

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

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1 **ABSTRACT**

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

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

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1 INTRODUCTION

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

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

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

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

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

41

42 LITERATURE OVERVIEW

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

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

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

34 A main drawback of all the aforementioned individual-based studies is that travel times
35 were usually obtained from underlying probability distributions that were not affected by the
36 travelers’ choices. Thus, the inherent link occurring on congested networks (recurring and non-
37 recurring) between travelers’ route choices and travel times is missing in the current literature.
38 (14) (15) (16) (7) (17) (18)(19) carried out route choice experiments in congested networks
39 where travel times are determined by subjects’ route choices through either travel performance
40 functions or traffic simulations. However, their networks were deterministic and the day-to-day
41 variations in travel times resulted purely from travelers’ departure time and/or route choice
42 variations, not disturbances that brought forth random capacity reductions. In the domain of RP
43 data, (20) showed that by broadcasting expected travel times, VMSs can improve the network
44 performance. However, such studies do not have detailed data on individual learning processes.

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

8 9 **METHODOLOGY**

10 **Experimental set up and design**

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

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

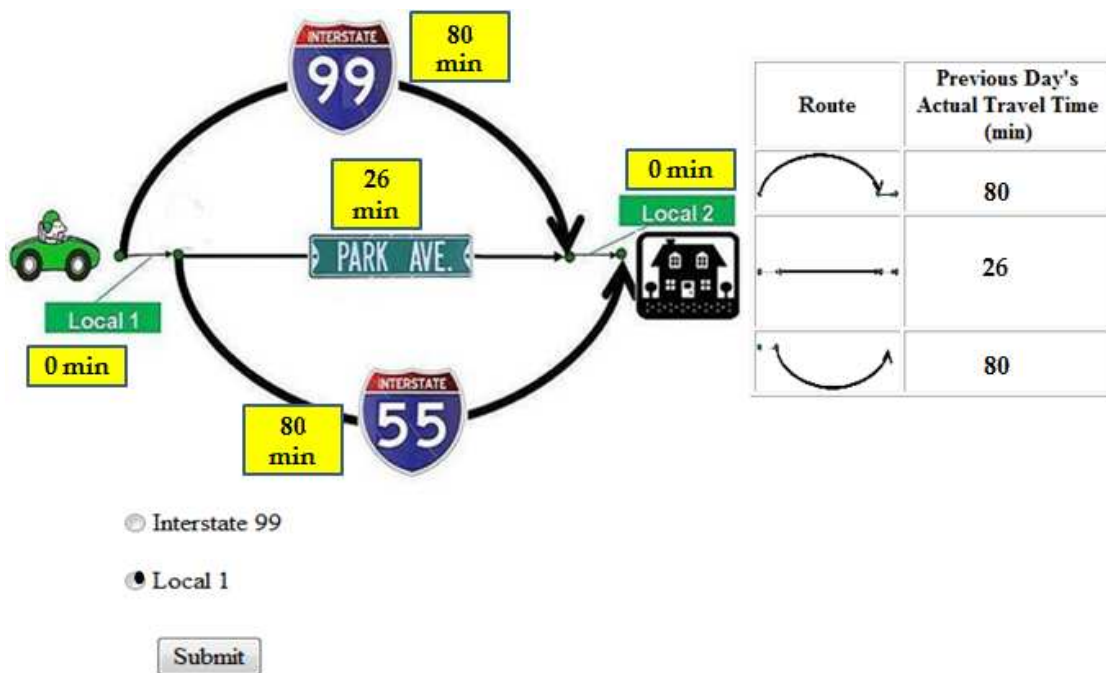


FIGURE 1 Screen shot of Initial Experiment's Presentation

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

1 neither necessary nor sufficient to ensure subjects' cooperativeness, thoughtfulness, or
2 truthfulness.

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

21

22 **Equilibrium design**

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

24 We use the following notation:

25 a : name of link
26 i : index of path (routing policy)
27 x_a : flow on link a
28 f_i : flow on path (routing policy) i
29 $C_a(x_a)$: link travel time as a function of flow on link a
30 e_i : (mean) travel time of path (routing policy) i

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

33 $C_{I-99}(x_{I-99}) = 80 + x_{I-99}$, $C_{I-55}(x_{I-55}) = 80 + x_{I-55}$, $C_{local1}(x_{local1}) = 4x_{local1}$,

34 $C_{local2}(x_{local2}) = 4x_{local2}$,

35 $C_{Park_ave}(x_{park_ave}) = 26 + 3x_{park_ave}$, with probability 0.75 (normal condition)

36 $26 + 55x_{park_ave}$, with probability 0.25 (incident condition)

37 The three paths are defined as follows:

38 Path 1: I-99-Local 2,

39 Path 2: Local 1-Park Avenue.-Local 2

40 Path 3: Local 1-I-55.

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

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

17 In contrast under the information case, we hypothesize routing-policy-based user
18 equilibrium where all used routing policies have equal and minimum mean travel times. There
19 are five possible routing policies in the network. Routing Policy 1 through 3 are Paths 1 through
20 3, and Routing Policy 4 is the one just discussed. Routing Policy 5 is the opposite of Routing
21 Policy 4, i.e. “first take Local 1, and if the incident has occurred, take Park Avenue and then
22 Local 2, otherwise take I-55”. Routing Policy 5 is conceivably inefficient. The equilibrium
23 solution’s flows are: $f_1 = f_3 = f_5 = 0$, $f_2 = 1$, $f_4 = 5$. We can verify that under these routing policy
24 flows, the network is in equilibrium such that Routing Policies 2 and 4 have equal and minimum
25 mean travel times of 96.25 minutes.

26 27 **Bootstrap statistical tests**

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

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

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

12

13 **RESULTS**

14 **Route Shares**

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

38

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

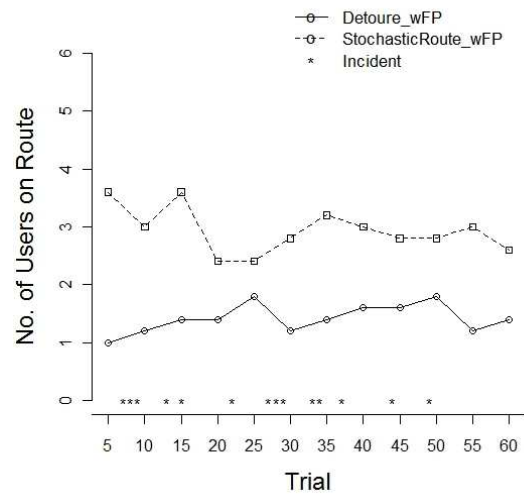
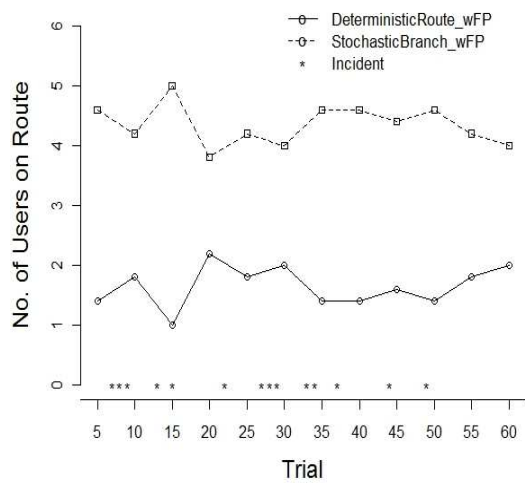
Performance Measure	Real-Time FP Information?		With FP	Without FP	Between Subjects P-value (one-sided)
	Real-Time Information?	FP Information?			
Travel Time (min)	Without real-time information		116	105.3	> 5%
	With real-time information		96.8	92.7	1.32%
	P-value (one-sided)		0.08%	0.67%	
Route Shares 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.

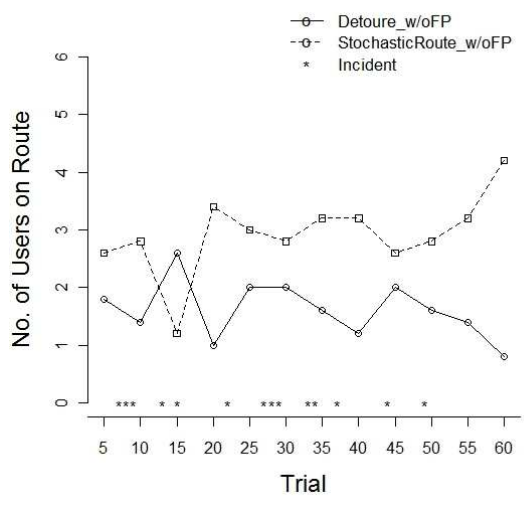
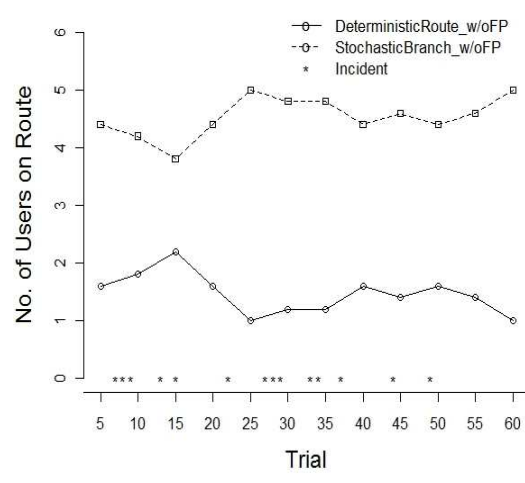
To find out how the network system performs over time, we plot in Figures 2 the average route shares for every five trials at the origin and intermediate nodes in both incident and information cases respectively. In Figure 2(1), shares are more stable over time with FP than without FP in the incident 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

1 the information case. Comparing the charts in Figures 2(1) and 2(2) with the same index, we find
 2 that shares in the information case are generally more stable compared to the incident case. This
 3 indicates that real-time incident information can improve the system's reliability.



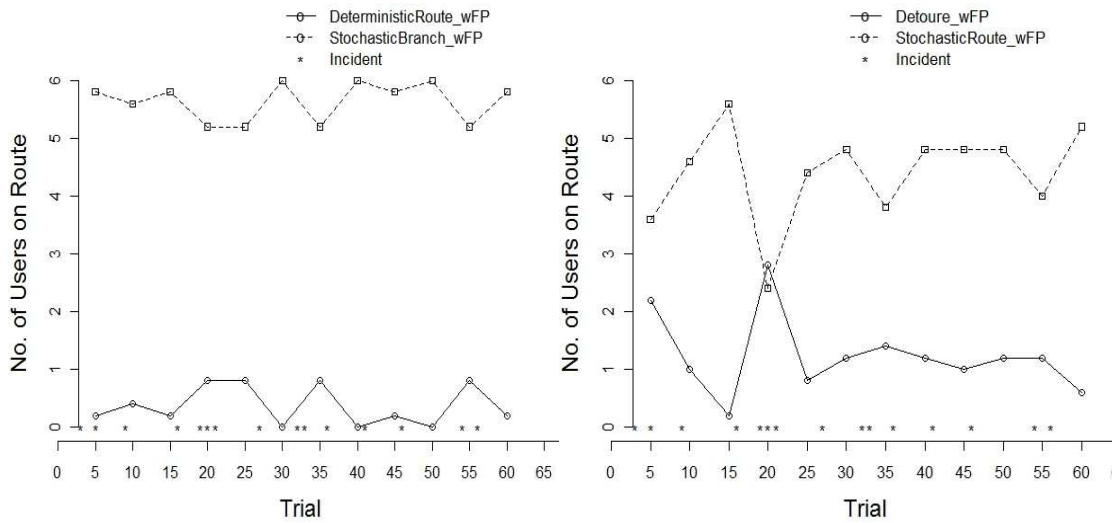
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(a) Route Shares at Origin Incident case with FPs (b) Route Shares at Stochastic Branch Incident case with FPs

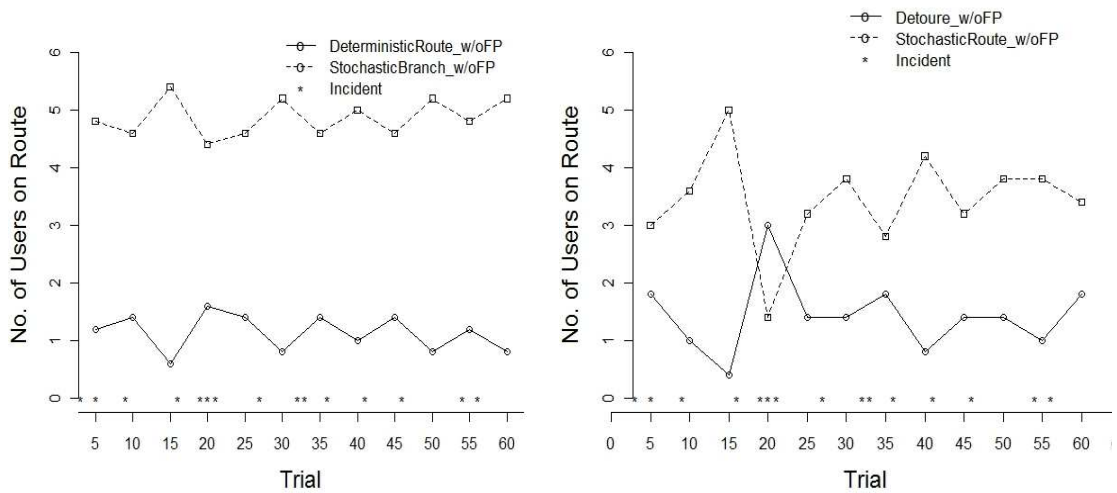


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(c) Route Shares at Origin Incident case w/o FPs (d) Route Shares at Stochastic Branch Incident case w/o FPs
 (1) Route Shares at Two Decision Nodes in Incident Case with and without FP



1
2 (a) Route Shares at Origin Information case with FPs (b) Route Shares at Stochastic Branch Information case with FPs



3
4 (c) Route Shares at Origin Information case w/o FPs (d) Route Shares at Stochastic Branch Information case w/o FPs

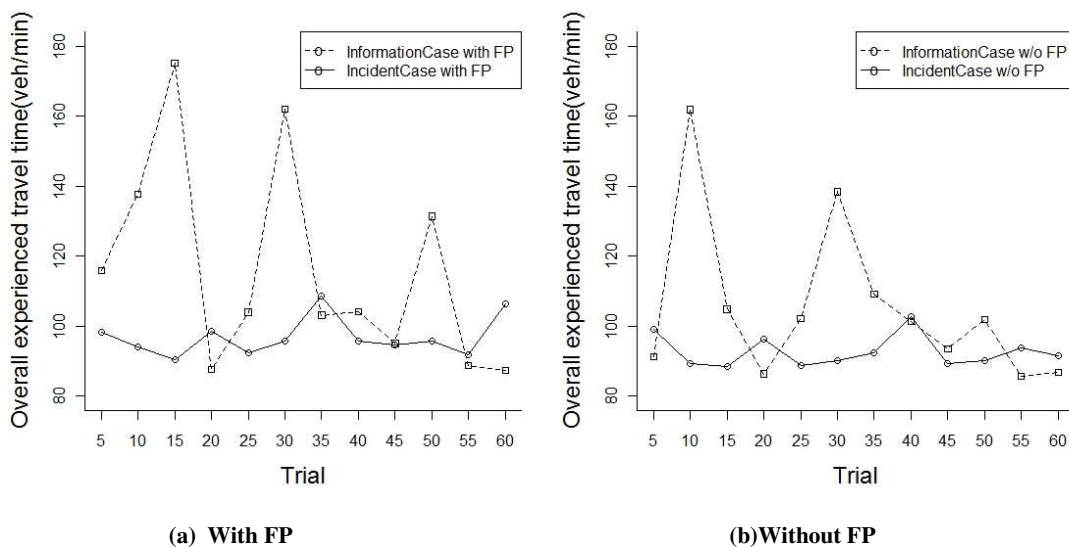
5 (2) Route Shares at Two Decision Nodes in Information Case with and without FP

6 FIGURE 2 Route Shares at Two Decision Nodes

7
8 **Network Travel Time**

9 The overall network travel time is presented in Figure 3, taking the average over every
10 five trials. Overall network travel time is the average experienced travel time accounting for all
11 participants' choices. Both Figure 3(a) and 3(b) show that average travel times are higher and
12 have larger volatility in the incident cases than in the information cases. This result indicates that
13 real-time incident information increases the efficiency and reliability of the network's
14 performance. We also employed the bootstrap statistics to check the significance of average

1 travel time differences when providing incident information. In both with and without FP cases,
 2 both differences are significant at the level of 1% (one-sided). Although in our designed user
 3 equilibrium, the difference of mean travel times between the incident and information cases was
 4 relatively small, with approximately 2.5 minutes difference, the actual observed difference is
 5 much larger - 19.16 (with FP) and 12.6 (without FP) minutes respectively. In our cases, the
 6 benefit that real-time information contributes to the network seems to be quite significant. It also
 7 seems that without complete feedbacks, travel time is even lower under information cases. The
 8 difference between the travel times with and without FP is significant at the level of 5% (one-
 9 sided) under real-time information cases. This can be explained as a result of the higher tendency
 10 to take the stochastic route in the FP group (more risk seeking). It also suggests that it may not
 11 always be advisable to provide full feedbacks on non-chosen alternatives.

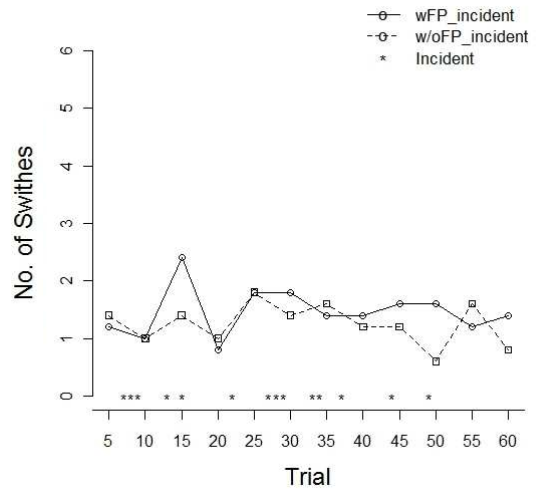
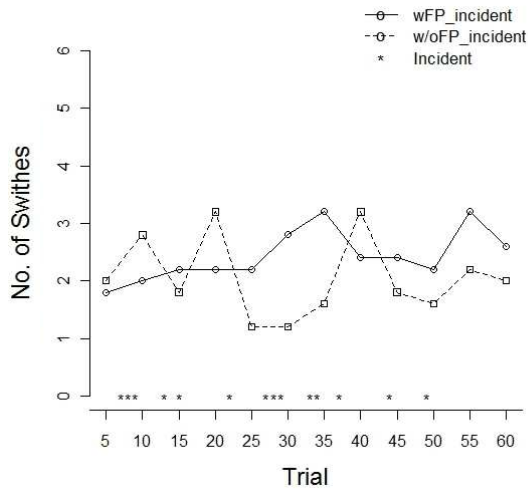


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FIGURE 3 Overall Network Travel Time

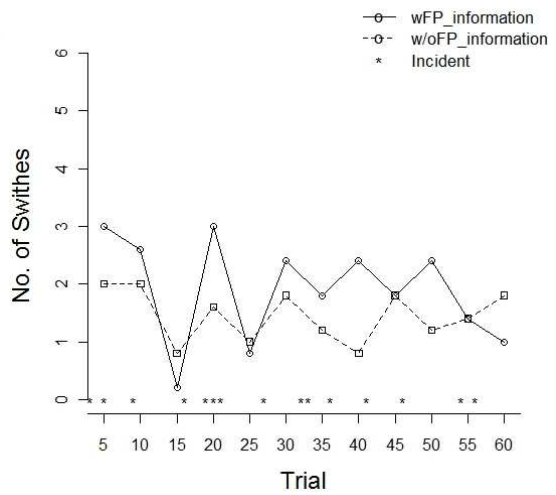
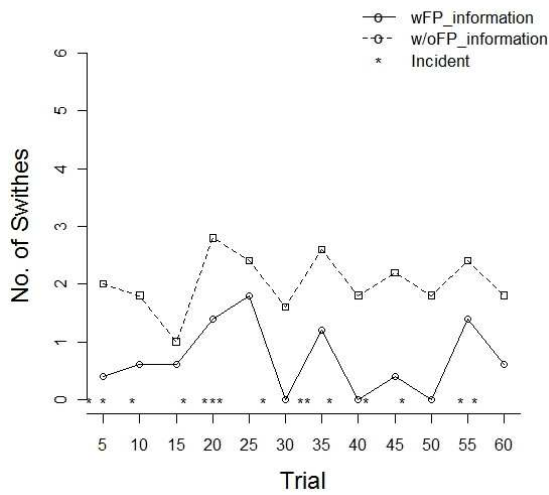
Route Switching

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

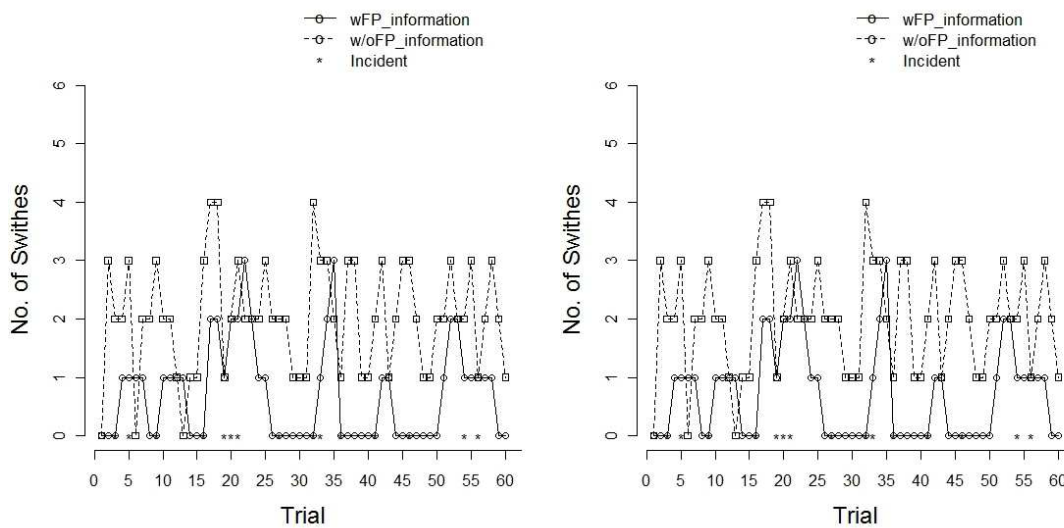
(b) Switch at Stochastic Branch Incident case



(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 indicator 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.

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

6 7 **CONCLUSION AND FUTURE DIRECTIONS**

8 In this paper, experimental observations of a day-to-day traffic pattern evolution are
9 obtained in a simple congested network under exogenous disruptions with a given probability
10 distribution. The effects of *en route* real-time traveler information and *ex post* FP information are
11 assessed by comparing traffic patterns in the presence of uncertain disruptions. The comparison
12 is in route flows, total system travel time, and the numbers of switches. Due to the limited
13 number of experiment sessions and the small number of participants in each session, preliminary
14 results and bootstrap statistics are provided in this paper. The hypotheses are between two
15 random processes rather than over a random sample of subjects. Bootstrap statistical analysis
16 sheds some light on the trends of the route choice random process over sixty ‘days’. Based on the
17 1000 Bootstrap resampling samples, it is valid to draw statistical conclusions between two
18 random processes.

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

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

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