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The combined effect of information and experience on drivers' route-choice behavior

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Abstract Advanced travel information systems (ATIS) are designed to provide real time information enabling drivers to choose efficiently among routes and save travel time. Psychological research suggests that route-choice models can be improved by adding realistic behavioral assumptions. However, different generalizations imply deviations in different directions. Specifically, different choices arise when decisions are taken on the basis of information compared to those taken on the basis of personal experience. An experimental study of route choices investigates the combined effects of information and experience on route choice decisions in a simulated environment whereby the participants can rely on a description of travel time variability and at the same time can rely also on personal experience through feedback. The experiment consisted of a simple two route network, one route on average faster than the other with three traffic scenarios representing different travel time ranges. Respondents were divided to two groups: with real-time information and without. Both groups received feedback information of their actual travel time. During the experiment, participants chose repeatedly between the routes and across scenarios. The results show that effect of information is positive and more evident when participants lack long-term experience on the distributions of travel times. Furthermore, information seems to increase initial risk seeking behavior, reduce initial exploration and contribute to between subject differences. These findings have implications for cost-effective ATIS design especially in the conditions characterized by non-recurrent congestion.

Keywords Experience · ATIS · Risk response · Route-choice · Travel time variability · Utility maximization

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Introduction

Advanced transportation information systems (ATIS) include all those systems that use information technology to inform, monitor control and even charge travelers for using the roads (Bonsall 2000). They are also a key component in development of cost effective congestion and demand management strategies. These complex technological systems of traffic surveillance and control are designed to provide real time information to drivers and network users about the surrounding traffic conditions. It is a common conviction that additional information together with advanced technologies like GPS is likely to reduce travel time uncertainty and enable drivers to choose efficiently among the available routes, saving precious travel time and reducing congestion. However, the exact impact of ATIS is likely to be sensitive to the drivers' reaction to the new information.

Mainstream transportation research addresses drivers' behavior with the assumption that individuals try to maximize expected utility. Most route choice studies focus on the wide family of discrete choice models. Discrete choice models are econometrically derived from random utility theory. An individual's utility for each route of an origin–destination pair is assumed to have a deterministic (or observable) component and a random component or error term, representing components of drivers' disutility that are not explained through observed attributes i.e. individual perception errors, measurement errors and specification errors. Choice probabilities are based on the observed utility values and the assumptions about the random error distribution. Prashker and Bekhor (2004) provide an extensive review of random utility models (RUM) and their application in route choice studies.

In relation to route choice, the wide RUM family includes three sub-family types. First, the classic Multinomial Logit Model (Daganzo and Sheffi 1977) and its applications: C-logit (Cascetta et al. 1996), IAP logit (Cascetta and Papola 1998) and Path-Size Logit (Ben-Akiva and Bierlaire 1999). Second, in recent years more flexible specifications were developed by applying the General Extreme Value theorem (McFadden 1978) including: Nested Logit (Ben-Akiva and Lerman 1985); Cross-Nested Logit (Vovsha 1997); General Nested Logit (Wen and Koppelman 2001) and Paired Combinatorial Logit (Chu 1989). Route choice applications of GEV models include an adaptation of GNL and PCL (Bekhor and Prashker 2001; Gliebe et al. 1999; Prashker and Bekhor 1988) and a GNL based Link Nested Logit (Vovsha and Bekhor 1988). Finally, the recent Mixed Logit or Logit Kernel model using a mixture between Probit and Logit models provides more general and flexible structures (McFadden and Train 2000; Ben-Akiva and Bolduc 1996). Bekhor et al. (2002) present an adaptation of Logit Kernel to route choice.

Although Discrete choice models provide parsimony and an elegant econometric generalization of Driver behavior, they do not include an explicit behavioral abstraction of the effect of the real-time information provided by ATIS. Capturing this effect on drivers within the framework of discrete choice models requires additional behavioral assumptions. Previous attempts to address the effect of partial information on drivers' behavior focus on three main approaches. Under one approach, the information affects the error term in the routes' utilities functions thus providing information implied less error in the system (e.g., Watling and Van Vuren 1993 and see review by Bonsall 2000). Another approach is to reduce system error by gaining more knowledge through reinforced learning. For example, Horowitz (1984) described a simple route choice model over time whereby decisions are based on the weighted average of previous travel decisions' utilities.

A third and different approach involves direct empirical research. Recent studies attempt to model the utilities of information and information acquisition through stated preference in laboratory simulations (e.g., Abdel Aty and Abdullah 2004; Peeta et al. 2000; Tong 2000; Wong-Wing Gun 1999; Sirnivasan and Mahamassani 1999; Mahmassani and Liu 1998; Abdel-Aty et al. 1997). Although similar in their approach to previous discrete choice studies (those without information effects) these studies enabled perception and processing mechanisms based on principles of bounded rationality (Simon 1982), simple heuristics and limited sets of choice rules. In addition, other studies applied fuzzy logic principles like "if-then" rules (Peeta and Yu 2005; Lotan 1993) or dynamic assignment and micro simulation using artificial agents (Nakayama et al. 2001; Nakayama and Kitamura 2000; Nakayama et al. 1999; Bonsall et al. 1997). A few studies attempted to investigate information impacts using revealed preference field studies of real locations or ATIS systems (Fujii and Kitamura 2000; Kraan et al. 1999; Deakin 1997; Wardman et al. 1997; Khattak and Khattak 1996). The current study is designed to contribute to this line of empirical research by building on recent basic behavioral research.

Insights from behavioral research

Despite of the extensive research efforts and advancements in computational possibilities, there is still a considerable lack of understanding of cognitive and behavioral aspects of drivers' decision-making processes under uncertain travel times (Gärling 1998; Gärling and Young 2001). This is a key role in designing state of the art cost-effective ATIS.

Behavioral decision research (e.g., Kahneman and Tversky 1984; Kahneman and Tversky 1979) shows violations of some of the assumptions shared by mainstream transportation models considered above. For example, in many cases decision makers are more sensitive to relative outcomes than to expected utilities. This research suggests that route choice models could be improved by adding more realistic behavioral assumptions. However, attempts to generalize recent behavioral findings to the context of route selection reveal that this task is not trivial. Whereas almost all these studies agree that people deviate from the predictions of rational decision theory (i.e., maximization of expected utility), different generalizations imply deviations in different directions. In order to clarify this problem it is constructive to start with a simple example.

Hypothetical example

Suppose a driver is faced with information, provided in real time, regarding the choice between two routes from work to home: a faster route (F) and a slower route (S). The average travel times on the faster route is predicted to be 25 min and on the slower one—30 min. The driver has no specific obligation to arrive home on a specific time, but obviously would like to drive the least amount of time. Suppose also that the driver is provided with real time information regarding the travel time ranges (the deviation around the mean value). The ranges are ±5 or ±15 min for each route. Combining means and ranges enables us to construct three possible travel time scenarios facing our driver (see Table 1). What will expected proportions of choices of the fast route, referred to as *maximization*, be in each of the three scenarios? The problem to predict our driver's choices although at first glance simple is not trivial. Moreover, three robust behavioral regularities that have been documented in basic decision research lead to contradicting predictions in the current example.

Table 1 Three possible travel time scenarios

Scenario	Travel time ranges (min)	
	Route F–25 min	Route S–30 min
Safer-Fast	±5	±15
Risky-Fast	±15	±5
Low-Risk	±5	±5

The 'hot stove' effect

Denrell and March (2001), and, Denrell (2007) demonstrate that when the feedback available to the decision makers is limited to their obtained payoff, experience reduces the tendency to select risky (high variance) alternatives. This pattern, referred to as the hot stove effect, is a natural consequence of the inherent asymmetry between the effect of good and bad experiences. In line with the 'classic' law of effect (Thorndike 1898), good outcomes are expected to increase the probability that a choice will be repeated and for that reason facilitate the collection of additional information concerning the value of the alternative that has yielded the good outcome. Bad outcomes are expected to reduce the probability that the choice will be repeated, and for that reason impair the collection of additional information concerning the value of the alternative that has yielded the bad outcome. As a result, the effect of bad outcomes is stronger (lasts longer) than the effect of good outcomes, and high variability decreases the tendency to choose the option associated with the high variability.

A generalization of the hot stove effect to the current context implies that repeated experience without ATIS is likely to lead drivers to deviate from maximization in the direction of risk aversion. Thus, ATIS is expected to increase maximization in scenario Risky-Fast, but to have little effect in the other two scenarios. A partial support to a risk-averse generalization in route choice was found by Abdel-Aty et al. (1997) and Abdel-Aty and Abdallah (2004).

Risk seeking in the loss domain

In their classical paper on Prospect Theory, Kahneman and Tversky (1979) and Tversky and Kahneman (1992) review the main deviation from rational choice in decisions under risk (one-shot decisions based on a complete description of the payoff distributions). One of the most important behavioral phenomena they highlight is the tendency to exhibit risk seeking in the loss domain (Tversky and Kahneman 1981). For example, most people prefer the gamble, or prospect {lose 4000 with probability 0.8; lose nothing otherwise}, over a sure loss of 3000.

A partial support to this generalization of Prospect Theory in route choice was found in the research by Katsikopoulos et al. (2002). The authors provided participants with descriptive information about the travel time ranges of two routes while the participants drove once through various traffic scenarios on a driving simulator. They found that in the case of gains (i.e., an alternative route is on average better off compared to a reference route) risk aversion in route selection emerges when the alternative route is riskier relative to the reference and risk seeking otherwise. In the case of losses (i.e., an alternative route is on average worse off compared to a reference route)–risk seeking in route selection emerges when the alternative route is riskier relative to the reference and risk averse otherwise.

A generalization of this observation to the current setting implies that the availability of ATIS (complete description of the payoff distribution) is expected to enhance risk-seeking behavior. Thus, ATIS is expected to increase maximization in scenario Risky-Fast and impair it in scenario Safer-Fast. Stronger assumptions (a stochastic response rule, and very few risk seeking drivers) predict that maximization might be higher in Scenario Risky-Fast than in Scenario Low-Risk.

The Payoff variability effect

Experimental study of the effect of experience on human choice behavior in repeated settings reveal a robust payoff variability effect (Myers and Sadler 1960; Busemeyer and Townsend 1993; and Erev and Barron 2005). The effect occurs when the decisions maker receives no information specifically describing the outcomes of choice and has to relay on feedback from past experience. Experience leads to adaptive learning but at the same time, it is also a function of sampling available information on the basis of past experience. Limited sampling can lead to inaccurate estimates and faulty decisions (e.g., Tversky and Kahneman 1974). According to the payoff variability effect, an increase in the variance of the payoff distribution of the possible outcomes appears to move aggregate choice behavior towards random choice.

Avinery and Prashker (2003) demonstrate the importance of this observation in the context of Driver behavior. They show that increasing travel time variability of the route with a higher expected travel time increases its popularity. Since the payoff variability effect is reduced by precise information (e.g., Barron and Erev 2003) it implies that ATIS will increase maximization in all the scenarios considered here. Moreover it implies that the effect will be particularly large in scenarios Risky-Fast and Safer-Fast.

The combined effect

The main goal of the current analysis is to improve our understanding of the joint effect of the three behavioral tendencies described above. In order to achieve this goal the current research examines choice behavior in an environment in which the decision makers receive partial descriptive information, and at the same time can rely also on their personal experience.

This relatively new approach combines together experience and description in the decision making process which, up till now, were treated separately. A recent study by Avinery and Prashker (2006) applied this approach by providing one group of participants with a single static description of route mean values (but not their variability) and subsequently allowing them to gain experience of their preferable route using feedback. The second group (the control), received only the latter (similar to their 2003 study). The study found that informed participants tend to prefer the safer and slower route (i.e., show risk aversion) while non-informed ones prefer the risky and fast one (i.e., show the expected preference for risk seeking). Our study continues with this approach whilst replacing the static information with dynamic real time information about the ranges of travel times on available routes, consequently providing participants with a description of travel time variability as would appear on a variable message sign (VMS). We think this will provide a more accurate representation of plausible travel time information while driving and making route choice decisions.

Hypotheses and experiment design

As discussed earlier we hypothesize three, partially contradicting, behavioral tendencies: Hot stove effect, risk seeking in the loss domain, and payoff variability effect. The main goal of the current study is to evaluate the relative importance of the three generalizations in the case of route choice with real time information provision.

The experiment included a simple road network with two routes from work to home. One route was on average faster, with mean travel time of 25 min and the other slower with a mean of 30 min. Participants in the experiment (49 under graduate Technion students) were divided randomly between two groups—one group ($N = 24$) received real time information continuously before each simulated choice and the chosen route's randomly drawn travel time after each choice was made (as a feedback). The other group ($N = 25$) the control received only the feedback information but no other information regarding the possible travel times on the routes. No foregone payoff was provided.

The participants' task was to repeatedly choose between the two routes simulating commuting days. In order to encourage participants to save travel time, each minute accrued in the experiment was set a cost of 0.1 NIS (1$US = 4.5 NIS) and deducted from their monetary budget. The average payoff per participant was about 4.5$). In each group participants were faced with three consecutive traffic scenarios (repeated measures) as presented in Table 1 in the hypothetical example. Each scenario was run 100 times so in total each participant provided 300 observations. The advantages of testing the same individuals in each experimental condition is that each participant serves as his own control limiting the confusion between individuals' characteristics and the manipulated variables. Thus less participants are needed and greater statistical power is achieved compared to using different groups of participants in each experimental condition (Randomized Block). The main concern in this type of design is carryover effects from one treatment (i.e., Scenario) to the next (see Levin 1998 and Girden 1992 for considerations under repeated measures designs).

This drawback was reduced by counterbalancing i.e., by dividing the order in which the scenarios were assigned in to the 3! possible arrangements—or in total to 6 blocks and assigning participants within each group randomly between these blocks. After each scenario was finished an announcement was given warning of the beginning of the next scenario. Participants were not informed in advance how many runs they were expected to complete.

The group provided with real time information received for each of the two routes the travel time range (the minimum and maximum travel times) as designed a priori for each scenario. This simulated a simple variable message sign (VMS). In order to allow a small variation in the provided information the mean of the travel time oscillated randomly between 0–5 (whole) minutes in respect to the initial scenario design and the travel time ranges shifted accordingly. For example, if in trial t the mean of the fast route was randomly set to $25 + 1 = 26$ min, then the group provided with real time information would see prior to their route choice a travel time range of *21–31* in the short range or *11–41* in the long range (depending on the relevant scenario). Thus although the means for each route changed in each trial the travel time ranges remained the same.

Following the route choice the participant received as a feedback for his next choice the 'actual' travel time on his chosen route but not of the alternative one. The travel time was randomly drawn (using a uniform distribution) from the provided travel time range to encourage user confidence in the information. The same treatments were given to the group without information the only difference is that they did not receive the VMS message.

Results

Figures 1, 2 and 3, present the proportions of choices of the faster route (the maximization rate) under the different scenarios as a function of the information condition and time (in blocks of 10 trials). Table 2 presents a summary of the average maximization rates per scenario over all 100 trials, in the first 10 trials, and in the last 50 trials. The analysis was conducted using the SPSS software package.

As expected, under all scenarios and conditions, the faster route (with the lower travel time mean) is chosen more often than the slower one. From Figs. 1–3, it is evident that participants who received no information behave more or less similarly in all of the three scenarios. The classical learning curve is obvious as it takes several trials to learn that the faster route minimizes travel times. A repeated measures ANOVA applying the Huynh-Feldt adjustment for the degrees of freedom (Huynh and Feldt 1970, 1976) did not show significance of difference between the mean proportions of the three scenarios for the without information condition ($F = 2.41$, $p > 0.05$). This was true also when analyzing only the first 10 trials. However, the within-group differences for the last 50 trials are significant ($F = 3.75$, $p < 0.05$). In addition, the means and standard deviations for the three scenarios without information are quite similar implying that the choice behavior appears more homogeneous.

Comparing the between-group effects over the 100 trials, it seems that participants who received information on the travel time ranges prior to their choice behave differently compared to those that did not receive it (See Table 2a). However, the between group *t*-test was significant only for Low-Risk ($t = 3.17$, $p < 0.05$). A repeated measures ANOVA shows the difference between means 'with information' is significant ($F = 3.51$, $p < 0.05$). Post hoc testing using contrasts show that the mean differences between Safer-Fast and Low-Risk is significant at 0.05 while the difference between Risky-Fast and Low-Risk is significant but only at 0.1. The difference between Safer-Fast and Risky-Fast is not significant. Standard deviations are larger in the 'with information' group compared to the 'without information' one (except under Low-Risk where information makes the better off route obvious). This results imply that participants receiving information are more heterogeneous in their choice behavior compared to the control group.

A linear mixed model (with fixed, repeated and random factors) was also estimated on the basis of the same data set. The linear mixed model expands the general linear model in analysis of variance so that the error terms and random effects are permitted to exhibit correlated and non-constant variability. This provides flexibility to model not only the mean of the response variable but its covariance structure as well. The model included

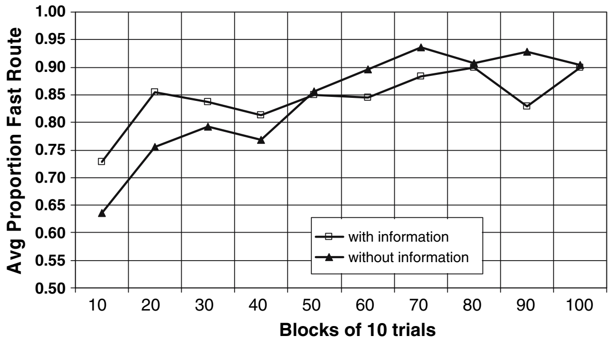

Fig. 1 Average maximization rate—Scenario Safer-Fast

Fig. 2 Average maximization rate—Scenario Risky-Fast

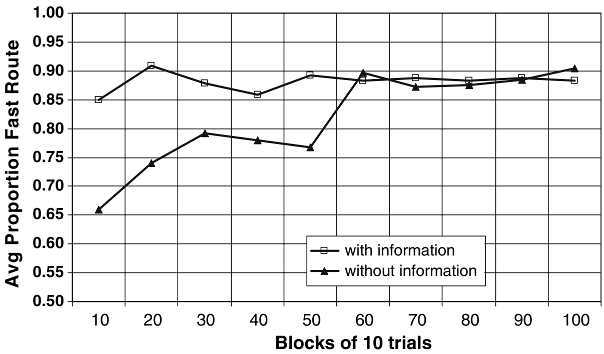

Fig. 3 Average maximization rate—Scenario Low-Risk

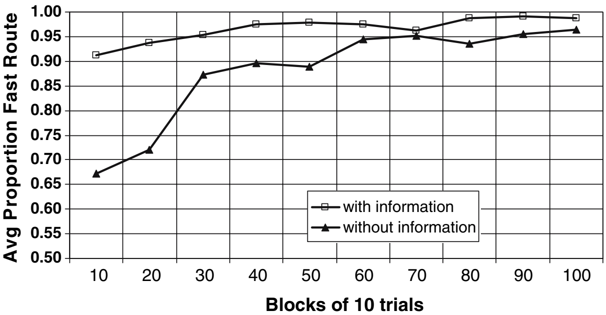

Table 2 Average maxmization rate (average proportions of 'fast' choices)

Scenario	Conditions (groups)[a]		Sig. between
	With information	Without information	
(a) Full data set			
Safer-Fast	.844 (.165)	.838 (.128)	–
Risky-Fast	.881 (.217)	.817 (.128)	–
Low-Risk	.966 (.069)	.880 (.115)	<0.05
Sig. within	<0.05	–	
(b) First 10 trials			
Safer-Fast	.729 (.219)	.636 (.173)	–
Risky-Fast	.850 (.228)	.660 (.187)	<0.05
Low-Risk	.912 (.136)	.672 (.196)	<0.05
Sig. within	<0.05	–	
(c) Last 50 trials			
Safer-Fast	.873 (.168)	.914 (.137)	–
Risky-Fast	.885 (.226)	.886 (.154)	–
Low-Risk	.986 (.046)	.954 (.091)	–
Sig. Within	<0.05	<0.05	

[a] Standard deviations are in parenthesis

three fixed factors and their interactions: ‘Group’, ‘Block’ (or scenarios’ order of appearance) and ‘Scenario (as a repeated effect) and a random factor, which relates to the participants. The results reveal that the effect of ‘Scenario’ (the repeated effect) is significant ($F = 7.89$, $p < 0.05$) as well as the effect of the ‘Group’ ($F = 4.44$, $p < 0.05$). The effects of the order of appearance (Block) and the interactions are not significant. Furthermore, the estimated 3×3 covariance matrix showed significant results only to the variances of the choice proportions of each scenario but not of their covariance. This implies that participants treated the traffic scenarios separately, thus no obvious carry over effects contaminated the results.

A clearer picture of the role of information and experience is provided with an analysis that distinguishes between the initial and the long-term effects. This analysis reveals a large difference between the first 10 trials and the last 50 trials (see Table 2b and 2c).

Comparison of the different scenarios in the first 10 trails without information shows that there are no significant within group differences between the scenarios. In contrast, the ‘with information’ group reveals the pattern predicted by the risk seeking hypothesis: The faster route was more attractive when it was associated with higher variability (85% in Scenario Risky-Fast) than when in was associated with lower variability (73% in Scenario Safer-Fast) and the within group difference is significant ($F = 5.46$, $p < 0.05$). Post hoc contrasts reveal that the mean difference is significant at the 0.05 level when comparing Safer-Fast to Low-Risk and at the 0.1 level when comparing Safer-Fast and Risky-Fast. The difference between Risky-Fast and Low-Risk was not significant. Furthermore, standard deviations are larger in the ‘with information’ group compared to the ‘without information’ one (except under Low-Risk). The between group t-tests shows that under Risky-Fast ($t = 3.19$, $p < 0.05$) and Low-Risk ($t = 4.95$, $p < 0.05$) the difference between group means are significant, but not under Safer-Fast.

A similar pattern with information was observed in the very first trial, which represents a one shot choice common to description based choice studies. Under Safer-Fast, 70% choose the faster route compared to 87% under Risky-Fast. Under Low-Risk the proportion of the faster route rises to 96% (within group $F = 2.73$, $p < 0.1$). Post hoc contrasts reveal that the difference between Safer-Fast and Low-Risk is significant at the 0.05 level. However the differences between Risky-Fast and Low-Risk and between Safer-Fast and Risky-Fast were not significant.

The risk-seeking tendency was eliminated by the effect of experience. Examination of the last 50 trials reveals that the differences between groups for all the scenarios are not significant. The group with information reveals significant within group differences ($F = 3.38$, $p < 0.05$). Post hoc contrasts show a significant difference at the 0.05 level between Safer-Fast and Low-Risk and between Risky-Fast and Low-Risk. As expected the difference between Safer-Fast and Risky-Fast was not significant. For the group without information we find a significant difference ($F = 3.75$, $p < 0.05$) whereby the difference between Risky-Fast and Low-Risk is significant at the 0.05 level but not for the other two contrasts. Under the last 50 trials The Low-Risk condition was associated with the highest maximization rate in both information conditions and with the lowest standard deviations. However, higher payoff variability associated with the Safer-Fast and with the Risky-Fast scenarios moved behavior towards random choice by decreasing the maximization rate compared to the Low-Risk scenario. The conclusion here is that only the payoff variability effect appears to be robust to experience.

Discussion

The current results highlight two behavioral regularities that are not modeled by mainstream models of travel behavior. As demonstrated by Avineri and Prashker 2003 (and see review in Erev and Barron 2005) the main behavioral tendencies in decisions from experience without a description of the relevant distributions (the 'without information' condition) reflect the *payoff variability effect*. We observe that an increase in either routes' variability (under scenarios Safer-Fast or Risky-Fast) moves behavior in the direction of random choice. This was most prominent under the last 50 trials where the within-group differences were also significant.

The results for the condition 'with information' suggest that the initial effect of information concerning the relevant distributions is consistent with the prediction of Prospect Theory i.e., risk seeking when travel times are framed in the domain of losses. In the first 10 trials, the observed behavior reflects more risk seeking than risk aversion. That is, the fast route was more attractive when it was risky (under Risky-Fast) than when it was associated with low variability (under Safer-Fast). However, longer experience moves behavior toward the predictions of the payoff variability effect. After 50 trials, the evidence for more risk seeking than risk aversion disappeared. The sole effect of variability was a reduction in the attractiveness of the faster route.

An examination of the net effect of information reveals an interesting pattern. As suggested by Avineri and Prashker (2006) the data shows that in certain settings information does not increase the proportion of faster route choices. Specifically, as seen in Fig. 1, after 50 trials, the maximization rate in the Safer-Fast scenario was somewhat reduced by the availability of the information (and to a lesser extent, as seen in Fig. 2, also in scenario Risky-Fast). In addition, the current results can be used to refine the explanation provided by Avineri and Prashker (2006) to this interesting pattern. They stress that the negative effect of information can be explained with the assertion that information increases risk aversion. The comparison of our replication of the scenario run by Avineri and Prashker (2006) i.e., Risky-Fast to the Low-Risk scenario, appears to support this assertion. However, a comparison of scenario Safer-Fast (that did not appear in their study) with the other scenarios demonstrates that the opposite pattern is stronger especially when the level of experience is low In this case, our data asserts that the typical effect of information is to increase risk seeking. Moreover, in the current study the initial effect of providing real time information was positive for all three scenarios.

Implications for ATIS design

We believe that current results suggest that information has three main effects. First, it reduces initial exploration (and for that reason it increases the maximization rate by inexperienced drivers). Second, it increases initial risk seeking. Finally it increases between-subjects' differences in response to variability or risk.

The main conclusion from the analysis is that the major benefits of providing real time information with ATIS are specifically when drivers lack long-term experience. Drivers that are new to the road network or that have limited knowledge of the travel time distributions common to it will benefit the most from the provided information. However, our results also show that the effect of information is somewhat limited for experienced drivers whom already have a good knowledge base of the possible travel conditions on the network. This is similar to the findings from previous studies of experience-based decisions (without information) mentioned above. It is worth noting that when traffic conditions change abruptly due to unexpected events like accidents or special events (example a large sport game) then the information has a key role by expediting the learning process of the drivers on the network. From a network planner or manager's view this has high significance since non-recurring congestion (in contrary to recurring congestion) is taking an ever larger role in many urban networks (Lomax and Schrank 2003). While recurring congestion can be dealt with long term learning by frequent users and commuters, better management of non-recurring congestion may be possible by providing real time information to the users. In these circumstances more research is necessary to understand the impacts of partially informed users on the general equilibrium of the transport network.

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