The impact of travel information's accuracy on route-choice

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ABSTRACT

ATIS (Advanced Travel Information Systems) are designed to assist travellers in making better travel choices by providing pre-trip and en-route information such as travel times on the relevant alternatives. Travellers' choices are likely to be sensitive to the accuracy of the provided information in addition to travel time uncertainty. A route-choice experiment with 36 participants, involving 20 repetitions under three different levels of information accuracy was conducted to investigate the impact of information accuracy. In each experiment respondents had to choose one of three routes (risky, useless and reliable). Provided information included descriptive information about the average estimated travel times for each route, prescriptive information regarding the suggested route and post-choice feedback information about the actual travel times on all routes. Aggregate analysis using non-parametric statistics and disaggregate analysis using a mixed logit choice model were applied. The results suggest decreasing accuracy shifts choices mainly from the riskier to the reliable route but also to the useless alternative. Prescriptive information has the largest behavioural impact followed by descriptive and experiential feedback information. Risk attitudes also seem to play a role. The implications for ATIS design and future research are further discussed.

KEY WORDS

Accuracy, ATIS, compliance, risk attitudes, reliability, route-choice, stated preference, travel information, uncertainty, travel simulator.

1 INTRODUCTION

Advanced travel information systems (ATIS) are designed to assist travellers in making better travel choices by providing information regarding the available travel alternatives. Without information, travellers' choices are based mainly on experiential information based on knowledge gained from learning of past experiences. ATIS enable travellers, in addition to experience, to base their choices on descriptive, prescriptive and even feedback information. Descriptive information usually consists of information about prevailing conditions such as current or predicted travel times. It can be provided either pre-trip e.g. via the internet or en-route e.g. through a variable message sign or personal or on-board devices. Prescriptive information usually suggests travellers the 'best' alternative e.g. the route with the shortest travel time. Traveller response is generally defined here in terms of compliance i.e. acceptance of the system's suggestions. Feedback information is usually ex-post relating to historical records of travel times on chosen and non-chosen routes (also called foregone payoffs).

The sensitivity of travellers' response to information, especially in the case of accepting route suggestions depends on their perceptions of the provided information's accuracy. Accuracy can be defined as the ability of the information system to reduce the discrepancy between estimated travel times and the actual ones experienced by the traveller. We refer to travel times estimated by the information system as descriptive information, to route suggestions made by the system as prescriptive information and to the actual travel times experienced by travellers as feedback information. The latter is assumed to be correct from the point of view of the traveller. In this context we can define two types of travel time uncertainty in the choice environment. The first one depends on the network's performance and is related to actual variability in travel time, while the second relates to the ability of the information system to correctly estimate prevailing traffic conditions, a task that becomes more complex as congestion levels increase, particularly non-recurring congestion which is difficult to predict.

Travellers could well exhibit different behaviours in contending with this complex range of uncertainty depending on their risk attitudes. Risk averse travellers are likely to prefer a more reliable route (i.e. a lower travel time variance) over an unreliable one with an average shorter travel time. Risk seeking travellers are likely to prefer an unreliable route that provides on average a shorter travel time. An inaccurate ATIS may be perceived by travellers as corresponding to higher risk and also possibly affect the response rates to prescriptive information.

Several route-choice studies have investigated the impact of information using different theoretical and methodological frameworks as discussed further in Section 2. To better understand the impact of information accuracy on route-choice this paper presents the design of a Stated Preference (SP) laboratory experiment as described in Section 3. The rest of the paper is organized in the following manner: Aggregate analysis using non-parametric statistics is described in section 4 followed by the results of disaggregate analysis using a mixed logit choice model in Section 5. Finally, conclusions and several future work directions are presented in Section 6.

2 LITERATURE REVIEW

Lacking other sources of information, travellers will base their route choices on the travel times they had experienced in previous trips (*Cascetta, 2001; Cascetta & Cantarella, 1991; Horowitz, 1984*). Experiential information, therefore, reinforces learning but, at the same time, it is also a function of sampling available information from memory about previous experiences. Psychologists have documented the payoff variability effect which suggests that increasing the level of variability in the decision environment inhibits reinforced learning (*Erev & Barron, 2005*). For example, *Avineri & Prashker (2003; 2005)* demonstrated that increasing a route's variability makes it appear more attractive.

With ATIS route-choice is influenced not only by experiential information, but also by the information provided by the system, e.g. a visual description of average travel times. Depending on the type of information, different results have been documented, in both SP and Revealed Preference (RP) settings, when comparing behaviour between informed (i.e. users assisted by an information system) and non-informed users (i.e. users who only receive experiential or feedback information). In the case of descriptive information, several SP experiments (e.g. *Abdel-Aty et al., 1997, Avineri & Prasker, 2006)* assert that travellers will tend to exhibit risk aversion when faced with travel time information. In a series of repeated choices, *Avineri & Prashker (2006*) compared the effect of providing respondents a-priori with static pre-trip information describing average expected travel times in addition to receiving feedback information about the chosen alternative. They demonstrated that informed respondents were more risk averse and preferred a more reliable route compared to the control group that could only learn through past experience. Their result illustrates indirectly how the effect of information accuracy might be explained by the perceived difference between the provided expected 'average' and the experienced outcomes. Conversely, *Ben-Elia et al. (2008)*, in a different repeated choice experiment, internalised inaccuracy by providing respondents with dynamic en-route information describing the ranges of travel times. They show that compared to non-informed respondents, informed ones learn faster and exhibit risk seeking behaviour (i.e. prefer a shorter and riskier route) in the short run which dissipates in the long run as experiential information becomes more dominant. Since the actual travel times experienced were always drawn within the descriptive range, no apparent discrepancy should have been perceived here between the information provided by the system and the outcome of choice. The two aforementioned studies illustrate the possible associations that could exist between the accuracy of information on one hand and changes in travellers risk attitudes on the other hand. Regarding feedback information, *Bogers et al. (2005)* showed that respondents who were provided with foregone payoffs (i.e. feedback on chosen and non-chosen alternatives alike) performed better in terms of travel time savings, though these benefits decreased over time as more experience was accumulated.

In an RP field study*, Fujii & Kitamura (2000)* investigated the effect of descriptive information in a real-life road closure situation. They found that drivers were more sensitive to descriptive travel time information than to experiential information. This result could be magnified by the high risk of delays involved in the road closure in the short run. *Hato et al*. *(1999)* refer directly to the impact of information accuracy. In a RP experiment they studied the cognitive aspects of route-choice with descriptive information to explain information acquisition (the share of drivers who acquired information by hearing or seeing, e.g. via radio or VMS) and information reference (the share of drivers who make reference to a certain source of information when choosing their route). Information accuracy which was only subjectively measured had a negative impact on information reference i.e. it reduced the likelihood to use information sources. This was more apparent with visual information.

In the case of prescriptive information, it is important to study compliance i.e. the acceptance of the system's suggestions. *Van Berkum & Van der Mede (1996)* demonstrate the mediating effects of habitual behaviour on compliance. Habitual behaviour is based on knowledge acquired in the long run though experiential information. Using both SP and RP settings, they found that the effect of both prescriptive (information regarding the shortest route) - and descriptive (providing estimated travel times of each route) information depends on habitual behaviour. In the case of prescriptive information route choice is further mediated by the decision to comply with suggestions. However, compliance was not directly related to accuracy of information, only to experience. *Srinivasan & Mahmassani (1999; 2002)* studied in an SP simulation the relationship between compliance and information's accuracy in terms of the share of times the system is inaccurate (10% or 30%). They assert that inaccuracy of information will increase the rate of route switching. *Bifulco et al. (2009)* and *Di Pace (2008)* investigated the impact of information type (descriptive vs. prescriptive) and feedback information (including foregone payoffs relating to non-chosen alternatives) on compliance. They found substantial variability in compliance rates for different forms of prescriptive/descriptive information. They also found that as the inaccuracy of the information increased there is a decrease in the average compliance rate.

Different theoretical and methodological frameworks have been applied to model the impacts of information on route-choice behaviour. The most fundamental approach is the Expected Utility - EU (*Von-Neumann & Morgenstern, 1944)* where the main assumption is that the 'rational' traveller seeks to maximize the perceived expected utility by choosing the alternative with the least expected costs (e.g. travel time). Discrete choice (random utility) models have widely adopted this approach allowing for systemically estimating the choice probabilities (see review by *Prashker & Bekhor, 2004*). Assuming utility maximization, information provided by the system is used repeatedly by travellers to update their knowledge on network performance. Thus route-choice is based on a process of adaptive learning (*Watling & van Vuren, 1993; Mahmassani & Liu, 1999; Srinivasan & Mahamassani, 2003*). *Chorus et al., (2009),* using a Bayesian approach (i.e. travel time probabilities are conditional on information provided) and numerical simulations showed that compliance is negatively associated with the perceived reliability of the information and the uncertainty regarding the travel time differences between (two) alternatives. In contrast to adaptive learning which is reactive in nature, travellers might behave strategically by planning ahead for information provided en-route, thus acquiring information as long as there is a reasonable gain from it (*Bonsall, 2004*). In this sense, the fact that a link of a route has an installed VMS can make it more attractive as demonstrated by *Razo & Gao (2010)* and *Tian et al. (2010)*.

Some studies formalized the choice paradigm by going beyond the classical EU theory. Game Theory (*Nash, 1950*) keeps the rational assumptions of behaviour but allows for competition between individuals who choose strategies that maximize potential payoffs. In a congestion game, each of the travellers choose a route and these result in endogenous volumes and travel times which are dependent on the complete set of choices. Thus, the inherent link occurring on recurring-congested networks between travellers' route choices and travel times is combined. *Selten et al. (2007)* demonstrated this in an interactive experiment.

Psychologists have been long aware that under conditions of uncertainty the rational utility maximization paradigm is likely inadequate *(Gärling & Young, 2001)*. Prospect Theory (*Kahneman & Tversky, 1979*) is orientated to analyze people's choice behaviour under uncertainty (in static conditions). The main idea is that choice is reference-based and that risk attitudes depend on the framing of the outcome in the form of gains or losses (*Kahneman & Tversky, 1984*). *Katsikopoulos et al. (2002)* demonstrated in a static SP experiment that a route that is perceived as a relative expected loss is preferred when its travel time range is greater than the reference (also implying risk seeking). In a synthetic (static) setup, *Gao et al., (2010)* showed that strategic behaviour is consistent with Prospect Theory. However, it should also be noted that in dynamic contexts (sequence of repeated choices), these results do not necessarily hold and reversals of behaviour can occur when learning is introduced in a sequence of choices *(Barron & Erev, 2003)*. For example, *Ben-Elia & Shiftan (2010)* found that risk seeking behaviour characterises mainly the short run whereas in the long run when learning is sufficiently reinforced the average trend is towards risk aversion. Moreover, they could not find Prospect Theory consistent behaviour when route-choice was conducted in a dynamic context.

Although these studies which have applied very different approaches to model the impacts of travel information provide valuable insights, the impact of information's accuracy is still not well understood. As noted by *Bifulco et al. (2007)*, this is a drawback in the state-of-the art, since at the network level ATIS requires a high degree of compliance to be effective. Compliance is likely to be induced when travel information is more accurate. Information is defined as accurate when the estimates made by ATIS are consistent with the travel times travellers have actually experienced. However, in situations characterized by (non-recurring) congestion precise forecasting of traffic conditions and ensuring consistency between the forecasted traffic conditions used to provide information and actual travel time is a difficult task. Moreover, in order to obtain accurate information, the suggestions based on the estimates on the predicted state of traffic conditions should also consider travellers' reactions to the information itself, as asserted in the anticipatory-route-guidance problem (*Bottom et al., 1998; Crittin & Bierlaire, 2001*). Yet it is still an open question how travellers will respond in terms of route-choice to ATIS advice and how this response depends on the level of ATIS accuracy. To answer these questions a simplified laboratory-based SP experiment is designed as described in the next section.

3 METHOD

Since gathering data on travel behaviour from the real world is extremely difficult, researchers often adopt a Stated Preference approach and carry out controlled experiments using computer-based travel simulators. Specific examples can be found in *Adler et al.(1993), Kraan et al. (2000), Mahmassani et al. (2003), and Avinieri and Prashker (2005; 2006)*

In this study we used a travel simulator designed by *Bifulco et al. (2009*). The development of this tool has been strongly influenced by the TSL (Travel Simulator Laboratory, *Hoogendoorn, 2004*), developed at the University of Delft, of which functionalities the authors have had access during previous studies (see *Bifulco et al., 2008; Di Pace, 2008*). This platform allows for a lot of flexibility in the experiment design and is based on state-of-art informatics technologies that ensure scalability and robustness of the experiment. The tool allows for asynchronous web-based responses by independent respondents. Respondents can participate in the experiment from an internet-connected PC, from any location, at any time they prefer within the agreed upon week-long experimental window.

3.1 Participants

An ad was posted at the University “Federico II” of Naples requesting volunteers to participate in the experiment. 36 participants were selected at random (11 women and 25 men) and invited to take part in the experiment. Most of them were students or staff of the university. They were not paid for participating. Table 1, presents the main characteristics of the sample.

Table 1 about here

3.2 Design

The experiment included three scenarios reflecting three different levels of information accuracy - high, intermediate and low. Accuracy is based on the discrepancy between estimated travel times and the actual ones. Feedback information is based on the actual travel times of the three routes. These are randomly drawn from three independent normal distributions as shown in Table 2. R1 (short and risky) is the shortest route in terms of the mean travel time but has the largest variance and subsequently a larger range of travel times which makes it the least reliable. R3 (long and reliable) has the second largest mean but with a very small variance, hence is the most reliable. R2 is basically a useless alternative as it has the largest mean travel time and the second largest variance.

*** Table 2 - About here ***

Descriptive information is manipulated through an estimation error made by the system which varies according to the level of accuracy. In the cases of high and intermediate accuracy, the error is obtained from a normal distribution with zero mean and with the standard deviation proportional to each routes’ coefficient of variation - CV (see Table 3). The standard deviation (SD) of the ATIS error is set to 0.25 times the CV of the actual travel-time in the high accuracy scenario. In the intermediate accuracy scenario, the standard deviation of the ATIS error is set to 0.6 times the CV of the actual travel-times. Thus, the SDs are different for R1, R2 and

R3 in all cases and proportional to two different parameters. The proportionality parameter is larger in the case of high accuracy since it is a more accurate level, and hence the ATIS error has to be smaller than in the intermediate level. For the low level of accuracy a uniform random distribution was applied whereby the considered boundaries (*a, b*) are the 85% of the minimum value of actual travel time and 115% of the maximum value of actual travel time.

The estimates for descriptive information were also employed in order to produce prescriptive suggestions (the suggested best route). Thus, they influence the number of times (out of 20 trials) for which the suggested route does not correspond with the actual shortest route received as feedback. In the case of high accuracy, the ratio of reliable prescriptive information is 18/20, at the intermediate level 11/20 and at the low level of accuracy only 6/20.

*** Table 3 – about here ***

3.3 Procedure and measurments

Participants were randomly assigned (equally distributed) to one of three scenarios. They were invited to participate in the experiment either by connecting to the web from their own premises at their convenience or by attending a pre-organized session (of up to 4 persons at a time) at the University lab. In the latter, each respondent was seated separately in front of a computer screen displaying the web-based simulation. Regardless of the setting, respondents were preliminarily instructed about the nature of the experiment involving route-choice. The length and type of road of each of the three route were described before starting the task: Route 1 (70 km) is a highway, Route 2 (90 km) is an urban road, Route 3 (85 Km) is a rural road. The task was described as making a series of 30 route choices by selecting form a dropdown list on the screen (see Figure 1). The total number of trips was disclosed in advance. In order to encourage realistic behaviour, they were asked to imagine that they were expected to arrive on time (9:00 AM) for an important job meeting. They were also informed that starting from the 11th trial they would receive route guidance that will assist them in choosing routes. They could also choose to depart freely at any time they wished. No other information was provided before beginning the experiment. For each trial the respondents were scored on the base of their ability in choosing the best route for arriving on time. The scores were shown and compared with the average score obtained by all other respondents, thus enabling a mild competition, oriented to increase the realism of the responses.

*** Figure 1 – about here ***

The task included making a series of 30 consecutive route choices. The first 10 choices were used as warm ups. These were made without any information preceding the choice. Following each choice, participants received the simulated actual travel times for all three routes – chosen and not chosen (i.e. foregone payoffs). Simulated travel times were randomly drawn according to the design in Table 2. This exercise assisted the participants to get acquainted with the network's performance through reinforced learning. Foregone payoffs were used to expedite learning of the expected travel times assuming that post-trip historical information is available, but without access to pre-trip information from ATIS. Note that the warm up observations were later excluded from further analysis.

In the remaining 20 choices, participants were provided with a simulated navigation assistant that supplied them with two types of information before choosing: descriptive - estimated mean travel times on each route; and prescriptive - the shortest route obtained on the basis of the minimum of the three estimated travel times. This information was the same for all participants in a specific scenario and changed from one trial to the next using random draws according to the design in Tables 3. Following each choice, feedback information was given about actual travel times of the chosen route and of the two non-chosen routes, similarly to the warm-up trials. Thus participants were able to compare the estimated travel times with the actual ones and subjectively evaluate the level of accuracy of the information system.

Several simplifications in the design are noted: First, although departure time was freely chosen it had no influence on the actual travel time obtained by the participant which as described before was randomly drawn from an exogenous probability distribution. Since this fact was not disclosed a priori to the participants one could argue that this aspect in the design would make participants see their choice as a possible bundle of route and departure time. Nonetheless, we have allowed the respondents to freely choose the departure time in order for them to mentally represent better a risky choice situation closer to a real life situation i.e. the need to arrive on time to a designated appointment and applying the necessary risky route-choice strategies to achieve this objective. In this way risk-prone respondents could choose a later departure time by moving all their bids to the choice of the faster route, while risk averse respondents could apply the opposite strategy. This behaviour can only be captured with a free choice of departure time. Otherwise respondent's strategy would consist only in choosing the fastest route. Consequently the arrival time would have no influence on respondents' choices and the analysis of risky choices would be incomplete. Moreover, the provision of complete feedback on all three alternative routes (both chosen and not chosen) can well verify that respondent quickly learn that route switching is the dominant strategy in achieving the arrival time objective, whereas the effect of change of departure time has only a minor influence. Hence, in further analysis we decided to ignore the effect of departure time.

Second, the provided information was not influenced by the choices. Third, simulated travel times also remained exogenous and were not influenced by the aggregation of the choices. This is not what happens in road networks in the real world where individual choices affect flows and derive travel times. However, it is consistent with the main aim of the experiment which focuses on travellers' behaviours in reaction to provided information (as characterised by a given level of accuracy). In this respect our experiment is more oriented towards a stated-choice experiment where the collective effect of travellers' route choices is less important. An example of an endogenous congested network study involving the effect of travel information (but not accuracy) is demonstrated by Lu et al. (2011).

Participants were also requested to fill in two questionnaires: one before and one after the experiment. In the ex-ante questionnaire participants were asked (in Italian) about their a-priori risk attitudes, specifically how they feel about arriving early or late by 5 or by 15 minutes to an important meeting. Three responses were possible: (1) -"very good", (2)-"it's not too bad, but I prefer it didn't happen", and (3)-"I will never let this happen again". The frequency of the responses is shown in Table 4. Other questions collected information on socio-demographic characteristics (see Table 1) as well as computer proficiency.

*** Table 4 – about here ***

The ex-post questions dealt with posterior subjective perceptions regarding the quality and usefulness of the provided information and those regarding the shortest and most reliable routes (see Table 5). These responses were employed in order to validate the design of the experiment. In retrospect, the subjective ratings regarding the routes, as well as that of the provided information were perceived by the respondents very similarly to the objective values applied in the experiment design. The ex-ante and ex-post factors were later also used to enrich the explanation of the observed behaviour in the discrete-choice analysis as described in Section 5. However, as later noted most of them were not found to have a significant influence on the choice behaviour.

*** Table 5 – about here ***

4 AGGREGATE RESULTS

Srinivasan and Mahmassani (2000) define compliance as the tendency of the trip-maker to comply with the best path (as recommended by ATIS). We use this definition for practical readability purposes. However, in our view compliance is a latent construct as we can't observed directly whether a respondent complies with ATIS suggestions or chooses the ATIS-recommended route because that is what he/she thinks is the best alternative, independently of ATIS. For the sake of accuracy, the weaker term concordance could be used to describe choices observed to be in accordance with the ATIS suggestions, regardless of the reason. In this regard compliance can be viewed as latent choice for which concordance is the observed one, where compliant travellers are a subset of concordant travellers. As we are mostly interested in the outcome choice and not in its mechanism, and to avoid confusion, we will refer in the following to the widely accepted term of compliance.

Aggregate statistical tests were conducted to verify whether any significant association can be found between the rates of compliance and route shares. These tests are based on each participant's average results over 20 trials. Since the sample in each scenario is relatively small we applied non parametric tests. The difference in average route shares across accuracy levels is tested using the Kruskall Wallis (KW) for between group differences. KW is a non parametric equivalent of one-way analysis of variance for independent groups using ranks of the data instead of the actual values. The differences in average route shares within each accuracy level are tested with the Friedman test. It applies rank data in the case of related samples such as repeated measurements of the same individual. Table 5 presents the results for the average rates of compliance and shares of each route across the accuracy levels, as well as the statistical tests.

The compliance ratio (*CR*) and route shares (R_i) are computed as:

$$CR = \sum_j nc_j \Big/ \sum_j n_j$$

$$R_i = \sum_j nr_{ij} \Big/ \sum_j n_j \ \forall\ i \in \{1,2,3\}$$

where:

i is a generic route

j is a generic trial

n_j is the number of respondents at trial j

nc_j is the number of compliant respondents at trial j

$nr_{i,j}$ is the number of respondents choosing route i at trial j

It is worth noting that at each trial $\sum_i \left(\frac{nr_{ij}}{n_j}\right) = 1\ (\forall\ j)$ and $\sum_i \left(\frac{nr_{ij}}{n_j}\right) + \left(\frac{nc_j}{n_j}\right) \geq 1\ (\forall\ j)$. Similarly, $\sum_i R_i = 1$ and $\sum_i R_i + C \geq 1$. As seen in Table 6, the rate of compliance decreases as accuracy decreases (from 82% to 62%) and this result is significant (p<.001). Pair-wise comparisons between the scenarios show that only the difference between the intermediate and high levels is not significant. The main effect of accuracy is therefore when moving from the intermediate to the low level. Surprisingly, even at a low level of accuracy, the rate of compliance is still quite high. Regarding route shares, the most attractive is R1. This suggests that on average participants preferred the short and risky route over the reliable route regardless of the level of accuracy. The decrease in the level of accuracy reduces the shares of R1 and increases the shares of the other two routes. The between group differences (KW) are significant for all three routes ($p<.001$). However pair-wise comparisons suggest that the main difference is associated with the change from intermediate to low level of accuracy, whereas the difference between high and intermediate are not statistically significant, apart for R2 ($p<.01$). This result indicates that a seemingly useless alternative can become more attractive when information accuracy decreases. Comparing the shares within each group the Friedman's test suggests that the differences are significantly different for the high and intermediate levels ($p<.001$). However, at the low level the shares are not significantly different from random choice (i.e. 33%) ($p>.05$). This suggests that when information accuracy is quite low participants become more risk averse, choosing the more reliable route R3.

*** Table 6 – about here ***

To understand better these changes in behaviour, we plot route shares and compliance across the 20 trials. Figure 2 represents in a different way the distribution of the compliance and of the observed route choices (*C, R1, R2* and *R3*) over each of the 20 trials when ATIS is simulated. The mean values of the compliances and of the shares (*MC, M1, M2* and *M3*) are represented as well. Here, *C* indicates compliance. *Ri* ($i \in \{1,2,3\}$) occurs for respondents observed to choose route *i* only if it is <u>not</u> the route suggested by the system. This is different from the definition from which table 5 has been computed; now at each trial (and for each accuracy level) *Ri* shares don't sum up to 100%, while Ri shares plus compliance sum up to 100%. Note that the route which is suggested in any particular trial is accounted in the computation of the compliance. Thus it does not appear in the charts in Figure 2 for the given trial and its share actually is the compliance rate.

As illustrated by the mean values in Figure 2, compliance decreases as the accuracy of information decreases, as expected. Regarding the low accuracy scenario (L), concentrated around trials 11-15 high compliance rates are exhibited. These trials are the first five after the warm-up and respondents may well have had insufficient time to learn that in this scenario the information system frequently fails. Also in the rest of the trials, compliance rates are slightly higher than what we would have expected given that the system (in L) suggests the correct route only one time in three. These results seem to indicate that even though the quality of information is poor, respondents will still use it as a source of support rather than base their choices on pure experience. In this sense this behaviour shows similarity with the anchoring heuristic (*Tversky & Kahneman, 1974).* This heuristic suggests that when faced with ambiguity, people prefer using even worthless information as a point of reference for problem solving.

*** Figure 2 – about here ***

Conversely, in the high (H) and intermediate (I) levels, compliance rates when R1 is not suggested abruptly decrease (e.g. in H trials: 17, 22, 24) towards relatively low values (somewhat higher for I compared to H). In other words, the respondents generally identify R1 as to be shorter but unreliable and they assume that if it is suggested by the system it really is the shortest route. As expected, this phenomenon is more evident if the accuracy is higher.

The average shares of the non-suggested alternatives are quite different for scenarios H and I. In H the probabilities of the non-suggested alternatives are in practice almost equal, while in I the probability of choosing alternative R1 (the shortest) is 24%, R3 (the most reliable) 14% and only 4% for R2 (the useless route).

This suggests that in H the respondents do not spend too much effort in order to learn the routes' characteristics from experience; rather they prefer to trust the information system, provided that it is strongly reliable. However, if the information system is less accurate (as in I) the respondents attempt to exploit their knowledge about the routes' characteristics ultimately preferring the shortest route. When the accuracy of the system is low (as in L), the respondents shift attitude from being compliant to choosing the most reliable route, while the probabilities of other routes (as non-suggested) remain on average practically the same (M1 = 21%, M2 = 10%, M3 = 24%).

5 Modelling

The results of the aggregate analysis suggest there is an association between compliance and information accuracy. To better understand the effect of information accuracy on route-choice behaviour and how this is associated with the three types of information, a discrete choice model is developed. Naturally, it would be preferable if compliance could have been estimated directly through a set of behavioural indicators which can measure the degree of compliant behaviour. Since such data is not available at this stage of the research, compliance's effect on route-choice is accounted for indirectly by using the prescriptive information regarding the suggested route as an explanatory variable instead.

5.1 Approach

To model route-choice behaviour when respondents' choices are repeated we apply a panel-based mixed logit model. Mixed Logit (MXL and also referred to as Logit Kernel) is a highly flexible discrete choice model that can be derived under a variety of different specifications (*Ben Akiva & Bolduc*, 1996; *Bhat*, 1998; *Revelt & Train*, 1998; *Hensher & Greene*, 2001), and is easily generalized to allow for repeated choices i.e. panel (*Bhat*, 1999; *Train*, 1999; *McFadden & Train*, 2000). The utility of alternative *i* in response *t* for person *n* is given by Eq. 1 and the probability (*P*) of person *n* choosing alternative *i* in response *t* is given by Eq. 2.

$$U_{nit} = \alpha_{ni} + \beta_n X_{nit} + \eta_i + \varepsilon_{nit}, \quad \alpha_{ni} \sim f_1(\alpha_0, \sigma_\alpha{}^2{}_{ni}), \quad \eta_i \sim f_2(0, \sigma_\eta{}^2{}_i), \quad \varepsilon_{ni} \sim iid\ \text{EV1} \quad (1)$$

$$P_n(Y_t = i) = \frac{e^{\alpha_{ni} + \beta_{ni} X_{nit}}}{\sum_{j=1, i \in J}^{J} e^{\alpha_{nj} + \beta_{nj} X_{njt}}} \quad (2)$$

where: P_{ni} is the conditional probability that person *n* chooses alternative *i* out of a set of *J* alternatives, *Y*, is an indicator that *i* is chosen at response *t*, *X* is a vector of explanatory factors, β, is a vector of fixed coefficients (including a constant), α is a vector of random parameters following a distribution f_1 (where α_0 is the mean and σ_α

is the variance) ; η is an error component with a distribution f_2 (with a mean of zero and variance represented by the parameter σ_η) and ε is a vector of independently, identically distributed extreme-value type one error terms. Parameters α_n represent individual specific error terms that capture the unobserved correlation within a panel of choices of the same individual. Here, a normal distribution is often assumed whereby σ_α captures respondents' standard deviations (s.d). In addition, different error components can be attributed to different alternatives creating specific correlation patterns. MXL is estimated using the maximum log-likelihood (*LL*) procedure (Eq. 3).

$$LL = \sum_{n=1}^{N} \log\left(P_{ni}\right) = \sum_{n=1}^{N} \log\left(\int_{\alpha} \prod_{t=1}^{T} \left(\frac{e^{\alpha_{ni}+\beta_{ni}X_{nit}}}{\sum_{j=1,i\in J}^{J} e^{\alpha_{nj}+\beta_{nj}X_{njt}}} \right) d\alpha \right) \tag{3}$$

However, as the unconditional probability is obtained by integration over the random factors and this integrand has no closed form, simulated log likelihood (SLL) is applied using random draws (*Bhat*, 2001; *Train*, 2002) (eq. 4).

$$SLL = \sum_{n=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \left(\frac{e^{\alpha_{ni}+\beta_{ni}X_{nit}}}{\sum_{j=1,i\in J}^{J} e^{\alpha_{nj}+\beta_{nj}X_{njt}}} \right) \tag{4}$$

where *R* is the number of draws (*r*). Halton draws (*Halton*, 1960) significantly reduce the number of draws required compared to pseudo-random draws (*Train*, 2000; *Bhat*, 2003). It is also important to verify correct model identification (see *Walker et al., 2004* for guidelines). We also compared the estimates obtained by model runs with 500, 1,000 and 2,000 Halton draws in the SLL estimation to verify their stability. Estimation of the model parameters was conducted using the BIOGEME software *(Bierlaire, 2003)* version 1.8 *(Bierlaire, 2009)* and applying the CFSQP algorithm *(Lawrence et al., 1997)*.

5.2 Specification

The model is developed under the assumption that most learning effects have already occurred in the first ten (warm-up) trials thus the set of repeated choices of each participant can be regarded as a set of consistent responses to the experimental stimuli. The chosen modelling approach accommodates this assumption by treating unobserved factors constant across the repeated set of observations of each participant. Consequently, the model is specified using linear utility functions for three alternatives with individual specific error terms (i.e. respondent s.d.) for capturing the panel effect. Following the rules of identification, these are specified for two out of three alternatives (R1, R2).

Participant specific attributes such as age and gender were tested (as alternative-specific) but found not to be of significance and consequently dropped from any further analysis. We attribute this result to the small sample dominated by students. The attributes of each alternative route included the travel times estimated by the information system (descriptive information) and the feedback information regarding actual travel times. The feedback travel times are specified as a lagged exogenous variable. In addition, the effect of prescriptive information is captured using a dummy variable which equals 1 when the route is suggested by the information system and 0 otherwise. Information accuracy levels were specified as alternative specific dummy variables with the high accuracy specified as the reference level. Ex ante and ex post questions were also scrutinized. The ex-post questions did not reveal any significant effects and were subsequently removed from further specifications. In the case of ex-ante questions we found a significant effect for the attitude towards arrival 5 minutes late. Constants were not included in the final specification. Given that the routes were characterized by travel time and variance, the constants come out correlated with these variables and therefore are not significant.

5.3 Results

Table 7 presents the results of the model estimation. 680 observations of 34 individuals are used (two participants with incomplete data sets were excluded from the estimation). For statistical reasons, the effect of accuracy of information is captured only for two out of three alternatives (R2 and R3). The results suggest that the choice of R3 is more sensitive to changes in levels of accuracy. As indicated in the aggregate results, a decrease in accuracy from high to intermediate and especially a decrease to low accuracy have a positive effect on choosing R3. R2 is only sensitive at low accuracy. The results assert that respondents shift from the riskier route (R1) to the reliable route (R3) as the accuracy of information decreases. Thus greater uncertainty in the choice environment encourages more risk averse behaviour. However, at low accuracy levels, R2 which is a useless alternative appears attractive whereas in high accuracy it is easier to identify that it is a redundant alternative. In the case of R1, participants with a higher risk aversion ("...won't happen again" if arriving 5 minutes late) are much less likely to choose R1, which, ceteris paribus, is associated with higher risk.

We found that specifying the information related variables: estimated and actual travel time and suggested route with generic (i.e. not alternative specific) and random coefficients results in a better fit to the data. This result implies that participants' sensitivity to information is not dependent on the specific route. Both estimated travel time and actual travel time are significant and with the correct sign. The coefficient of the estimated travel time is larger than that of actual travel times which suggests the descriptive information provided by the information system has a greater effect than feedback information. Prescriptive information about the suggested route is significant and positive and has the strongest effect of all variables. Thus the probability of choosing a route increases substantially when that route is also suggested by the information system. This result indicates indirectly the strength of compliance. However, the variance of this effect is quite large which suggests that there is a large degree of heterogeneity in how prescriptive information and hence compliance affects different respondents. This is true though to a lesser degree also for descriptive and feedback information.

We also investigated different interactions between accuracy levels and information factors. However, the coefficients for all three types of information were not significant. This result seems appropriate given that the aggregate analysis showed that even at the low accuracy level compliance is still quite high. Moreover, the decrease in mean compliance as observed in Table 6 and Figure 2, does not imply that sensitivity to information necessarily is lower when choice behaviour is observed disaggregately. Rather that sensitivity to information (at least in the short run) is not necessarily related to its accuracy. *Ben-Elia & Shiftan (2010)* also assert that information is more dominant when travellers have not had sufficient time to gain considerable experience with the travel time distributions. However, as already noted, accuracy seems to influence risk aversion (consistently with findings from the aggregate analyses), as shown by the coefficients for R3 (β3_AcuLow, β3_AcuInt).

6 CONCLUSIONS

Various studies involving travel information have been conducted in the past to address the effects of different types of information on travellers' route-choice behaviour; static or dynamic, descriptive or prescriptive, empirical or numerical etc. However, a key issue raised in this study is the accuracy of the provided information (descriptive and prescriptive) and its impact on travellers' behaviour. It has been argued that although ATIS could well reduce the perception of travel time uncertainty, the accuracy of provided information could affect this perception. In this study, both travel time uncertainty and information accuracy were accounted for in an attempt to empirically investigate how information accuracy affects route-choice behaviour and specifically the effect of route suggestions.

The analysis demonstrates the negative effect of (in)accuracy on compliance. This result is statistically significant and more evident between the intermediate and the low level of accuracy. Moreover, decreasing accuracy leads to a decrease in the share of the short and risky route and an increase in the choices of the other two routes implying a trend towards risk aversion. This can also be compared to *Avineri & Prashker, (2006)* results, where risk aversion was more prominent with prior pre-trip information, a pattern which does not appear in *Ben-Elia et al, (2008)* where information was always regarded as accurate enough by defining ranges of travel time. Thus it can be asserted that discrepancies between descriptive information and experience can lead to greater risk aversion. In addition, the results verify the robustness of the payoff variability effect (e.g. *Erev & Barron, 2005* and *Ben-Elia & Shiftan, 2010*), whereby increasing the level of uncertainty in the choice environment moves the route shares closer to random choice. In this sense it can be asserted that information inaccuracy is additive to the uncertainty attributed to travel times.

A mixed multinomial logit model (MXL) was estimated to better understand these impacts at a disaggregate level. First, the model asserts the strength of prescriptive information on route-choice, indicating, though at this stage only indirectly, the strong effect of suggestions on compliance. Furthermore, the influence of suggestions does not change when accuracy declines. This suggests travellers still prefer to anchor their decisions even to worthless information (as in low accuracy), as also asserted by *Tversky & Kahneman (1974)* in their description of the anchoring heuristic. Second, the model explains that a decrease in the level of accuracy increases the likelihood of choosing the reliable route as demonstrated also by the aggregate analysis which implies greater tendency towards risk aversion when uncertainty increases. Moreover, when accuracy is low, even a useless alternative (R2) may appear attractive. Here the payoff variability effect would suggest that the high level of variability in the choice environment is inhibiting learning and causing greater confusion. Third, the model suggests that predominantly risk averse participants are, ceteris paribus, less likely to choose the shorter and riskier route. Thus for predominantly risk averse travellers, suggestions indicating a risky route would be likely ignored. Fourth, the model asserts that travellers will have greater sensitivity to descriptive information compared to feedback information based on experience and foregone payoffs demonstrating the importance of information. *Fujii & Kitamura (2000)* also showed greater sensitivity to information compared to experience, and *Ben-Elia & Shiftan (2010)* verified this for the short run when knowledge about the network performance is relatively low. However, more trials (than the twenty in our case) are needed to verify this result.

In terms of policy recommendations, this study indicates that care should be given to the design of information systems in respect to presentation forms of travel time information. The results indicate travellers are likely to be sensitive to inaccuracy of information, which leads them to reflect on the discrepancies between what they visualize and what they experience. This also increases their tendency to switch to longer and more reliable routes. It is likely that information provided on non-chosen alternatives i.e. foregone payoffs will increase this sensitivity. However, a traffic control centre is not necessarily interested in encouraging extensive route switching from a motorway to urban or rural routes with less capacity. It is possible that providing information in the form of ranges of travel times, as suggested by *Ben-Elia & Shiftan (2010),* instead of a single value could mitigate this effect. The range can be designed to reflect the level of inaccuracy. Travellers will then be able to incorporate the level of risk attributed to the range of travel times in their choice behaviour. However, more research is needed in this respect dealing also with cases when the actual outcome does not fall within the expected range.

Several future research directions can be recommended. First, compliance has to be modelled explicitly through the use of behavioural indicators and measurements equations using a latent variable framework (as described by *Walker, 2001*). Second, more insights are required, by carrying out new experiments, on the effects of learning and habitual behaviour as in *Van der Mede & Van Berkum* (1996), *Bogers et al.* (2007) and *Ben-Elia & Shiftan (2010)*. Third, at this stage the model is based on accuracy at an indicative level. In future work various analytical formulations of accuracy should be considered and incorporated as an attribute in route choice models. Fourth, the descriptive information so far is only related to expected travel times; however, as discussed above, it would be beneficial to explore the effect of accuracy through presentation of variability information (e.g. the travel time range as in *Katsikopoulos et al. 2002* in static designs, and in *Ben-Elia & Shiftan, 2010* in dynamic designs*)* as well as investigate the effect of information reliability where outcomes fall outside the expected range. Fifth, strategic routing identified by *Razo & Gao (2010)* seems of added value. Here the effect of anticipating information can be tested by providing information both at the origin to the trip and downstream before a secondary diversion node. Last, as noted earlier, our study was conducted with lack of interaction between participants' choices and with exogenous travel times. There is great importance in modelling network effects such that choices are endogenously linked to network performance and provided information is reflected in network parameters. *Lu et al. (2011)* show a promising direction of research here, and it would be of added value to incorporate accuracy of travel information in addition to uncertainty in network travel times. Notwithstanding, this work can lead to better considerations of traveller response when designing travel information architecture that is suitable and useful to travellers needs and traffic control centres policies.

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Table 1: Description of the sample

Variable	Frequency (%)
Age	
23-30	51
31-40	29
41-62	20
Education attainment level	
Bachelor Degree	34
Master Degree	40
PhD	17
Secondary School	9
Occupation	
Students	43
University lecturers/Researchers/Teachers	28
Office workers/ Freelances	23
Housewives/Unemployed people	6

Table 2: Distributions of actual travel times

Route	Mean [min]	Variance	Coef. of Var.	Range [min]
R1 – short and risky	42.83	179.53	0.31282	[30;66]=36
R2 – useless	53.03	54.83	0.13963	[42;63]=21
R3 – long and reliable	52.10	2.490	0.03029	[50;55]= 5

Table 3: Distribution of information error

Level of Accuracy		Route	Mean[1]	Standard deviation[1]
Information Error distribution	High (18/20)	R1 R2 R3	0	$[0.25\ \mathrm{CV_j}] \times \begin{cases}0.07821\\0.03491\\0.00757\end{cases}$
Information Error distribution	Intermediate (11/20)	R1 R2 R3	0	$[0.60\ \mathrm{CV_j}] \times \begin{cases}0.18769\\0.08378\\0.01817\end{cases}$
Information distribution[2]	Low (6/20) $a = 0.85 * Min\ \ ActualTT_j$ $b = 1.15 * Max\ \ ActualTT_j$	R1 R2 R3	$\left[\frac{a+b}{2}\right] \times \begin{cases}50.70\\54.08\\52.88\end{cases}$	$\left[\frac{(b-a)}{\sqrt{12}}\right] \times \begin{cases}14.55\\10.60\\5.99\end{cases}$

1. Expressions in square brackets have been applied to calculate means and standard deviations;
2. Means in Low accuracy are in minutes.

Table 4: Frequency of answers (ex- ante questions)

	Ex ante questions: "You arrived with…				
Sensitivity level	..more than 15 min early" (%)	..more than 15 min late" (%)	..more than 5 min early" (%)	.. more than 5 min late" (%)	... with less than 5 min early or on time" (%)
Very good	25.0	0.0	64.0	5.6	69.4
not too bad	55.0	14.0	33.3	64.0	25.0
won't happen again	20.0	86.0	2.7	30.4	5.6

Table 5: Frequency of answers (ex-post questions)

Accuracy level	Information's perceptions			Routes' perceptions		
	Answer	Usefulness (%)	Quality (%)	Answer	Reliable route (%)	Shortest route (%)
High	No use	10.0	0.0	R1	50.0	100.0
	Poor	0.0	0.0	R2	20.0	0.0
	Sufficient	50.0	40.0	R3	30.0	0.0
	Excellent	40.0	60.0			
Intermediate	No use	0.0	0.0	R1	33.3	88.0
	Poor	0.0	0.0	R2	20.0	6.0
	Sufficient	53.3	60.0	R3	46.7	6.0
	Excellent	46.7	40.0			
Low	No use	11.1	0.0	R1	33.3	66.7
	Poor	22.2	0.0	R2	11.1	22.2
	Sufficient	66.7	55.5	R3	55.6	11.1
	Excellent	0.0	44.5			

Table 6: Average shares of choices and compliance and significance tests

Choices	**% Share**			**Kruskall Wallis Test (Asymp. Sig.)**			
	H	***I***	***L***	***H-I-L***	***H-I***	***H-L***	***I-L***
Compliance	82.0	77.3	62.7	0.000	0.208	0.000	0.000
R1 (Short and Risky)	69.0	63.0	37.3	0.000	0.167	0.002	0.000
R2 (Useless)	9.50	18.0	27.3	0.000	0.008	0.000	0.012
R3 (Long and Reliable)	21.5	19.0	35.4	0.000	0.494	0.002	0.000
Friedman's Test (Asymp. Sig.)	0.000	0.000	0.154	-	-	-	-

Table 7: Model estimation results

Parameter	**Description**	**Estimate**	**Std err***	**t-test**	**p-value**
β2_Aculow	Low accuracy - R2	1.20	0.434	2.77	0.010
β3_Aculow	Low accuracy - R3	2.27	0.512	4.43	<0.001
β3_Acuint	Int. accuracy -R3	0.699	0.299	2.34	0.020
β1Late5neg	'I will not let it happen again' if arriving 5 min. late (R1)	-1.72	0.308	-5.60	<0.001
β Disc	Est. Travel time (descriptive info) min.	-0.0591	0.0124	-4.76	<0.001
β Fdbk	Actual travel time (feedback info) min.	-0.0232	0.0048	-4.73	<0.001
β Prsc	Route is suggested by system (prescriptive info)	1.91	0.316	6.05	<0.001
σ_Resp	s.d respondent	1.36	0.321	4.24	<0.001
σ Disc	s.d est. travel time	0.063	0.0126	5.00	<0.001
σ Fdbk	s.d actual travel time	0.015	0.00392	3.84	<0.001
σ Prsc	s.d suggested route	1.68	0.507	3.31	<0.001
	No. of Halton draws	2000			
	No. of observations:	680			
	No. of individuals:	34			
$L(0)$	Null LL	-747.05			
$L(\beta)$	Final LL	-366.12			
ρ^2		0.510			
$\overline{\rho^2}$		0.495			

* Robust std. error estimates