases was relatively small, with approximately 2.5 minutes difference, the actual observed difference is much larger - 19.16 (with FP) and 12.6 (without FP) minutes respectively. In our cases, the benefit that real-time information contributes to the network seems to be quite significant. It also seems that without complete feedbacks, travel time is even lower under information cases. The difference between the travel times with and without FP is significant at the level of 5% (one-sided) under real-time information cases. This can be explained as a result of the higher tendency to take the stochastic route in the FP group (more risk seeking). It also suggests that it may not always be advisable to provide full feedbacks on non-chosen alternatives.

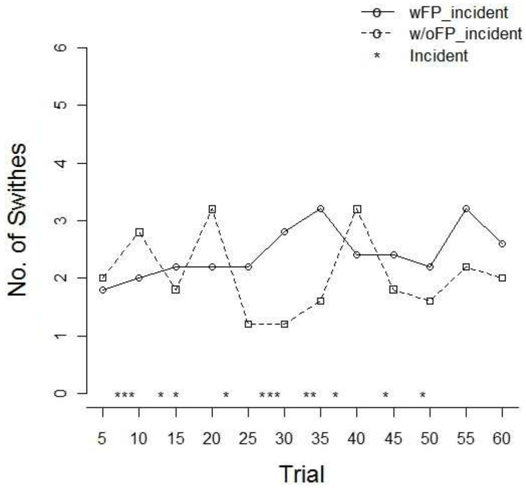


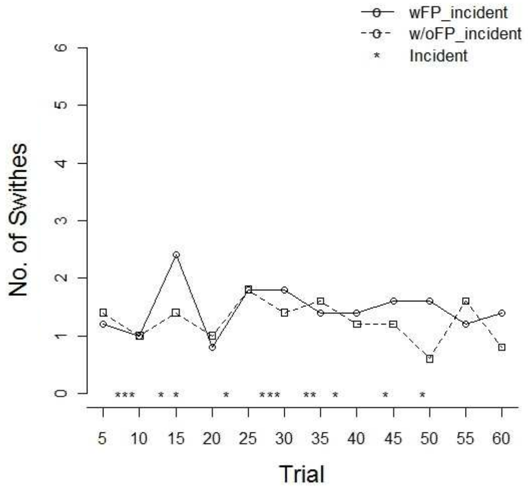
(a) With FP **(b)Without FP**

FIGURE 3 Overall Network Travel Time

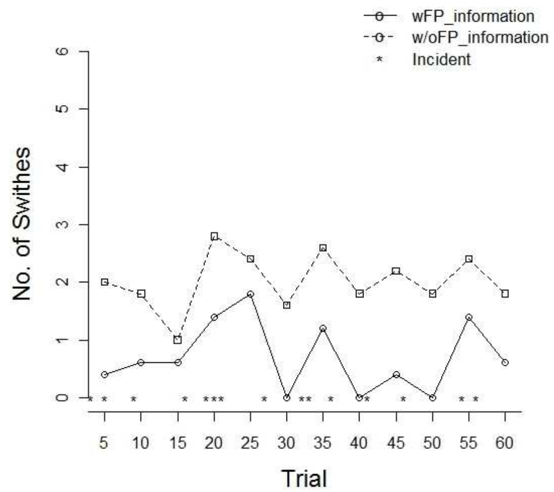
Route Switching

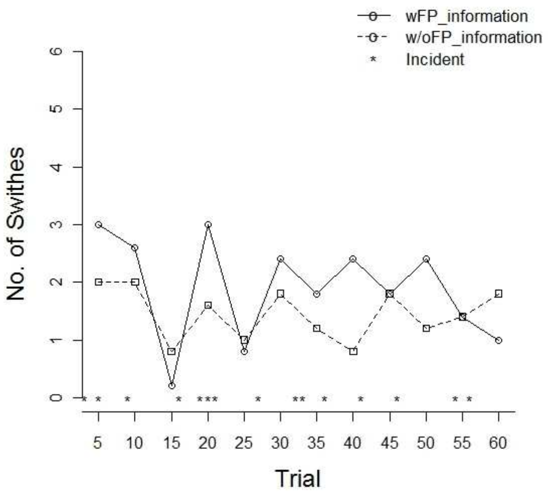
Route switches during the whole trip have been divided into two decision stages: one at the origin, and the other at the intermediate node. A switch at origin is counted when a participant switches to/from Path 1 from/to the stochastic branch, Path 2 or 3. A switch at stochastic branch is counted only when a participant switches to/from Path 2 from/to Path 3. Results from the four scenarios have been plotted in Figures 4 and 5.





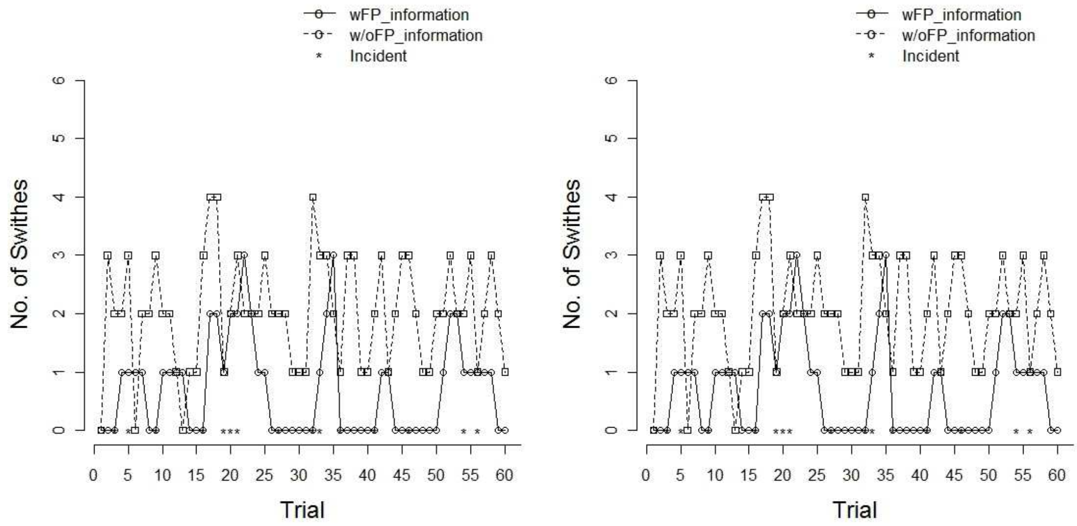
(a)Switch at Origin Incident case **(b) Switch at Stochastic Branch Incident case**





(c) Switches at Origin Information case **(d) Switches at Stochastic Branch Information case**

FIGURE 4 Switches at Two Decision Nodes in Information and Incident Cases



(a)Switches at Origin Information case (b) Switches at Stochastic Branch Information case

FIGURE 5 Daily Route Switches in the Information Cases

In Figure 4(a), in the incident scenarios the number of switches with FP is higher than that of without FP at the origin node, with the difference significant at the level of 5% (one-sided) from the bootstrap statistical test. This is because participants with FP may experience two situations; first - if no incident happens, travel time on Park Avenue is much lower than the other two alternatives; second - if there is an incident and most participants choose the stochastic branch, the deterministic route (I-99 –Local 2) has the least travel time. Without an incident indictor assisting in making strategic choices, participants have to take their decision at the origin and stick to it. For participants with neither information nor FP, if they find that the deterministic route is acceptable, they tend to avoid unnecessary risk given that congestion is quite significant when an incident occurs. This result is similar to those from previous studies relating to individual choices *(e.g., 6)* that the lack of information increases risk-averse behavior.

However, under the information scenario in Figure 4(c) the trend is opposite, whereby with FP provided, participants tend to switch less than without FP at the origin. This has also been verified by a p-value of 0%. This is because real-time information at the branch allows participants to make adaptive route choices to avoid the incident. When FP is provided, they realize that choosing the branch also turns out to be an optimal decision. The impact of FP on switching behavior is more significant at the origin than at the intermediate node, where incident information has the decisive effect. In our experiments, the four scenarios stand for four uncertainty levels. Participants tend to switch less in the two extreme conditions, when the uncertainty level is either very low (with information and FP) or significantly high (without information and without FP). Under the former condition, the situation becomes pretty clear, so switching is unnecessary once participants learn which alternative is the optimal one. However, in the latter condition, switches are avoided because very little feedback is provided, learning is more difficult and participants tend to avoid unnecessary risks. The latter follows the predictions of the payoff variability effect.

Finally, in Figure 5 we present the number of switches in each trial rather than an average over five trials for the information case. It can been seen that, regardless of the FP, most participants respond and take advantage of the information provided at the intermediate node, which indicates that strategic behavior (Routing Policy 4) has been widely adopted in the information case.

CONCLUSION AND FUTURE DIRECTIONS

In this paper, experimental observations of a day-to-day traffic pattern evolution are obtained in a simple congested network under exogenous disruptions with a given probability distribution. The effects of *en route* real-time traveler information and *ex post* FP information are assessed by comparing traffic patterns in the presence of uncertain disruptions. The comparison is in route flows, total system travel time, and the numbers of switches. Due to the limited number of experiment sessions and the small number of participants in each session, preliminary results and bootstrap statistics are provided in this paper. The hypotheses are between two random processes rather than over a random sample of subjects. Bootstrap statistical analysis sheds some light on the trends of the route choice random process over sixty 'days'. Based on the 1000 Bootstrap resampling samples, it is valid to draw statistical conclusions between two random processes.

It is observed that *en route* real-time information leads to travel time savings. Providing FP information makes the route flows closer to the user equilibrium pattern. However, this seems to cause network travel time to increase and bootstrap statistics verify the trend in the information case (but not in the incident case). The least network travel time is obtained under the scenario 'with *en route* information and without FP'. Therefore, travel time saving also depend to a certain extent on the network's design. This adds to the empirical evidences that more information in not necessarily better in a congested network. Route shares at the origin show significant differences between with and without real-time information, which indicate that travelers would plan in advance for the future availability of a VMS system. Last but not least, it shows that participants in with FP scenarios are more risk seeking than those in without FP scenarios regardless of information provision. FP information encourages route switching without real-time information, but suppresses them with real-time information.

We are now conducting more experiment sessions with a larger sample size so that statistical tests over the subject population can also be carried out. Another interesting direction is to develop a traffic prediction model that can provide reasonably accurate predictions of the experimental results. Such a model needs to explicitly work in a stochastic network, capture travelers' risk attitudes, strategic behavior, and learning behavior.

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