Can Psychological Questions Help Predict Managed Lane Use?

by

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ABSTRACT
Managed lanes (MLs) are being used in many congested cities across America. While the socioeconomic characteristics of travelers, along with their trip characteristics, are commonly used to model ML choice behavior, other variables—such as psychological characteristics of travelers—may be beneficial in better understanding travel behavior on MLs. Preliminary research performed by Burris et al. (9) collected psychological data from ML users and determined that in their psychological construct form, psychological traits provided little benefit in creating models that accurately predicted managed lane use. This paper uses these data to further consider the impact on discrete choice modeling when individual psychological variables are considered in a more disaggregate fashion; helping to uncover the information that may be masked when these data are considered only in the psychological construct form. Among the important conclusions are that some of the psychological questions, working in tandem with typical socioeconomic and trip characteristic variables, do indeed appear to contribute toward the creation of improved models of ML choice. Specifically, questions taken from the constructs measuring Personal Need for Structure, and Driving Risk Perceptions and Driving Style appear most promising. The questions highlighted within this paper provide direction in guiding future psychological question development within the transportation framework.

INTRODUCTION
Managed lanes (MLs) are being used in many congested cities across America. Generally, MLs are offered in conjunction with adjacent general purpose lanes (GPLs), with each ML location having its own unique vehicle occupancy requirements, mode restrictions, and tolling schemes (1). Several critical issues surround MLs—including equity (2), the public’s opinion of, and reaction to, MLs (3), and the effectiveness of MLs (4). Among the fundamental issues to consider is traveler use of MLs. What factors influence travelers’ behavior in general, and what information do we know about drivers on MLs that can help us better understand and predict ML use? Discrete choice models encompassing socioeconomic variables and trip characteristics are commonly used in answering these types of questions. However, there may be traits beyond the typical socioeconomic and trip related variables that could be beneficial in further understanding ML use. Specifically, do psychological traits influence whether people choose to use MLs; and if so, to what extent can these traits be useful in better understanding ML use decisions and travel behavior in general?

LITERATURE REVIEW
This literature review contains findings from research performed on the impact of psychological traits on transportation related behavior. Iversen and Rundmo studied the impact of personality and risk taking tendencies on accident involvement, speeding, and rules violations using a survey performed in Norway. They specifically considered risky driving, accident involvement, normlessness, sensation-seeking, locus of control and driver anger (5). The authors found that those who were sensation seekers and those with high normlessness and driver anger scores were more likely to speed and break rules—or at least to report doing so. These same three traits also affected involvement in accidents, with risky driving style having the greatest direct effect (5).
Arthur and Doverspike studied the link between conscientiousness and crashes. The research included having 48 participants answer questions related to driving knowledge concepts, as well as personality questions related to conscientiousness. Interestingly, they found that conscientiousness was significantly negatively correlated to both not-at-fault and total crashes, while driving knowledge was not significantly correlated to any type of crash—which may suggest that crash prevention efforts should be geared towards altering conscientiousness-related behaviors rather than merely emphasizing driving knowledge (6).

Oltedal and Rundmo investigated the relationship between risky driving behavior, personality traits, and gender with linear regression analysis—using data from 4,397 Norwegian teenagers. Among the personality traits tested (anxiety, excitement-seeking, aggression, irritability, normlessness), normlessness was found to have the highest correlation to risky driving behavior; while males were found to generally display a higher level of risky driving behavior than females (7).

While a variety of research has been performed germane to transportation and psychology in general, the existing body of literature on the psychology behind ML use is limited. However, further research on this topic is certainly warranted because some drivers choose to pay to use MLs, despite the fact that traffic on the adjacent GPL is traveling at nearly the same speed. Research performed using data collected on I-394 in Minneapolis and I-15 in San Diego cited that drivers were willing to pay a toll for relatively small travel time savings (8). The authors theorize that this may partially be a reflection of travelers’ willingness to pay for travel time reliability (8). While the desire for reliability may very well be an incentive for some travelers to pay to use the ML, decisions regarding using the ML or the adjacent GPL, and whether to drive alone or carpool may also partially be a reflection of psychological traits.

Burris et al. 2012, performed preliminary research on this topic (9). As part of their research, responses to the psychological constructs of conscientiousness; general locus of control; personal need for structure; risk tolerance; and driving risk perceptions and driving style were used in creating mixed logit mode choice models. Because of their frequent use throughout this paper, it is important to define construct and scale. According to the Psychology Glossary, “Construct refers to any complex psychological concept. Examples would be a person’s motivation, anger, personality, intelligence, love, attachment or fear (10).” Psychological scales can be thought of as a measurement method, where “measurement concerns the assignment of numbers to objects to represent quantities of attributes (11).” A 9-point Likert Scale was used in measuring the questions within each of the constructs listed previously; except for general locus of control, for which a forced choice format between two alternatives was used. In this research several related psychological questions are grouped together and their overall result is the psychological construct.

The alternatives considered, within the context of three stated preference questions asked of respondents, included drive-alone general purpose lane (DA-GPL); carpool general purpose lane (CP-GPL); drive-alone managed lane (DA-ML); and carpool managed lane (CP-ML). Responses were collected from individuals in the cities of San Diego, Miami, and Denver. While a handful of psychological constructs appeared to be significant in models developed by Burris et al. (9), they largely did not appear to be very useful in improving the discrete choice
models. The notable exceptions were that respondents with high risky driving styles were more likely to choose CP-GPL over DA-GPL; and those with a high conscientiousness score were also more likely to choose the CP-GPL than DA-GPL (9).

However, this preliminary research did not consider the more disaggregate approach of using individual psychological questions within the mixed logit mode choice models, rather than the more aggregated construct approach. Thus, there is great potential to perform further, more in-depth, research using this rich psychological dataset to see what psychological questions—if any—appear to be promising items to include in future discrete choice models.

RESEARCH OBJECTIVE
The overarching goal of this research was to better understand travel behavior on managed lanes. In meeting this objective, the psychological data that were collected as part of the research performed by Burris et al. were analyzed in a more disaggregate manner (i.e., at the individual question level, rather than the more aggregate psychological scale construct level). It was anticipated that this more finite analysis would yield results that—while possibly instructive in-and-of themselves—would ultimately serve to highlight specific psychological areas and questions showing promise for further investigation in a future survey.

DATA
As previously mentioned, Burris et al. collected the data that were used in this research analysis (9). Initially, efforts were made to recruit respondents from four cities (San Diego, Miami, Denver, and Seattle). However, the number of surveys completed in Seattle was so low that these responses were not included in analysis. Within the survey, information was collected on the following:

- Respondent’s most recent trip along the appropriate I-25 in Denver, I-95 in Miami, I-15 in San Diego or S.R. 167 in Seattle
- Respondent’s managed lane use, or lack of managed lane use
- Stated preference questions
- Psychological constructs of interest
- Reasons for carpooling, or not carpooling
- Respondent’s demographic information

Efforts to recruit online survey respondents varied for each city, but they consisted of some combination of web banners, email blasts, Twitter posts, Facebook, and posts on government organization pages. Each respondent was presented with three stated preference questions. After filtering out those stated preference questions that were not answered, 2015 useable stated preference responses were obtained from 664 respondents (9).

RESEARCH METHODOLOGY
One goal of this research was to see if including psychological questions improved the discrete choice models used to predict managed lane choice. The two main criteria used to check for improved models were the adjusted rho squared value and the percent correctly predicted. The adjusted rho squared value takes into account the number of variables included in the model; essentially enforcing a penalty to the rho squared value for every additional variable included in
the model (12). Ultimately, the set of models of interest allowed for a comparison of a model containing common socioeconomic and trip-characteristic variables, and this same model with psychological variables of interest also included in the model. Models that had both an improved adjusted rho squared value and an improved percent correctly predicted value helped in identifying the best models containing psychological questions. Some of the models of interest discussed later in this paper only met one of these two criteria, but still produced a reasonable model that provides insight into those psychological questions that have potential in helping to better understand ML use.

Responses to dozens of psychological questions were available in the dataset. As mentioned, five scales measuring psychological constructs were part of the survey, with the construct measured by Scale E: Driving Risk Perceptions and Driving Style containing three subscales. Each of the seven scales (or subscales) included between six and eleven questions, for a total of 66 psychological questions. A summary of the constructs is provided in Table 1. Given this large number of psychological questions to consider, it was important to follow a somewhat systematic approach in deciding upon which questions to focus on in working to develop the mode choice models. The process that was followed is described in the following section.

Table 1. Summary of Constructs

<table>
<thead>
<tr>
<th>Scale (Subscale)</th>
<th>Construct</th>
<th>Description</th>
<th>Number of Questions</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Conscientiousness</td>
<td>Associated with the traits of careful, reliable, organized, self-disciplined, persevering, and detail oriented (13)</td>
<td>10</td>
</tr>
<tr>
<td>B</td>
<td>General Locus of Control</td>
<td>Extent to which individuals perceive they have control over outcomes (14)</td>
<td>10</td>
</tr>
<tr>
<td>C</td>
<td>Personal Need for Structure</td>
<td>Preference for structure and simplicity (15)</td>
<td>10</td>
</tr>
<tr>
<td>D</td>
<td>Risk Tolerance</td>
<td>Orientation in deciding to take or avoid risk (specifically considered financial risk) (16)</td>
<td>10</td>
</tr>
<tr>
<td>E</td>
<td>Driving Risk Perceptions and Driving Style</td>
<td><em><strong>See subscales below</strong></em></td>
<td>26</td>
</tr>
<tr>
<td>(E1)</td>
<td>Driving Risk Perceptions</td>
<td>Individual’s reactions to traffic safety (17-18)</td>
<td>6</td>
</tr>
<tr>
<td>(E2)</td>
<td>Careful Driving Style</td>
<td>Reflection of way drivers habitually drive (19)</td>
<td>11</td>
</tr>
<tr>
<td>(E3)</td>
<td>Risky Driving Style</td>
<td>Reflection of way drivers habitually drive (19)</td>
<td>9</td>
</tr>
</tbody>
</table>

MODEL CREATION PROCESS

To begin, models containing alternative specific constants (ASCs), travel time, toll, and the aggregated psychological constructs for each of the seven constructs (including those associated with subscales) were developed. As found by Burris et al., (though in models also containing socioeconomic and trip characteristic variables) aggregated psychological construct variables appear to have little power in improving models. Though these models are very basic in nature, this statement is supported by the results shown in Table 2. Note that the models shown within Table 2 and Table 3 were developed using models with 200 points and a max of 200 iterations.
Table 2. Basic Models with Travel Time, Toll, and Psychological Constructs

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>DA-GPLs</td>
<td>-</td>
<td>-4.04 ***</td>
<td>-8.45 ***</td>
<td>-17.45*</td>
<td>-14.83***</td>
<td>-4.38***</td>
<td>-5.19***</td>
</tr>
<tr>
<td>CP-GPLs</td>
<td>-1.01xTT***</td>
<td>-0.30xTT***</td>
<td>-0.25xTT***</td>
<td>-0.46xTT***</td>
<td>-0.35xTT***</td>
<td>-0.26xTT***</td>
<td>-0.16xTT***</td>
</tr>
<tr>
<td>DA-MLs</td>
<td>-1.01xTT***</td>
<td>-0.62</td>
<td>-1.58***</td>
<td>-1.25***</td>
<td>-1.04*</td>
<td>-1.16***</td>
<td>-0.26xRISK</td>
</tr>
<tr>
<td>CP-MLs</td>
<td>-1.01xTT***</td>
<td>-0.46xLOC</td>
<td>-2.77</td>
<td>-3.04***</td>
<td>-0.98**</td>
<td>-0.38</td>
<td>-1.43***</td>
</tr>
<tr>
<td>Travel Time</td>
<td>3.39***</td>
<td>0.34***</td>
<td>0.06</td>
<td>0.31**</td>
<td>0.17**</td>
<td>0.16**</td>
<td>0.16**</td>
</tr>
<tr>
<td>ASC-CP-GPLs</td>
<td>2.89**</td>
<td>5.55***</td>
<td>8.88**</td>
<td>6.72***</td>
<td>1.70***</td>
<td>1.63***</td>
<td>1.68***</td>
</tr>
<tr>
<td>ASC-DA-MLs</td>
<td>3.26***</td>
<td>1.72***</td>
<td>1.99***</td>
<td>2.17***</td>
<td>0.90***</td>
<td>0.91***</td>
<td>0.88***</td>
</tr>
<tr>
<td>ASC-CP-MLs</td>
<td>4.17***</td>
<td>5.93***</td>
<td>7.38***</td>
<td>6.28***</td>
<td>2.16***</td>
<td>2.16***</td>
<td>2.16***</td>
</tr>
</tbody>
</table>

Standard Deviations

| VTTS ($/hr) | 274.36 | 38.98 | 30.71 | 45.64 | 199.98 | 205.93 | 207.55 |
| LLF | -939.48 | -871.53 | -887.6 | -845.91 | -1067.6 | -1067.88 | -1068.62 |
| K (DOF) | 12 | 12 | 12 | 12 | 12 | 12 | 12 |
| p² | 0.3006 | 0.3592 | 0.3943 | 0.370281 | 0.2588 | 0.2586 | 0.2581 |
| Adjusted p² | 0.2917 | 0.3503 | 0.3861 | 0.361348 | 0.2505 | 0.2503 | 0.2498 |
| % Cor. Pre. | 39.4 | 41.7 | 40.9 | 42.0 | 41.0 | 42.0 | 40.4 |

- VTTS=Value of Travel Time Savings
- LLF=Log Likelihood Function
- DOF=Degrees of Freedom
- p² = Rho Squared
- % Cor. Pre.=Percent Correctly Predicted
- ***=Significant at 99% Confidence Level; **=Significant at 95% Confidence Level; *=Significant at 90% Confidence Level
- TT=Travel Time; HINC=High Income (Household Income Above $100,000); MINC=Medium Income (Household Income between $50,000 and $99,999); REC=Recreational Trip; HHM=Respondent from Married Household without Children

The aggregated nature of the psychological constructs may mask useful information available from the individual psychological questions. As a starting point in determining which questions may be useful in modeling, models similar to those in Table 2 were developed; with the only difference being that the aggregated psychological constructs were replaced by the individual psychological questions contained within each of the constructs. The value in this step was not so much in assessing how the overall model itself changed, but in determining which of the psychological questions were significant. Significance was defined at a 90% confidence level. This approach produced results with dozens of the psychological variables being significant, in the models of at least one of the ML choice alternatives.
Next, an attempt was made to develop a reasonable model containing common socioeconomic and trip-type characteristics. The variables were chosen both from an intuitive perspective and based and consideration of some of the variables used in models produced by Burris et al. (9). Those variables found to be significant were retained in the model that was used as the base socioeconomic, trip-characteristic model. This base model (Model 8) was used in analyzing the subsequent models that were created using these socioeconomic and trip-type characteristics, along with the psychological questions from the constructs that were described previously.

Models were created by including the psychological questions that were significant in models containing ASCs, travel time, toll, and the significant psychological questions within a given construct. While the significance of psychological variables was determined using only questions from one construct at a time, the significant psychological variables identified in this manner were subsequently combined with psychological variables from two constructs. Interestingly, all of the models that produced results for the socioeconomic, trip characteristic, and two-construct psychological models had a higher percent correctly predicted and higher rho-squared value than the base socioeconomic, trip characteristic model. However, when considering the adjusted rho square value, all but one of the models containing the two-construct psychological variables produced a lower value than the base model. This is a reflection of the large number of psychological questions contained in these models. The one model that had a higher adjusted rho square value than the base model, despite all of the extra psychological variables included in the model, implies that the psychological variables help the model beyond the penalty created by the adjusted rho squared value. This model will be discussed further in the results section (see Model 9).

At this point, we took a step back and considered models created by adding the significant psychological variables (determined in the manner described previously) from just one psychological construct at a time to the base Model 8. Subsequently, similar models were created by dropping out variables that failed to retain their significance in the model. Interestingly, through this search process, models containing various combinations of either psychological questions from the construct measured by Scale C: Personal Need for Structure or the construct measured by Scale E: Driving Risk Perceptions and Driving Style were found to produce models with improved adjusted rho squared values and percent correctly predicted, compared to the base Model 8. Because of the large overlap associated with these models and Model 9, which simultaneously contained variables from both of these constructs, the outputs for these models are not included within this paper. However, this finding does strengthen the idea that questions from the constructs measured by Scale C and Scale E show the most promise in helping to understand ML use.

Despite the fact that no models associated with Scale A: Conscientiousness, Scale B: General Locus of Control, or Scale D: Risk Tolerance were found to meet both the criteria of a higher adjusted rho squared value and a higher percent correctly predicted value, there were some models that came close to meeting one of the criteria, and met the other. These models were considered reasonable and the best “reasonable” model associated with questions from these three constructs are included in Table 3 to find if any of the psychological questions were worth further investigation (Models 10-12).
The method used to determine psychological question significance in these original models was determined prior to the inclusion of socioeconomic and trip characteristic variables. It was assumed that this method would produce reasonable results, which indeed was the case given the reasonably good models containing psychological variables that are contained in Table 3. However, to test for any difference in which psychological variables were considered significant, and how that affected the resulting models, models were created using ACS, travel time, toll, socioeconomic and trip characteristics, and all of the psychological questions from a given construct.

Though some differences in significant psychological variables were found, running models including these newly established significant psychological variables, and base Model 8, largely overlapped with the previous findings. This appeared to specifically be the case in terms of desirable model outcomes (i.e., higher adjusted rho squared and percent correctly predicted values) for questions stemming from the construct measured using Scale E: Driving Risk Perceptions and Driving Style. Though some of the significant psychological questions from this scale differed between the two approaches, this finding reinforces the importance of questions from this construct in better understanding ML choices. However, for the sake of brevity and given the large amount of overlap between these models and other models already slated for inclusion in the paper, these models are not shown.

Though preliminary efforts were made to go one step further by creating models including the variables in Model 8 plus all of the questions from two constructs, many of these models initially created would not run within NLOGIT. This result was largely a byproduct of having too many variables with too little data, or variability in the data, to fit a model. This brings up a limitation inherent in the data. Because of the large number of psychological questions being considered, a block design was used in the survey when the data were collected (9), and roughly only half of the respondents answered any given psychological question. This approach helped to minimize respondent burden; however, it is a limiting factor in modeling using the psychological variables because the sample size shrinks by half with each construct used in the model.
### Table 3. Models of Interest.

<table>
<thead>
<tr>
<th>Mode</th>
<th>Model 8: Base Model for Comparison (Socioeconomic and Trip Characteristics) (n=1814)</th>
<th>Model 9: Base Model plus Variables taken from Constructs Measured by Scale C and Scale E (n=389)</th>
<th>Model 10: Base Model plus Variable taken from Construct Measured by Scale A (n=883)</th>
<th>Model 11: Model plus Variables taken from Construct Measured by Scale B (n=785)</th>
<th>Model 12: Model plus Variables taken from Construct Measured by Scale D (n=858)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DA-GPLs</td>
<td>-12.67*** -0.30xTT*** -0.59xTOLL*** -7.34xHINC** -4.51xMINC* +3.32xMALE*** +2.34xREC* +2.97xHHM**</td>
<td>-14.42 -0.32xTT*** -0.79xTOLL*** -38.04xHINC -17.56xMINC +18.98xMALE +19.85xREC +54.45xHHM +9.45xC6 +0.07xC7</td>
<td>-7.29*** -0.27xTT*** -0.51xTOLL*** -1.04xHINC -1.23xMINC +2.49xMALE* +0.76xREC +1.05xHHM</td>
<td>-8.37** -0.35xTT*** -0.66xTOLL*** -6.09xHINC* -10.12xMINC* +2.96xMALE +2.81xREC +3.96xHHM*</td>
<td>-16.24*** -0.26xTT*** -0.43xTOLL*** +2.35xHINC +0.78xMINC +3.90xMALE* +2.70xREC* +1.82xHHM</td>
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<tr>
<td>CP-GPLs</td>
<td>-1.55*** -0.30xTT*** -0.59xTOLL*** +1.49xHINC*** +0.79xMINC -1.15xMALE*** -0.71xREC*</td>
<td>+0.11 -0.32xTT*** -0.79xTOLL*** +1.27xHINC -0.16xMINC -1.06xMALE -2.21xREC* +0.17xC9 -0.35xE1_1* +0.06xE211</td>
<td>-2.81*** -0.27xTT*** -0.51xTOLL*** -1.61xHINC*** +0.48xMINC -1.70xMALE*** -0.46xREC +0.21xA4*</td>
<td>-0.52 -0.35xTT*** -0.66xTOLL*** +0.003xHINC -0.41xMINC -1.08xMALE** -0.76xREC +1.32xB1*** -1.08xB3**</td>
<td>-1.96** -0.26xTT*** -0.43xTOLL*** +1.73xHINC** +1.30xMINC* -1.33xMALE*** -0.65xREC +0.31xD7*** -0.27xD8**</td>
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<tr>
<td>DA-MLs</td>
<td>-6.97*** -0.30xTT*** -0.59xTOLL*** +1.49xHINC*** +0.79xMINC -1.15xMALE*** -0.71xREC*</td>
<td>-2.22 -0.32xTT*** -0.79xTOLL*** +1.27xHINC -0.16xMINC -1.06xMALE -2.21xREC* +0.17xC9 -0.35xE1_1* +0.06xE211</td>
<td>-9.69*** -0.27xTT*** -0.51xTOLL*** +5.11xHINC*** +4.50xMINC*** +4.57xREC***</td>
<td>-6.09*** -0.35xTT*** -0.66xTOLL*** +0.55xHINC -0.42xMINC +3.97xREC*** +2.49xB2** -2.19xB3 +1.67xB8 -3.35xB9**</td>
<td>-3.18* -0.26xTT*** -0.43xTOLL*** +3.22xHINC* +3.14xMINC* +0.47xREC -1.73xD1*** -0.59xD3*** +0.64xD7***</td>
</tr>
<tr>
<td>CP-MLs</td>
<td>-6.97*** -0.30xTT*** -0.59xTOLL*** +2.04xHINC** +2.01xMINC* +3.30xREC***</td>
<td>-2.22 -0.32xTT*** -0.79xTOLL*** +1.27xHINC -0.16xMINC -1.06xMALE -2.21xREC* +0.17xC9 -0.35xE1_1* +0.06xE211</td>
<td>-9.69*** -0.27xTT*** -0.51xTOLL*** +5.11xHINC*** +4.50xMINC*** +4.57xREC***</td>
<td>-6.09*** -0.35xTT*** -0.66xTOLL*** +0.55xHINC -0.42xMINC +3.97xREC*** +2.49xB2** -2.19xB3 +1.67xB8 -3.35xB9**</td>
<td>-3.18* -0.26xTT*** -0.43xTOLL*** +3.22xHINC* +3.14xMINC* +0.47xREC -1.73xD1*** -0.59xD3*** +0.64xD7***</td>
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#### Standard Deviations

<table>
<thead>
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<th>Travel Time</th>
<th>0.27***</th>
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<th>0.22**</th>
<th>0.40***</th>
<th>0.19**</th>
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<td>ASC-CP-GPLs</td>
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<td>0.006</td>
<td>3.10***</td>
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<td>5.80***</td>
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<td>ASC-DA-MLs</td>
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<td>2.25***</td>
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<tr>
<td>ASC-CP-MLs</td>
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<td>9.28***</td>
<td>7.10***</td>
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#### Information Related to Model Fit

<table>
<thead>
<tr>
<th>VTTS ($/hr)</th>
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</tr>
<tr>
<td>$\hat{p}^2$</td>
<td>0.3930</td>
<td>0.4679</td>
<td>0.3989</td>
<td>0.4079</td>
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<tr>
<td>Adjusted $\hat{p}^2$</td>
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<td>0.4067</td>
<td>0.3810</td>
<td>0.3831</td>
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<tr>
<td>% Cor. Pre.</td>
<td>44.4</td>
<td>50.9</td>
<td>46.6</td>
<td>48.2</td>
<td>44.9</td>
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</table>
RESULTS AND DISCUSSION
The models shown in Table 3 are of particular interest in better understanding how psychological questions can aid in modeling ML choices, and warrant further discussion.

Model 8: Base Model for Comparison (Socioeconomic and Trip Characteristics)
First, consider the base model for socioeconomic and trip characteristics, Model 7. Travel time and toll both have negative coefficients, as expected. These variables and beta coefficients all seem reasonable and logical, and the Value of Travel Time Savings (VTTS) also seems reasonable ($31.14/hour)—with the VTTS seeming reasonable for all models shown in Table 3 (ranging from $23.92/hour to $35.54/hour).

Model 9: Base Model plus Variables taken from Constructs Measured by Scale C and Scale E
In Model 9, the variables from Model 8 were retained, with psychological questions found to be significant within models containing ASCs, travel time, toll, and the psychological questions from the respective scales of Scale C: Personal Need for Structure and Scale E: Driving Risk Perceptions and Driving Style.

The following provides a summary of the psychological questions that were included in this model.

**CP-GPL**
- Question C6: I hate to change my plans last minute.
- Question C7: I hate to be with people who are unpredictable.

**DA-ML**
- Question C9: I do NOT enjoy the exhilaration of being in unpredictable situations.
- Question E1_1: I mostly respect speed limits.
- Question E211: I drive cautiously.

**CP-ML**
- Question C1: It upsets me to get into a situation without knowing what I can expect from it.
- Question E1_1: I mostly respect speed limits.
- Question E3_8: I get impatient during rush hour.
Including all of these variables, in tandem with the socioeconomic and trip characteristic variables from Model 8, produces a model with a higher percent correctly predicted value, and a higher adjusted rho squared value. Although the overall model produces good results, it should be noted that the model does not produce good results for the CP-GPL alternative—with many of the p-values equaling 1.00, the confidence intervals not being given, and all of the variables included in the CP-GPL alternative utility function not being significant. This is largely a reflection of the small proportion of respondents (4 out of 389 respondents) who chose the CP-GPL alternative.

Despite this combination of variables producing a good model, the only psychological questions that were significant in this model were Question E1_1: “I mostly respect speed limits” for the DA-ML alternative utility function and Question C1: “It upsets me to go into a situation without knowing what I can expect from it” for the CP-ML alternative utility function. Based on this model, those who “mostly respect speed limits” are less likely to choose DA-ML than DA-GPL. This result seems logical, as the GPL speed is assumed to be the same or slower than the adjacent ML. It seems plausible that people who “mostly respect speed limits” would be content to drive alone in the free GPL, rather than pay to use the ML that generally has speeds of equal or higher values.

Those who “get upset when they get into a situation without knowing what they can expect from it” are less likely to select CP-ML than DA-GPL. A comparison between the CP-ML and DA-GPL alternatives allows for more open-ended interpretation of the results since it is not possible to determine if the difference is caused by difference in lane type (GPL vs. ML) or the difference in vehicle occupancy (i.e., DA vs. CP). Thus, there are multiple logical explanations, with a combination of multiple explanations probably providing the best explanation. One possible explanation is that these individuals avoid carpooling because of the uncertainty associated with either picking up passengers or waiting for their ride to pick them up. In terms of lane type choice, these individuals may not like performing a mental cost-benefit analysis in every situations to assess whether selecting the ML would derive a benefit to them over using the GPL. Thus, in order to avoid making this decision, without knowing whether it will turn out to be beneficial or not prior to making it, they prefer to select the DA-GPL option. It would be interesting to further investigate this question, to see how results change for different trip types, times of day, etc.

**Model 10: Base Model plus Variables taken from Construct Measured by Scale A**

Despite the fact that Model 10 has a slightly lower adjusted rho squared value than Model 8 (0.3810 vs. 0.3846), including Question A4 in the DA-MLs alternative results in an increase of over 2 percent in percent correctly predicted. Question A4: “Do NOT make a mess of things” is significant in the model, and it is further described below.

**DA-ML**

- Question A4: I do NOT make a mess of things.
Based on this model, those who “do NOT make a mess of things” are more likely to select the DA-ML option than the DA-GPL option. This seems logical, as driving on the ML may be associated with less of a “traffic mess” in the form of congestion.

**Model 11: Model plus Variables taken from Construct Measured by Scale B**

As with Model 10, the adjusted rho squared value for Model 11 was slightly lower than the adjusted rho squared value for Model 7 (0.3931 vs. 0.3846), but the percent correctly predicted was over 3.7 percent higher (48.15% vs. 44.43%) This model contains multiple questions from the construct measured by Scale B: General Locus of Control, as listed below.

**DA-ML**
- Question B1: I have often found that what is going to happen will happen.
- Question B3: The average citizen can have an influence in government decisions.

**CP-ML**
- Question B2: Getting a good job depends mainly on being in the right place at the right time.
- Question B3: The average citizen can have an influence in government decisions.
- Question B8: It is difficult for people to have much control over the things politicians do in office.
- Question B9: Sometimes I can’t understand how teachers arrive at the grades they give.

Those who “often find that what is going to happen will happen” are significantly more likely to select DA-ML than DA-GPL, while those who believe that “the average citizen can have an influence in government decisions” are less likely to select DA-ML than DA-GPL. These results seem counter-intuitive. Logically it would seem that those who do not feel they can affect their surroundings would opt for the less predictable GPL, and those who feel that their voice matters would select the ML—thereby taking control of their driving situations by ensuring a trip of higher travel time reliability. It is possible that those who believe “the average citizen can have an influence in government decisions” are more prone to select DA-GPL because they do not like the idea of an authoritative entity imposing a toll on their driving, so they choose the free option (i.e., DA-GPL) in an effort to voice their opinion that free is better.

Two of the psychological questions related to the CP-ML alternative were significant. Those who feel that “getting a job depends mainly on being in the right place at the right time” are more likely to select the CP-ML option than the DA-GPL option. Additionally, those who “sometimes can’t understand how teachers arrive at the grades they give” are less likely to select the CP-ML option than the DA-GPL option. Again, making the comparison between CP-ML and DA-GPL allows for more open-endedness in interpreting the results because both the lane vehicle occupancy and lane type are different. The first of these conclusions may be related to those opting to carpool in the ML wanting to ensure that they are able to use the ML (i.e., be in the right place) without having to pay (or at least getting a discounted rate). Those who “sometimes can’t understand how teachers arrive at the grades they give” may be wary of people and their motives and thus don’t opt to carpool.
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Model 12: Model plus Variables taken from Construct Measured by Scale D
As with Model 10 and Model 11, the adjusted rho squared value for the best model developed using questions from Scale D: Risk Tolerance was slightly lower (0.3836 vs. 0.3846) than that for Model 8. However, the percent correctly predicted was slightly higher than that of Model 8 (44.87% vs. 44.43%). All of the psychological questions included in this model were significant, and are described below.

DA-ML
- Question D7: Lending a friend an amount of money equivalent to one month’s income.
- Question D8: Spending money impulsively without thinking about the consequences.

CP-ML
- Question D1: Betting a day’s income at the horse races.
- Question D3: Investing 10% of your annual income in a blue chip stock.
- Question D7: Lending a friend an amount of money equivalent to one month’s income.

Those prone to “lend a friend an amount of money equivalent to one month’s income” were more likely to select DA-ML than DA-GPL. Similarly, those who “spend money impulsively without thinking about the consequences” were also more likely to select DA-ML than DA-GPL. This result seems logical given that agreement with Question D7 and Question D8 suggests someone who is willing to take risks with their money and someone who is willing to spend money impulsively, respectively. Thus, it makes sense that people agreeing with these statements would be willing to pay to use the ML, even if there is some risk involved because they are not entirely sure whether paying to use the ML will actually pay off in the form of saved time.

In terms of the CP-ML option, those prone to “bet a day’s income at the horse races” and those likely to “invest 10% of their annual income in a blue chip stock” are less likely to choose CP-ML than DA-GPL. One logical explanation may be that these individuals are willing to risk traveling in the potentially congested GPL in order to forgo needing to deal with the hassle of carpooling. Interestingly, those willing to “lend a friend an amount of money equivalent to one month’s income” are more likely to select CP-ML than DA-GPL. In contrast to Question D1 and D3, this question incorporates the human factor of attaching the financial risk to helping out a friend. Thus, people willing to lend money to a friend may be more willing to carpool in an effort to help others get to their destination or to help society as a whole by cutting back on pollution.

SUMMARY AND CONCLUSIONS
This research provides insights into the role that psychological questions can play in better understanding travel behavior in ML choices. Based on the models discussed from Table 3, the model (Model 9) containing questions from the constructs measured by Scale C: Personal Need for Structure and Scale E: Driving Risk Perceptions and Driving Style, resulted in the most promising models containing psychological variables. Not only did Model 9 result in a higher
adjusted rho squared value than Model 8, it also produced the highest percent correctly predicted value of all models contained in Table 3. Because the construct measured by Scale E specifically focuses on driving (i.e., a transportation related activity) it makes sense that including some of the questions from this construct within a model would contribute toward a good model.

Based on this model, those who “mostly respect speed limits” are significantly less likely to choose DA-ML than DA-GPL. This result seems logical, as the GPL speed is assumed to be the same or slower than the adjacent ML. It seems plausible that people who “mostly respect speed limits” would be content to drive alone in the free GPL, rather than pay to use the ML that generally has speeds of equal or higher values. Also, those who “get upset when they get into a situation without knowing what they can expect from it” are significantly less likely to select CP-ML than DA-GPL. One possible explanation is that these individuals avoid carpooling because of the uncertainty associated with either picking up passengers or waiting for their ride to pick them up. In terms of lane type choice, these individuals may not like performing a mental cost-benefit analysis in every situations to assess whether selecting the ML would derive a benefit to them over using the GPL. Thus, in order to avoid making this decision, without knowing whether it will turn out to be beneficial or not prior to making it, they prefer to select the DA-GPL option.

However, insights into ML use were pulled from each of the models contained in Table 3. The following provides a summary of those questions included within these models. The impact of those variables found to be significant is included. No added information is given for variables included in a model but not significant at the 90% level of confidence.

**CP-GPL**

- Question C6: I hate to change my plans last minute (Model 9).
- Question C7: I hate to be with people who are unpredictable (Model 9).

**DA-ML**

- Question C9: I do NOT enjoy the exhilaration of being in unpredictable situations (Model 9).
- Question E1_1: I mostly respect speed limits (Model 9).
  - Less likely to select DA-ML than DA-GPL
- Question E211: I drive cautiously (Model 9).
- Question A4: I do NOT make a mess of things (Model 10).
  - More likely to select DA-ML than DA-GPL
- Question B1: I have often found that what is going to happen will happen (Model 11).
  - More likely to select DA-ML than DA-GPL
- Question B3: The average citizen can have an influence in government decisions (Model 11).
  - More likely to select DA-ML than DA-GPL
- Question D7: Lending a friend an amount of money equivalent to one month’s income (Model 12).
  - More likely to select DA-ML than DA-GPL
• Question D8: Spending money impulsively without thinking about the consequences (Model 12).
  o Less likely to select DA-ML than DA-GPL

**CP-ML**

• Question C1: It upsets me to get into a situation without knowing what I can expect from it (Model 9).
  o Less likely to select CP-ML than DA-GPL
• Question E1_1: I mostly respect speed limits (Model 9).
• Question E3_8: I get impatient during rush hour (Model 9).
• Question B2: Getting a good job depends mainly on being in the right place at the right time (Model 11).
  o More likely to select CP-ML than DA-GPL
• Question B3: The average citizen can have an influence in government decisions (Model 11).
• Question B8: It is difficult for people to have much control over the things politicians do in office (Model 11).
• Question B9: Sometimes I can’t understand how teachers arrive at the grades they give (Model 11).
  o Less likely to select CP-ML than DA-GPL
• Question D1: Betting a day’s income at the horse races (Model 12).
  o Less likely to select CP-ML than DA-GPL
• Question D3: Investing 10% of your annual income in a blue chip stock (Model 12).
  o Less likely to select CP-ML than DA-GPL
• Question D7: Lending a friend an amount of money equivalent to one month’s income (Model 12).
  o More likely to select CP-ML than DA-GPL

**FUTURE RESEARCH**

There are some limitations associated with this research that can be further addressed in future research. Because each of the models included in Table 3 have different sample sizes, it is difficult to compare the log likelihood values in an objective manner and determine if in fact the more unrestricted models (Models 9-12) are statistically better than the most restricted of all of these models (Model 8). Developing a survey wherein each respondent answers every psychological question will address this limitation and allow for more direct comparisons across models containing different psychological variables. Not only that, but it will be possible to develop models containing psychological variables from multiple constructs (not just a maximum of two constructs at a time).

The next step will be to take those psychological questions that seem promising and develop related questions that are framed in the context of transportation. The transportation context already exists with several of the questions taken from the construct measured by Scale E—though additional questions related to those questions of particular interest stemming from the construct measured by Scale E will also be developed. Further analyses of the data will be performed prior to this step. This may include developing different base models containing socioeconomic and trip characteristic variables to see if different or additional psychological
variables of interest arise when comparing psychological variables under slightly different conditions. Ultimately, the goal is to compile these questions to form a scale that will allow for better ML use modeling in the future, and better understanding of ML travel behavior.

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REFERENCES