Can We Model Driver Perceptions? An In-Situ Experiment in Real-World Conditions

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ABSTRACT
It is clear that perceptions play a significant role in traveler decisions. Consequently, traveler perceptions are a corner stone in the feasibility of traveler information systems; for traveler information systems are only valuable if the drivers are incapable of accurately acquiring the provided information on their own, and if the provided information is relevant for the drivers' decision criteria. Accuracy of traveler perceptions has been repeatedly researched in public transportation, and has been found to vary according to different reasons. However, in spite of the clear significance of traveler perceptions, minimal effort has been put into modeling it. Almost all travel behavior models are based on traveler experiences, which are assumed to reflect traveler perceptions via the addition of some random error component. This works introduces an alternative approach: instead of adding an error component to represent driver perceptions, it proposes to model driver perceptions. This work is based on a real-world route choice experiment of a sample of 20 drivers who made more than 2,000 real-world route choices. Each of the drivers' experiences, perceptions, and choices were recorded, analyzed and cross examined. The paper demonstrates that: i) driver experiences are different from driver perceptions, ii) driver perceptions explain driver choices better than driver experiences, iii) it is possible to model and predict driver perceptions of travel distance, time and speed.

1. INTRODUCTION

It is clear that perceptions play a significant role in traveler decisions. Consequently, traveler perceptions are a corner stone in the feasibility of advanced traveler information systems (ATISs); for ATISs are only valuable if the drivers are incapable of accurately acquiring the provided information on their own, and if the provided information is relevant for the drivers' decision criteria. ATISs are the branch of Intelligent Transportation Systems (ITSs) that entail providing travelers with information to help them make informed decisions. ITSs refer to transportation systems that make use of information technology and communication to tackle negative transportation impacts, such as to mitigate traffic congestion and to reduce accidents.

Accuracy of traveler perceptions has been repeatedly researched in public transportation, and has been found to vary according to different reasons. For example Moreau has found that perceptions of wait time can significantly differ from actual times [1]. Other studies have shown that travel time perceptions can vary according to whether the time is spent traveling or waiting [2, 3], whether the waiting time is expected or not [4], and whether the traveler experiences time drag [1]. Another recent study showed that travel time perceptions can vary according to the drivers' familiarity with the destination [5].

Similarly, a few driver behavior articles discuss variations in value of travel time under different travel conditions. For example, under stopped and moving freeway travel conditions [6]; under free-flow, slowed-down, and stop-and-go travel times [7]; and between ramp-delay and freeway travel times [8].

In spite of the clear significance of traveler perceptions, minimal effort has been put into modeling it. One possible explanation may be attributed to cost and past technological limitations. It is because of these two reasons that most travel research, in general, and route choice, in particular, is based on either stated preference surveys [9, 10] or travel simulators [11, 14]; both of which are characterized with limitations due to their inability to address the accuracy of travelers' perceptions. Stated preference surveys are surveys in which drivers answer questions about their behavior in hypothetical situations. Travel simulators are computer based programs that digitally display the choice situation and its characteristics for a participant. Then the participant makes his/her choice. There are guidelines to make these methods more realistic [15]. Nonetheless, since drivers do not actually live the choice situation, it is impossible for either of the two methods to capture drivers' perceptions of real-world traffic conditions. This been said, it is important to point out that GPS-based and real-life experiments are becoming the norm in travel behavior research [16, 20].

Driver perceptions of travel conditions remains to be an under-researched area. Almost all travel behavior models are based on traveler experiences, which are assumed to reflect traveler perceptions via the addition of some random error component [21, 24]. This works introduces a base for an alternative approach: instead of adding an error component to represent driver perceptions, it proposes to model driver perceptions. This work is based on an in-situ real-world route choice experiment of a sample of 20 drivers who made more than 2,000 real-world route choices. Each of the drivers' experiences, perceptions, and choices were recorded, analyzed and cross examined. The paper demonstrates that driver experiences are different from driver perceptions, drivers choices are better explained by their perceptions, models driver perceptions of travel distance, time, and speed, and demonstrates driver perceptions are "model-able".

In the following sections, the authors present the objectives of the study, followed by a brief explanation of the study approach: experiment description, network and surveys. In the third section, the authors present the experimental results, perception models, and discussion. The fourth section ends the paper with the study conclusions and recommendations for further research.

2. STUDY OBJECTIVES

The main objective of this study is to use actual real-world driving data to: a) investigate the accuracy of driver perceptions, b) demonstrate that driver perceptions explain choices better than driver experiences, and c) explore the possibility of predicting driver perceptions. It should be noted that objectives (a) and (b) were discussed in further detail in a previous presentation [25].

3. STUDY APPROACH

This section presents basic information about the study experiment. For further details, the reader is referred to earlier publications [19, 20, 25].

3.1 Experiment Description

This experiment is based on real-world GPS-recorded data of 20 participants; each making 100 choices. It is also supplemented with a pre-experiment stated preference survey and a post-experiment stated preference survey.

Each participant was asked to complete 20 trials during regular school days of the academic spring semester of the year 2011. During each trial each participant was asked to drive a research vehicle on the road network of the New River Valley and was required to make 5 route choices. At the beginning of the experiment, participants were given 5 Google Map print outs. Each map representing 1 trip: 1 point of origin, 1 point of destination, and two alternative routes. These maps were the same for all participants. On each trial, participants were asked to make these 5 trips assuming that the provided alternative routes were the only routes available between the points of origin and destination. The trips and the alternative routes were pre-selected by the researchers to ensure differences in the 5 choice situations (Table 1). All drivers' choices as well as the travel conditions were recorded via a GPS unit placed onboard of the vehicle and a research escort that always accompanied the participants. Participants were instructed to behave in the same manner they behave in the real life.

It should be noted that in this experiment, each trip represented a choice situation for the participants. Hence, in many occasions in this paper the terms "trips" and "choices" refer to the same thing and are used interchangeably.

3.2 Participants and Incentives

Experiment participants were selected to ensure variability over their demographic, and study network and route experiences (ranges of experiment variables can be seen in the fourth column of Table 3).

Table 1: Description of the five trips

Trip #	Trip origin	Trip destination	Alternative routes		Route description (and speed limits)
			Route #	Route Name	
1	Point 1 (VTTI)	Point 2 (Walmart)	Route 1	US460 Bypass	Mostly a high speed (65 mph) freeway
			Route 2	US460 Business	High speed (45 mph) urban highway
2	Point 2 (Walmart)	Point 3 (Foodlion1)	Route 3	Merrimac	Mostly a shorter, low speed (30 mph) back road with a lot of curves
			Route 4	Peppers Ferry	Mostly a longer, high speed (55 mph) rural highway
3	Point 3 (Foodlion1)	Point 4 (Foodlion2)	Route 5	US460 Bypass	A longer high speed (65 mph) freeway followed by a low speed (25 mph) urban road
			Route 6	N. Main St.	A shorter urban route (40 and 35 mph)
4	Point 4 (Foodlion2)	Point 5 (Stadium)	Route 7	Toms Creek	A short urban route that passes through campus (25 and 35 mph)
			Route 8	US460 Bypass	Primarily a long high speed (65 mph) freeway and low speed (25 mph) urban roads
5	Point 5 (Stadium)	Point 1 (VTTI)	Route 9	S. Main St.	A long urban road that passes through town (35 mph)
			Route 10	Ramble St.	A short unpopular low speed (25 and 35 mph) back road that passes by a small airport.

Since route choice behavior is documented to vary with trip purpose, a few of measures were designed to ensure that participants will not consider experiment time as leisure. First, participants' compensation was not a function of the time spent in the experiment; participants were provided a flat monetary amount per trial. Second, the experiment was not entertaining (experiment routes were not scenic, and participants were not allowed to listen to any entertainment, use their cellphone, or chat with the research escort). Hence, if any, participants had stealth incentives to reduce their experiment (and travel) times.

3.3 Network

Table 1 demonstrates the origin, destination, and alternative routes specific to each of the five choice situations. It also shows a brief description of each of the routes. More information about the routes can be seen in Figure 1 and are provided in Table 2. Figure 1 shows a map depicting all five points of trip origins and destinations as well as the ten alternative routes provided.

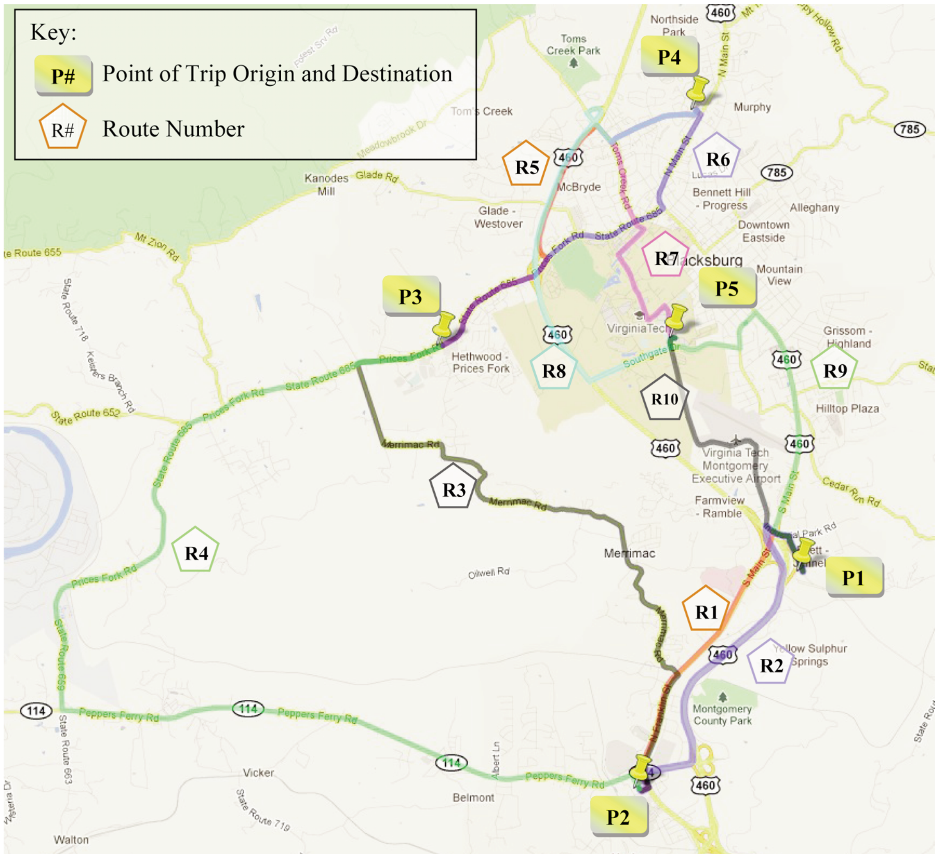

Figure 1. Map of the experiment network (Source: Google Maps)

3.4 Pre-experiment Survey

The pre-experiment survey collected information about the participants' demographics (age, gender, ethnicity, education level, etc.) and driving experiences (number of driving years, annual driven miles, etc.).

3.5 Post-experiment Survey

The post-experiment survey was divided into two sections. The first section collected information about the participants' perceptions of the traffic conditions on the alternative routes (distance, travel time, travel speed, and traffic level), as well as the participants preference levels of the routes. In the second section the participants were asked to fill in a personality inventory, the NEO Personality Inventory-Revised [26]. This is a psychological personality inventory that is based on the Five Factor Model. It measures five personality traits: neuroticism extraversion, openness to experience,

Table 2: Characteristics of the alternative routes per trip

Trip #	Route #	Distance (km)	Avg. travel time (min)	Avg. travel speed (kph)	Number of intersections		Number of left turns	Number of merges and diverges	Number of horizontal curves
					Signalized	Unsignalized			
1	1	5.1*	8.5	36.4	10	3*	3*	1*	2*
	2	6.0	8.4*	43.3*	5*	4	4	5	3
2	3	11.1*	15.2*	42.6	5	2	3	1*	30
	4	17.4	16.7	63.2*	2*	2	2*	2	11*
3	5	5.8	7.7*	44.5*	5*	3	3	2	2
	6	5.5*	9.3	37.8	8	3	2*	1*	2
4	7	5.0*	10.2	29.5	5*	3	4	1*	0*
	8	7.7	9.6*	48.2*	6	2*	2*	4	1
5	9	5.8	10.5	33.3	8	4	4	1*	1*
	10	4.7*	8.0*	34.0*	3*	1*	3*	2	6

* Better route

agreeableness, and conscientiousness. In addition, each personality trait measures six subordinate dimensions (sometimes referred to as facets).

Neuroticism measures the tendency of a person to experience negative emotions such as anxiety, guilt, frustration, and depression. Persons who score high on neuroticism are usually self-conscious, and are associated with low self-esteem and irrational thinking. The six subordinate dimensions of neuroticism are: anxiety, hostility, depression, self-consciousness, impulsiveness, and vulnerability to stress. Extraversion measures the tendency towards positive emotionality. The six subordinate dimensions of extraversion are: warmth, gregariousness, assertiveness, activity, excitement seeking, and positive emotion. Openness to Experiences measures the imaginative tendency of individuals, their attentiveness to inner emotions, and their sensitiveness towards art and beauty. The six subordinate dimensions of openness to experience are: fantasy, aesthetics, feelings, actions, ideas, and values. Agreeableness measures the more humane aspects of the personality. The six subordinate dimensions of agreeableness are: trust, straightforwardness, altruism, compliance, modesty, and tender mindedness. Last, Conscientiousness measures personality tendencies towards being diligence, thoroughness and being governed by conscience. The six subordinate dimensions of conscientiousness are: competence, order, dutifulness, achievement striving, self-discipline, and deliberation. For further details about these personality traits, or about the Five Factor Model or the NEO Personality traits, the reader is referred to literature on personality traits [26, 28].

4. RESULTS AND ANALYSIS

This section starts by presenting observed discrepancies between driver experiences and perceptions and shows that driver perceptions explain driver choices better than experiences. For a further detailed discussion of drivers experiences, perceptions and choices, the reader is referred to earlier publications [25, 29]. This sections ends by developing and discussing models of driver perceptions of travel distance, time, and speed.

4.1 How Accurate are Driver Perceptions?

In this section, driver perceptions of travel distance, time, and speed are contrasted against their experiences, and are depicted in Figure 2.

Comparing driver experiences to their perceptions is based on two groups of experiences and three groups of perceptions. The two groups of experiences are: i) drivers who tried both routes and as a result have recorded experiences on both routes, and ii) drivers who tried only one of the two alternative routes (they never tried the other route) and thus have recorded experiences for only one of the two alternatives. On the other hand, the three groups of driver perceptions are: i) drivers whose perceptions match their recorded experiences, ii) drivers whose perceptions contradict their recorded experiences, and iii) drivers who do not perceive a difference between the alternative routes. Figure 2a, 2b and 2c present the results of cross examining these two groups of experiences and three groups of perceptions over the entire experiment. It should be noted that it is not possible to judge the correctness of the perceptions of the

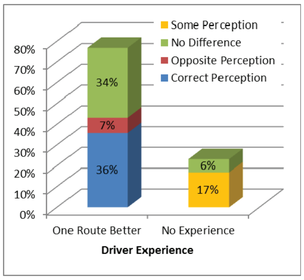

Figure 2a: Travel Distance

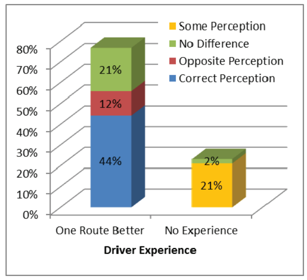

Figure 2b: Travel Time

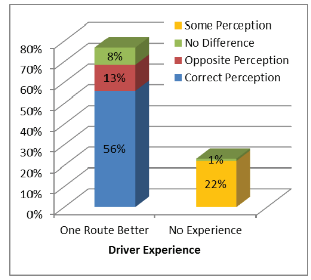

Figure 2c: Travel Speed

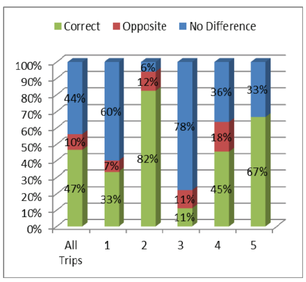

Figure 2d: Travel Distance Per Trip

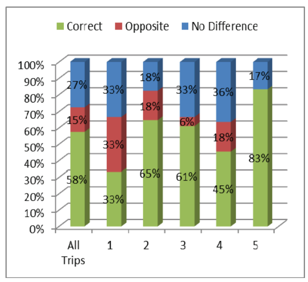

Figure 2e: Travel Time Per Trip

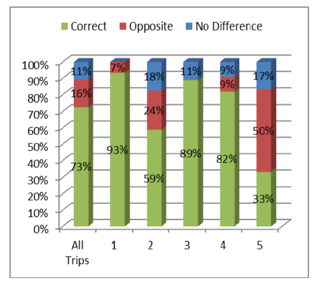

Figure 2f: Travel Speed Per Trip

Figure 2. Cross examining driver experiences and perceptions of travel distance, time, and speed

drivers who have experienced only one of the two routes; because they have no recorded experiences on the other route. Figures 2d, 2e and 2f present the results for only the drives that experienced both alternatives in our experiment, broken down by choice situation.

Figure 2 reveals the observed discrepancies between driver experiences and perceptions. For a thorough discussion, the reader is referred to an earlier publication [25].

4.2 Are Driver Choices Better Explained by Their Experiences or Perceptions?

While Figure 3 presents a comparison between driver experiences and their reported choices, Figure 4 presents a comparison between driver perceptions and their reported choices. Driver reported choices are the choices that were stated in their post-experiment survey. Comparing the two figures indicates that driver choices are better explained by driver perceptions, since the "red" percentages (the percentage of choices that are opposite to the expected rational driver behavior) on the perceptions figures are smaller in value than on the corresponding figures of driver experiences.

It is worth noting that all driver experiences presented in this article are based on the average of all previous trials. However, in the earlier publication, a Markov process for the calculation of the experienced travel time was also used [25]. The following equation was used for the calculation of the average experienced travel time. The average experienced travel speed was calculated similarly.

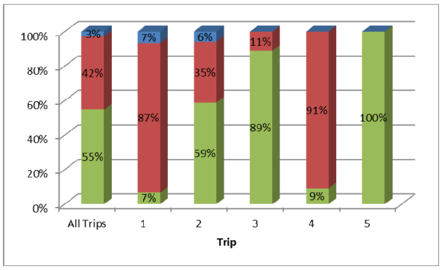

Figure 3a: Travel Distance Experiences vs. Choices

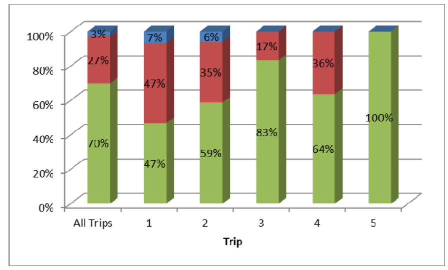

Figure 3b: Travel Time Experiences vs. Choices

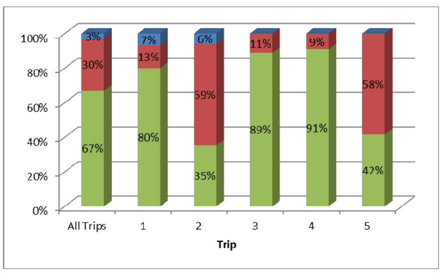

Figure 3c: Travel Speed Experiences vs. Choices

Identical Experience and Choice
Opposite Experience and Choice
Certain Experience but No Choice

Figure 3. Driver disaggregate experiences versus reported choices

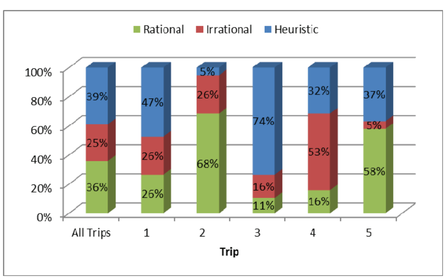

Figure 4a: Travel Distance Perceptions versus Choices

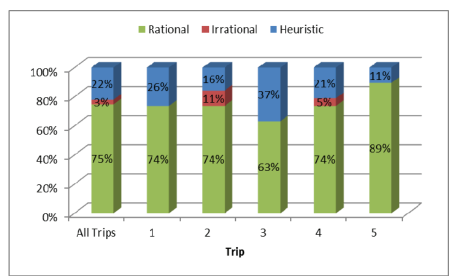

Figure 4b: Travel Time Perceptions versus Choices

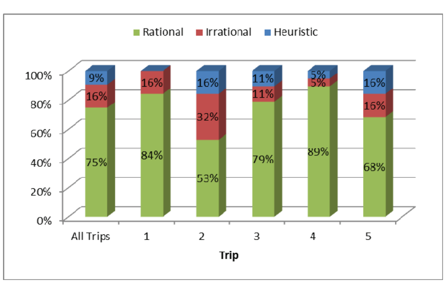

Figure 4c: Travel Speed Perceptions versus Choices

Figure 4. Driver choices versus perceptions of travel distance, time, speed, and traffic

$$AETT_{irt} = \frac{\sum_{t=1}^{t-1} \delta_{irt} \cdot TT_{it}}{\sum_{t=1}^{t-1} \delta_{irt}}$$

where,

$AETT_{irt}$ is the average experienced travel time of person i on route r up till trial t

δ_{irt} = 1 if person i chooses route r at trial t, and 0 otherwise

TT_{it} is the travel time experienced by person i at trial t

4.3 Perception Models

According to the previous sections, travel perceptions seem to be a better predictor for driver choices than travel experiences. Accordingly, identifying factors that influence travel perceptions could be very beneficial from two different perspectives. From the modeling perspective, incorporating models of driver perceptions in transportation models can improve the fidelity of the model outcomes. On the other hand, from the perspective of Intelligent Transportation Systems (ITSs), identifying drivers that are less capable of achieving correct travel perceptions highlights a target market for ITS services. This section presents perception models for three travel variables: travel distance, travel time, and travel speed.

4.3.1 Response Variable

The modeled response is an ordinal three-level perception. The lowest level is an opposite perception, the middle level is a no-difference perception, and the highest level is a correct perception. Three different models were estimated: travel distance perceptions, travel time perceptions, and travel speed perceptions.

4.3.2 Independent Variables

The independent variables investigated in this work are presented in Table 3. As can be seen in the table, four groups of covariates are considered: driver demographics, driver personality traits, driver experiences, and driver stated familiarity with the choice situations prior to the experiment.

4.3.3 Model Structure

The model used is an ordered mixed effects generalized linear model with a probit link function. Because each driver was asked about his/her perception on five different choice situations, one random parameter, the intercept, is estimated over all individuals instead of all observations. This takes into account the average dependence effects between observations of the same driver. The model has the following structure.

$$y_{ic} \sim Multin(p_{ic1}, p_{ic2}, p_{ic2})$$

$$p_{icm} = \phi\left\{\zeta_m - (x_{ic}^{'}\beta + \theta_{\text{i}})\right\} - \phi\left\{\zeta_{m-1} - (x_{ic}^{'}\beta + \theta_{\text{i}})\right\}$$

$$\theta_i \sim N(0, \varphi)$$

where,

y_{ic} = 1 if person i's perception at choice situation c is correct

y_{ic} = 0 if person i perceives no difference at choice situation c

$y_{ic} = -1$ if person i's perception at choice situation c is opposite
Multin is the Multinomial distribution
p_{icm} is the probability that person i's perception at choice situation c will be of level m
m is the responce level (1: opposite, 2: no difference, 3: correct)
Φ is the cumulative Normal distribution function
ζ_m is the break point for response level m ($-\infty = \zeta_0 < \zeta_1 = 0 < \zeta_2 < \zeta_3 = \infty$)
x_{ic} is the vector of covariates for person i at choice situation c
β is a vector of the parameters
θ_i is the random component of person i
N is the Normal distribution
φ is the variance

4.3.4 Model Results

Table 4 presents the results of the estimated models. It is satisfying that variables belonging to three of the investigated variable groups were found significant. The only group of variables that was not found significant is the driver stated familiarity with the choice situation prior to the experiment. This too is satisfying because it could imply that the twenty experiment runs were sufficient for the drivers to construct adequate experience with the choice situations. Furthermore, the number of switches seems to have a positive effect on constructing correct perceptions on travel distances; implying that the more times a driver experiences the alternative routes, the more accurate are the driver's perceptions of the differences between the two routes. The same variable was possibly not found significant in travel time and speed perceptions because of the stochastic nature of these variables, which makes correct perceptions more difficult.

None of the estimated model parameters seems to be illogical. In general as the signal strength for travel distance, time, or speed increased (i.e. became more salient), the more accurate were the drivers perceptions of travel distance, time, and speed, respectively. As the age of the drivers increased and as the number of driving years increased, drivers' perceptions of travel time and distance decreased, respectively. Three possible explanations for this are: a) older drivers cognitive abilities are lower than those of younger drivers; b) older drivers have more to think about than younger drivers, therefore have less attention resources to assign to travel conditions; or c) as a driver becomes more accustomed to driving, the driver becomes less sensitive about driving a few extra minutes or miles and loses some interest in continuously trying to evaluate differences in travel conditions.

The signs of the personality trait variables also seem logical. First it is probably expected that correct perceptions are positively related to conscientiousness. Similarly, agreeableness was found to be positively related to correct perceptions. Of all variables, this is probably the least intuitive relation. A possible explanation for this is that: as presented in Figures 4d, 4e and 4f, driver perceptions were generally more correct than not. Hence, if a driver relies more on the collective judgments of others, this driver is more likely to construct correct perceptions. On the other hand, driver perceptions seem to be inversely related to their openness to experience. Although this might not seem intuitive for a reader that is unfamiliar with the personality traits, the authors believe it is logical. Openness to experience measures six facets. These are: fantasy, aesthetics, feelings, actions, ideas and values. It seems logical that when a driver that is more open

Table 3: Perception model independent variables

#	Variable names	Variable description	Variable values
Variables of Driver Demographics			
1	Age_i^*	Age of participant *i*	18 to 68
2	$Gender_i$	Gender of participant *i*	M or F**
3	$Ethnicity_i$	Ethnicity of participant *i*	W or NW**
4	$Education_i$	Education level of participant *i*	G or NG**
5	$DrYears_i^*$	Number of years participant *i* has been a licensed driver	2 to 52
6	Dr $Miles_i$	Annual number of miles participant *i* drives (thousands)	2 to 35
7	$Residency_i$	Number of years participant *i* has been residing in the area	1 to 56
Variables of Driver Personality Traits			
1	N_i	Neuroticism of participant *i*	7 to 30
2	E_i	Extraversion of participant *i*	19 to 43
3	O_i	Openness to experience of participant *i*	20 to 31
4	A_i	Agreeableness of participant *i*	22 to 42
5	C_i	Conscientiousness of participant *i*	26 to 47
Variables of Driver Experience ***			
1	$TDPrc_c$	Percentage difference in experienced distance between the two alternative routes of choice situation *c*	5.7 to 44.8
2	$TTPrc_{ic}^{****}$	Percentage difference in mean experienced travel times by driver *i* between the two alternatives of choice situation *c*	0.2 to 46.1
3	$TTVPrc_{ic}^{****}$	Percentage difference in mean experienced travel time variances by driver *i* between the two alternatives of choice situation *c*	2.9 to 180.5

4	$TSPrc_{ic}$****	Percentage difference in mean experienced travel speeds by driver *i* between the two alternatives of choice situation *c*	0.1 to 49.0
5	$TSVPrc_{ic}$****	Percentage difference in mean experienced travel speed variances by driver *i* between the two alternatives of choice situation *c*	0.9 to 188.9
6	$Switches_{ic}$	Number of switches driver *i* made during his/her 20 experiment runs of situation c	1 to 13*****
Variables of Driver-Choice Combination			
1	$PriorAvgFam_{ic}$	Stated average familiarity of driver *i* with the two routes of choice *c* prior to experiment	1 to 5
2	$PriorMaxFam_{ic}$	Stated maximum familiarity of driver *i* with the two routes of choice *c* prior to experiment	1 to 5

* Because of the high correlation between Age and DrYears, the two variables were not allowed to be in the same model at the same time

** M: male, F: female, W: white, NW: non-white, NG: no post-graduate degree, G: post-graduate degree

*** Percentage difference calculated as difference between experiences on the two routes divided by the average of the two routes

**** All travel time and travel speed calculations are based on actual driver experiences; collected GPS data

***** Drivers that have not experienced both routes were dropped from the analysis because of missing experience data

Table 4: Significant variables of the driver perception models*

Variables	Perception models					
	Travel distance		Travel time		Travel speed	
	Beta	p-value	Beta	p-value	Beta	p-value
(Intercept)	1.927	0.000	1.258	0.000	1.938	0.000
Age	n/s	n/s	-0.544	0.011	n/s	n/s
EducationG	2.090	0.001	n/s	n/s	n/s	n/s
DrYears	-0.711	0.004	n/s	n/s	n/s	n/s
O	-0.716	0.015	n/s	n/s	-0.950	0.008
A	0.503	0.077	n/s	n/s	0.577	0.096
C	n/s	n/s	0.733	0.003	n/s	n/s
Switches	0.597	0.024	n/s	n/s	n/s	n/s
TDPrc	0.981	0.002	n/s	n/s	-1.285	0.001
TTPrc	n/s	n/s	0.669	0.009	n/s	n/s
TSPrc	-0.590	0.045	0.409	0.043	0.858	0.009
ζ_2	2.984	0.000	1.199	0.000	0.769	0.003

* n/s stands for not significant

to experience switches and tries alternative routes, this driver will be focusing on other aspects that are more closely related to the six listed facets than focusing on comparing the travel conditions. In addition, in another article, openness to experience was found to be inversely related to the probability of route choice switching. Decreased switching implies decreased experience of the alternative routes, which in turn, can result in a decrease in the probability of correct perceptions.

The effect of travel speed and travel distance experiences seem to be inversely related to the correct perceptions of travel distance and travel speed perceptions, respectively. This seems logical given that in a previous section travel time was found to be the best variable that explains route choices. Since travel time is directly proportional to distance and inversely proportional to speed, it seems logical that the effects of drivers travel distance and speed experiences are inversely related. Last, as differences in travel speed were more salient, drivers were more capable of perceiving travel time differences correctly. This finding might be specific to this experiment, because in this experiment faster speed routes were in aggregate also characterized with lower travel times, as presented in Table 3.

To be able to compare the importance of the different variables on driver perceptions, all variable values were normalized (with the exception of nominal variables). Hence, the absolute values of the estimated model parameters can reasonably reflect the relative importance of these variables in the estimated models. With this in mind, it is extremely interesting that variables of personality traits seem to be as important as – and sometimes more important than – variables of travel experience. This finding underscores the possible benefits of incorporating variables of personality traits in travel behavior models.

5. STUDY CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

In this work, an in-situ real-world route choice experiment was conducted with the objective of investigating the capability of drivers to accurately perceive travel conditions (travel distance, time, and speed) and to explore the possibility of modeling driver perceptions. Route choice literature is dense with studies of route choice models; however, very little attention has been given to the accuracy of driver perceptions, where almost all route choice models substitute driver perceptions with an addition of a random error term to driver experiences. This work was conducted on a sample of 20 drivers that were each faced with 5 route choice situations and who collectively made more than 2,000 real-world choices. All the driver choices and the prevailing conditions were recorded, and in this work the drivers experienced travel conditions, reported perceptions, and recorded choices were contrasted and analyzed.

It was observed that driver perceptions were, in general, around only 60% accurate. The drivers were able to perceive travel speeds best and travel distances least; with travel time perceptions being in between. It was also observed that the greater the difference in a characteristic between the alternative routes, the more accurate was the driver perceptions.

Comparing driver choices to their experiences and perceptions revealed that driver perceptions explain their choices more accurately than their experiences. This was insinuated because the percentage of unexplainable behavior was lower when driver perceptions were considered.

Finally, models of driver perceptions were estimated. Variables belonging to driver demographics, personality traits, and route experiences were found significant in predicting correct predictions of travel conditions. As expected, the salience of signal strength was found significant for correct predictions. However, it is extremely interesting that for correct predictions, variables of personality traits were found to be as important as variables of travel experiences.

The findings of this work could be significant; especially if models of driver perceptions were to be incorporated in travel behavior models – instead of the addition of the random error terms. A number of further research directions include: the investigation of possible events that could result in the change of driver preference; examining if the same results could be replicated in a travel or a driving simulator; and examining the effect of information on driver perceptions.

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