# Deriving metrics of driving comfort for autonomous vehicles: A dynamic latent variable model of speed choice

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**Abstract**

While the interest of the transport research community and automotive industry is increasingly turning towards developments and improvements in the field of autonomous vehicles, there is a need for a better understanding of the end users' preferences regarding perceived passenger comfort, in order to improve acceptance and intention to use. The present study is based on a driving simulator experiment conducted at the University of Leeds Driving Simulator (UoLDS) and approaches the issue of comfort via observed speed choice behaviour. Participants drove a series of driving simulator scenarios composed of road segments of different road type, road geometry, risk level at the road edge, and oncoming traffic. They also completed a series of self-report questionnaires, including Arnett's Inventory of Sensation-seeking. A set of models, was developed in order to investigate the effects of road environment and sensation-seeking on speed behaviour. The initial model only considered explanatory variables related to the road environment and accounted for individual unobserved heterogeneity. Past behaviour, serial correlation and heterogeneity in road environment were then introduced in the model specification. The autoregressive disturbance term that accounted for serial correlation was also applied in the form of a random variable and significantly improved model fit. Finally, sensation-seeking was incorporated in the model as a latent variable. The results showed a significant impact of most of the road elements as road type, curvature, risk type at the road edge on observed behaviour, implying a future need for the development of autonomous vehicle controllers that adapt their performance based on the road environment. Moreover, sensation-seeking had a significant and positive effect on speed, which indicates a potential future demand for personalised controllers to meet the users' individual preferences.

Keywords: Speed choice; Latent variable; Sensation-seeking; Random autoregressive disturbance; Driving simulator; Perceived comfort

## 1. Introduction

Following the technological advances over the past decade, autonomous vehicles (AVs) have been a major topic of discussion and debate in the automotive industry and transportation research community. The active involvement of many large automakers in AVs testing (Gandia et al., 2019) is an indication that the operation of current transportation systems is at the brink of immense changes caused by the on-road presence of this new technology. The mass deployment of AVs is expected to have multiple benefits: crash rate reduction, decrease of gas emissions, fuel savings and improvement of mobility opportunities (Zhang et al., 2019). However, their successful integration highly depends on user trust, acceptance and intention to use. Other issues range from willingness to purchase (Daziano et al., 2017; Menon et al., 2020) or share (Webb et al., 2019) to safety perception of vulnerable road users about AVs (Merat et al., 2018) and morality issues (Bonnefon et al., 2016). From a passenger perspective (i.e. a driver ceding control to the vehicle or a passenger in the back seat), intention to use AVs has been found to be influenced by their attitudes towards this technology and psychosocial factors

(Buckley et al., 2018) but other streams of research have focused on the impacts of perceived comfort (or discomfort) and safety that emerge from the performance and driving styles of autonomous vehicles.

The notion of comfort in autonomous vehicles has not been clearly defined in existing literature; however, it has been linked to research related to the development of accepted AV driving styles (Bellem et al., 2018). Elbanhawi et al. (2015) defined AV-related comfort as a framework related to issues both relevant to conventional vehicles (i.e. ergonomic factors) and specific issues, such as natural manoeuvring, apparent safety, disturbances that arise from the road-vehicle interaction leading to vibrations and finally, motion sickness. The concept of comfort has been approximated from various perspectives. For instance, Basu et al. (2016) conducted a simulator study where participants had to evaluate different autonomous driving styles in terms of comfort, safety, preference for every-day use and similarity to own driving, using self-report questionnaires. This approach is differentiated from the framework of Elbanhawi et al. (2015), where comfort and safety were treated as two different components. Towards the same direction, Yusof et al., (2016) considered comfort together with safety and pleasantness, to evaluate drivers' preference regarding acceleration-deceleration, speed hump and cornering, in a naturalistic study. The aforementioned studies based their outcomes on single responses after the end of a drive/scenario. In a different approach, Hartwich et al. (2018) investigated comfort in a simulator study via similar responses to questionnaires, but participants also used a handset controller to assess discomfort in real time. A similar device for the evaluation of discomfort was also used by Telpaz et al. (2018) in a naturalistic environment context. Finally, Bellem et al. (2016) approximated comfort based on manoeuvring behaviour in manual driving, to derive different driving styles. To that end, they analysed acceleration, jerk, lane-change and headway in rural/urban and motorway scenarios.

Existing literature on AV comfort and safety usually focuses on different driving styles and behaviour overall, omitting, however, the impact of the road environment on drivers' perception. The latter has been investigated in the context of manual driving. Goralzik & Vollrath (2017) found in a simulator study that decrease of lane width and road radius significantly affect speed choice for a speed limit of 50kmh, however, the effect of these road factors was irrelevant at lower speed limits (30kmh). Also, Bella (2013) conducted a driving simulator study and reported a significant drop of speed at high-curvature road segments. Moreover, Ben-Bassat & Shinar (2011) found similar effects of road curvature on speed but, they also mentioned a positive impact of shoulder presence, yet no impact of guardrails. Van Der Horst & De Ridder (2007) investigated the effects of road infrastructure on speed and lateral offset. Amongst their most interesting findings is the negative effect of trees on speed, unless they are placed closer to the road edge (2m). In another simulator study, Calvi (2015) also concluded that the presence of trees is related to significant speed reduction, when they are close to the road edge (1.5m). Similar effects, with respect to the presence of vegetation were also reported in other studies (Antonson et al., 2009; Fitzpatrick et al., 2014; Stamatiadis et al., 2010). Although these findings were not directly related to comfort, the changes in behaviour reported might still be an indication of how drivers would prefer to be driven in specific road environments and contexts.

The current paper presents the results of an analysis conducted within the context of the UK-funded HumanDrive project, which focuses on the development of natural, human-like controllers for autonomous vehicles. This type of controller is employed in an effort to improve perceived comfort, safety and, thus, acceptance and intention to use autonomous vehicles. The study gradually builds knowledge and understanding with an ultimate goal to implement elements of observed manual driving behaviour into autonomous vehicles. The results presented in this paper are part of the initial data collection based on manual driving observations at the University of Leeds Driving Simulator (UoLDS). The driving simulator scenarios were fundamentally designed to identify characteristics of natural driving, by exposing participants to scenarios containing varying hazards related to road type, road geometry, oncoming traffic, lane width, and lateral risk elements, such as presence of parked cars and roadworks. The study aims to contribute to the existing knowledge and investigate how these factors should be considered in the development of future AV controllers. Although various driving behaviour indicators of longitudinal and latitudinal control can be considered, the present analysis explicitly focuses on the development of a model to investigate speed choice behaviour.

The use of driving simulators is gaining popularity as a tool for the estimation of mathematical driving behaviour models. Existing applications include traditional types of driving behaviour models such as car-following (Hoogendoorn et al. 2010) or overtaking (Farah et al., 2009) but also extend to and incorporating other aspects of driving behaviour related to risk-taking and human factors. For instance, Danaf et al. (2015) developed models of intersection crossing, considering the effects of anger, and aggressive driving behaviour, while Tran et al. (2015) modelled yellow light crossing, and time spent at the junction during the red phase via a two-part regression model. Finally, Sarwar et al. (2017) and Fountas et al. (2019) developed models to compare perceived and observed aggressive driving behaviour, using driving simulator data.

In terms of modelling, the issue of unobserved heterogeneity has been addressed in many studies related to road safety and driving behaviour. Anastopoulos & Mannering (2016) used random parameters to investigate stated speed choice and compliance with speed limit, using survey data. Moreover, Mannering et al. (2016) highlighted the importance of accounting for unobserved heterogeneity on statistical analysis of accident data. Guo et al. (2018) approximated cyclists' red-light running via Bayesian random parameters for the explanatory variables of a logistic regression. Yasmin et al. (2014) incorporated heterogeneity in pedestrian injury severity via discrete latent classes in an ordered logit model. In the same study, the authors considered random thresholds for the various levels of their model. The concept of random thresholds was also used in the context of an ordered probit model by Fountas & Anastopoulos (2017) to model the severity of accident injury severity. With respect to the same issue, Islam and Mannering (2020) approximated injury severity assuming heterogeneity both in the means and the variances of the random parameters. Finally, on a different topic, Eker et al. (2020), addressed the issue of unobserved heterogeneity to model perception about flying cars.

The current analysis is revolving around the specification and estimation of a speed choice model, considering the effects of road environment. At the same time, the effects of unobserved heterogeneity and individual traits are also considered in the analysis. The remainder of the paper is organised as follows: Section 2 presents the experimental design and data collection process, Section 3 describes the methodological approach followed, including the specification of the various models, while the results are presented in Section 4. The paper concludes with a summary and directions for future research.

## 2. Data collection

2.1 The University of Leeds Driving Simulator (UoLDS)

The University of Leeds Driving Simulator (UoLDS, Figure 1) was used to record driving performance. The simulator's vehicle cab is based around a 2006 Jaguar S-type, housed within a 4m diameter, spherical projection dome. Eight visual channels are rendered at 60 frames/s, predominantly at a resolution of 1920×1200. The five forward channels are front-projected providing a horizontal field of view of 270°. The three rear channels can be seen through the vehicle's central view and side mirrors, the latter both physically modified to accommodate 800x480 LCD panels. The simulator also incorporates an eight degree-of-freedom electrical motion system. This consists of a 500mm stroke-length hexapod motion platform that is mounted on a railed gantry providing a further 5m of effective travel in surge and sway. The simulator system collects data relating to driver behaviour (vehicle controls), the vehicle (position, speed, accelerations, etc.) and other autonomous vehicles in the scene (e.g. identity, position and speed) at a rate of 60Hz.

**Figure 1:** The University of Leeds Driving Simulator (UoLDS)

2.2 Experimental design and procedure

One of the main objectives of the study was to investigate the impacts of perceived risk on driving behaviour. Variability in vehicle control was examined around a steady state, via a set of repeatable conditions, environmental factors and levels of contextual risk that had the potential to shape the perception of a driving environment, resulting in definable behaviours. The initial experimental design consisted of two 80km roads from 32 different 250m road segments (tiles), each with an associated contextual risk, and repeated 10 times to facilitate multiple exposures to that risk. The rationale for selecting multiple repetitions of 250m segments was to vary the entry speed and lateral position into a particular segment, by preceding it with different segments of varying demand. Drivers were thereby encouraged to adopt behaviours that they felt were suitable to an ever-changing environmental context of risk. Both drives were identical, except that one included oncoming vehicles (to further increase risk level), whilst the other did not. The order of these two drives was counterbalanced across participants. The various components of the risk profiles are presented in Table 1.

This original experimental design resulted in a number of dropouts (5 participants out of 12 initially recruited), which was caused by the discomfort associated with the long exposure to the simulator. The road was, thus, redesigned to reduce simulator exposure. The new design was composed of four shorter 15-minute drives, three of which contained oncoming cars. Further time reductions were achieved by removing some of the more extreme contextual risk road segments, to provide a more comfortable, and less demanding, simulator experience for participants. As in the early phase of the trial, the experiment was counterbalanced, so participants experienced oncoming vehicles in different orders.

Each data collection session was scheduled for 2½ hours. On arrival, each participant was greeted by a member of UoLDS research staff and provided with an experimental briefing to read through. The researcher then verbally explained the key elements of the data collection period, described the simulator and gave a safety briefing. Once the associated experimental requirements and associated risks had been understood, and any participant queries answered, the researcher asked the participant to sign an informed consent to participate.

**Table 1:** Risk profiles used in the study

| Risk Context | Factor Levels | Description |
|---|---|---|
| **Environment** | Rural, Urban | Open rural road (60 mph speed limit) and built-up urban areas (speed limit 40mph), representative of a real-world route in Cranfield, UK. |
| **Oncoming vehicles** | Oncoming, Non-oncoming | On-oncoming vehicles were included to induce predictable, but high energy, safety threats. |
| **Road curvature** | Straight, 100m,170m, 250m, 750m | In the rural environment, both straight and curved sections were modelled, with curves varying in radius between 100m and 250m. In the urban environment, a 750 m radius curve was chosen. |
| **Lane width** | Narrow, Wide | In the rural areas, sections of roadway were modelled that corresponded with existing standards (3.65 m lane width) as well as sub-standard elements that more closely matched the Cranfield route (2.9 m lane width). |
| **Levels of contextual risk** | Hard, Soft and Raised Roadside Areas, Lane Markings, Cycle Lanes, Pedestrian Refuges, Parked Vehicles and Roadworks | In rural areas, risk was varied via the lateral risk profile and corresponding availability of the driving lane through permanent (hard, soft, raised roadside areas) and temporary narrowing (stationary vehicles, roadworks). In urban areas, lateral profile varied with lane markings, cycle lanes, pedestrian refuges, parked vehicles and roadworks. |
| **Persistence of contextual risk** | 20 m risk, 250 m risk | The perceived risk existed both over the full 250 m road segment and a shorter 20m area midway through a segment. This was to explore whether drivers were vigilant to adjust their behaviour to more unexpected/unpredictable risk factors. |

Participants' first drive of the simulator was to familiarise themselves with the operation and handling of the vehicle in the presence, and under the guidance of, the researcher. The researcher followed a standard, and established, procedure to ensure the participant was fully competent and proficient at handling the vehicle over a period of 15-20 minutes, depending on the confidence of the individual concerned. As well as demonstrating competence, the familiarisation drive was also used to ensure the participant suffered no ill-effects from simulator exposure such as nausea, vertigo or visual/vestibular discrepancies. After a safety demonstration of the simulator emergency evacuation measures, the participant then returned to the briefing area. This was followed by the main drives of the study.

### 2.3 Subjective measures

The data collection process also involved a set of questionnaires that participants completed at the end of the experiment. Although filling out the questionnaires post-driving might have some impact on participants' responses, this has also been the practice in other driving simulator studies that involved model estimation (e.g. Danaf et al., 2015), as completing questionnaires before the simulator experiment may affect driving behaviour. Another approach could be to repeat the questionnaires before and after the experiment and control for differences, however, as most of them revolved around personality traits, we did not expect to see major differences before and after the drive. The questionnaires included the Arnett Inventory of Sensation Seeking (AISS) questionnaire (Arnett, 1994), the Traffic Locus of Control (T-LOC) questionnaire (Őzkan & Lajunen, 2005), and the Driver Style Questionnaire (DSQ; West et al., 1992). Based on findings of previous analysis of the data (Louw et al., 2019), only the AISS was considered in the present paper. The model specification, including the

AISS items, is presented in Section 3.1. while further details about the results, including indicators of sensation-seeking are included in Sections 4.3 and 4.4.

2.4 Sample characteristics

It total, 34 individuals (16 female and 18 male) were considered for the analysis, of which seven completed the two main roads of the initial experimental design while the rest of the participants completed the modified design composed of four shorter roads. Participants were recruited via the University of Leeds Driving Simulator database. Using crash-based statistics (Loughran & Seabury, 2007) it was assumed that driving style might be affected by age and experience. Thus, participants were recruited from different age groups in order to collect data from a wider range of drivers. The detailed distribution of participants in each age group is presented in Table 2. One of the participants did not report age and thus these details were not included in the table. The average age of all participants was approximately 37.6 years (minimum 18 and maximum 64 years) while average driving experience was 20 years, ranging from 1 to 48 years. Finally, participants reported approximately 6500 miles per year of driving.

**Table 2:** Sample characteristics

| Age group | Gender (n) | | Age | Years with UK License | Annual Mileage |
|---|---|---|---|---|---|
| | M | F | M (SD) | M (SD) | M (SD) |
| **< 25 yrs(n=8)** | 2 | 6 | 19.75 (2.29) | 2.88 (2.10) | 4250 (3229.77) |
| **25-40 yrs(n=11)** | 7 | 4 | 36 (3.41) | 15.36 (5.43) | 5781.82 (3516.20) |
| **40-50 yrs (n=10)** | 7 | 3 | 43.90 (3) | 26.90 (3.78) | 7900 (2766.87) |
| **Over 60 yrs(n=4)** | 1 | 3 | 62.25 (1.5) | 44.50 (3.42) | 8000 (4966.56) |

## 3. Methodological framework

3.1 Model specification

The present work is focusing on the development of a model to approximate speed choice behaviour. Given the continuous nature of the dependent variable, a linear regression might have seemed as an appropriate choice for the model specification. However, because of the panel nature of the data i.e. multiple observations per participant, several of the linear regression assumptions are expected to be violated. For instance, the disturbances of the model are likely to be correlated for the same individual, due to unobserved characteristics or can be time-related, since the structure of the data is in essence a time series. Moreover, differences in the characteristics of the road environment (e.g. urban and rural) can also affect the variance of the disturbances, leading to heteroskedasticity. Thus, an extension of linear regression was considered for the model specification to account for the effects of the aforementioned issues. These additions included a disturbance term to capture unobserved heterogeneity (Section 3.1.1), the use of an autoregressive disturbance and lagged dependent variable to account for time correlations (Section 3.1.2) and the use of a heteroskedastic scale term to investigate the effects of road environment on the i.i.d. disturbance term of the model (3.1.3). Given that the model estimation included different drivers, individual specific serial correlation was introduced in Section 3.1.4. Ultimately, the model specification was modified to incorporate sensation-seeking as a latent variable (3.1.5).

3.1.1 Basic structure – The "random heterogeneity" model

If it is assumed that – ignoring time correlation - average speed in each tile of a given road is a linear function of the road environment and unobserved drivers' heterogeneity (that also accounts for the fact that each series of data has been derived from the same individual), this relationship can be represented as shown in Eq. 1:

$$Y_{nit}=\mu_{nit}+\varepsilon_{nit}=b_o+\mathbf{bX_{nit}}+a\upsilon_n+\varepsilon_{nit} \tag{1}$$

where $Y_{nit}$ is average speed of individual n at tile t of road (run) i, $\mathbf{X_{nit}}$ are the explanatory variables, $b_o$ is a constant and **b** a vector of parameters to be estimated. Also, $\upsilon_n$ is a standard normally distributed disturbance with a its parameter to be estimated and finally, $\varepsilon_{nit}$ is an i.i.d. normally distributed disturbance term. The $a\upsilon_n$ term is used to capture the impact of unobserved drivers' characteristics and consequently the panel nature of the data. Similar disturbance terms have been used in literature related to driving behaviour modelling (Ben-Akiva et al., 2006; Toledo, 2002; Toledo and Katz, 2009; Varotto et al., 2018). Following the assumption of normality for $\varepsilon_{nit}$, the probability density function of average speed observations can be represented as (Eq. 2):

$$f(Y_{nit})=\frac{1}{\sigma_\varepsilon}\varphi\left(\frac{Y_{nit}-\mu_{nit}}{\sigma_\varepsilon}\right)=\frac{1}{\sigma_\varepsilon\sqrt{2\pi}}e^{\left(-\frac{1}{2}\left(\frac{Y_{nit}-\mu_{nit}}{\sigma_\varepsilon}\right)^2\right)} \tag{2}$$

where $\varphi(.)$ represents the density of standard normal distribution, $\mu_{nit}$ is the mean and $\sigma_{nit}$ is the standard deviation of the distribution. Assuming that for each individual there is a series of observations, the total likelihood is given, conditionally on $\upsilon$ as (Eq. 3):

$$f(Y_{ni2},Y_{ni3},\ldots,Y_{niT}|\upsilon_n)=\prod_{i=1}^{I}\prod_{t=2}^{T}f(Y_{nit}|\upsilon_n) \tag{3}$$

The unconditional form of the above distribution can be calculated by integrating over $\upsilon$ (Eq. 4)

$$L_n=f(Y_{ni2},Y_{ni3},\ldots,Y_{niT})=\int_{\upsilon}\prod_{i=1}^{I}\prod_{t=2}^{T}f(Y_{ni2},Y_{ni3},\ldots,Y_{niT}|\upsilon_n)f(\upsilon_n)\,du \tag{4}$$

while the total log-likelihood across all individuals is presented in Eq. 5:

$$LL=\sum_{n=1}^{N}\ln(L_n) \tag{5}$$

The rationale for starting the numbering of the product operator that represents the road tiles from the second observation is later explained in Section 3.1.2. This approach was decided to ensure that all models in the current paper are estimated using the same observations and thus, it is feasible to compare them in terms of fit. Moreover, the integral presented in Eq. 4, has been solved using 1000 standard normally distributed Halon draws (Halton, 1960). For convenience, this model will be mentioned as the "random heterogeneity" model (or Model 1) in the remainder of the paper. The estimation of this, and all models presented in the next sections, was based on an adaptation of the R package 'Apollo' (Hess & Palma, 2019) using the R software (RC Team, 2013).

3.1.2 Introduction of time correlation – The "autoregressive" model

*Incorporation of lagged speed*

A reasonable expectation with respect to speed choice is related to the correlation of past and current speed choice behaviour. In the current approach, the average speed of the previous tile was considered as past speed. The addition of the lagged dependent variable results, as shown in Eq. 6 in:

$$Y_{nit}=\theta Y_{nit-1} + \mu_{nit}+\varepsilon_{nit}=\theta Y_{nit-1} + b_o+\mathbf{bX_{nit}}+a\upsilon_n+\varepsilon_{nit} \quad (6)$$

where the model specification is also including $Y_{nit-1}$ that is the average speed of the previous tile and $\theta$ a parameter to be estimated, in addition to the terms presented in Eq 1. A major issue that arises from the model specification of Eq. 6 is a potential correlation of the lagged variable with the disturbance term that is used to captured unobserved drivers' heterogeneity. To be more concrete, the model specification assumes that at tile t, average speed is a function of $Y_{nit-1}$ and $\upsilon_n$, but the latter has been also used as an explanatory variable of $Y_{nit-1}$ in the previous observation. This model specification is violating the assumption of regression models regarding the independence among explanatory variables, as the lagged dependent variable and the random heterogeneity term are endogenous. To address the issue of endogeneity, it is required to make an assumption about the initial observation of an individual and the individual-specific term. In the existing literature, Heckman (1987) suggested the estimation of a reduced model for the initial observation of individuals, using a different set of parameters for the explanatory variables. Another approach is the Conditional Maximum Likelihood (CML) estimation suggested by Wooldridge (2005). The latter has been applied in the current paper. Following this approach, the unobserved heterogeneity is expressed as a function of the initial value of the dependent variable and exogenous time-variant variables, as shown in Eq. 7:

$$z_{nit}=\gamma+\alpha_0 Y_{0nit}+\boldsymbol{\beta}\mathbf{X'_{nit}}+a\upsilon_n \quad (7)$$

where $Y_{0ni}$ is the initial observation of the dependent variable, $\mathbf{X'_{nit}}$ represents the exogenous explanatory variables as: $\mathbf{X'_{nit}}=X'_{ni1},\ldots,X'_{niT}$, and $\alpha_0$, $\beta$, $\gamma$ are parameters to be estimated. In relevant existing literature (Drakos & Konstantinou, 2013; Elliot et al., 2019; Michaud & Tatsiramos, 2011) the explanatory variables are replaced by the average values of the time-dependent explanatory variables, to capture the correlation between the former and the random heterogeneity term $\upsilon_n$. However, in the current work all time-variant explanatory variables are related to the road environment and are not expected to correlate with the unobserved heterogeneity term, which is primarily used to capture the effects of unobserved drivers' characteristics. Therefore, this term been dropped from Eq. 7. Moreover, it should be mentioned that, for model identification reasons, $\gamma$ cannot be estimated separately from $b_o$ and thus this term is also dropped. Thus, the model specification after incorporating the effects of lagged speed is (Eq. 8):

$$Y_{nit}=\alpha_0 Y_{0nit}+\theta Y_{nit-1}+b_o+\mathbf{bX_{nit}}+a\upsilon_n+\varepsilon_{nit} \quad (8)$$

for t=2,3,…,T of each run i=1,2,…,I of an individual.

*Serially correlated disturbance term*

Thus far, $\varepsilon_{nit}$ has been treated as an i.i.d. disturbance term. However, in panel data, the disturbances are likely to be correlated across time. In the present paper, serial correlation with the previous periods (tiles) was captured via a first-order autoregressive disturbance term thus $\varepsilon_{nit}$ can be expanded as $\varepsilon_{nit} = \rho\varepsilon_{nit-1} + \nu_{nit}$, where $\rho$ is a correlation parameter and $\nu_{nit}$ is an i.i.d normal disturbance term with variance $\delta_{\nu}^{2}$. The value of the lagged disturbance term can be obtained as $\varepsilon_{nit-1}=Y_{nit-1}-\widetilde{Y}_{nit-1}$, where $\widetilde{Y}_{nit-1}$ is the predicted value of the dependent variable at tile t-1.

Following this modification, the model specification is (Eq. 9):

$$Y_{nit}=\alpha_0 Y_{0nit}+\theta Y_{nit-1}+b_o+\mathbf{bX_{nit}}+a\upsilon_n+\rho\varepsilon_{nit-1}+\nu_{nit} \tag{9}$$

Given that the model is solved conditionally on the initial observation (at tile t=1) of each run, there is no estimate for this speed value, as it is always used as an explanatory variable only. Therefore, the second tile observation of each run should have been also dropped from the estimation, since, in Eq. 9, it is not feasible to include the $\varepsilon_{nit-1}$ term in the specification for the first tile, as it is not available. However, with reference to Davidson and MacKinnon (2004), $\varepsilon_{ni2}$ is normally distributed as: $\varepsilon_{ni2} \sim N[0, \sigma_{\nu}^{2}/\left(1/(1-\rho^{2})\right)]$. Hence, when formulating the likelihood function for the second observation of each run (based on Eq. 2) the standard deviation term can be modified following the abovementioned specification of $\varepsilon_{ni2}$ and normally include this speed observation in the model estimation. The model presented in the current section will be reported as the "autoregressive" model (or Model 2) for the remainder of the paper.

3.1.3 Heteroskedastic variance structure – The "autoregressive-heteroskedastic" model

As described in Section 2.2, the road environment included both rural and urban/village areas with different speed limits. The average effect of speed limit on speed can be captured using different parameters for both road types. However, the variance of the i.i.d. disturbance term $\nu_n$ is also expected to vary between the two road types. Thus, the density of a single speed observation can be expanded as (Eq. 14):

$$f(Y_{nit})=\frac{1}{\sigma_{\nu,rural}\sigma_{\nu,urban}^{(urban==1)}}\varphi\left(\frac{Y_{nit}-\mu_{nit}}{\sigma_{\nu,rural}\sigma_{\nu,urban}^{(urban==1)}}\right) \tag{14}$$

In Eq. 13, if the estimate of $\sigma_{\nu,urban}$ is significantly different from 1, then this implies that the variance between the two road environments is statistically significant. Similar variance structures are usually applied to deal with heteroskedasticity. It should be mentioned that parameter estimates are still unbiased under the presence of heteroskedasticity however, the calculation of standard errors and consequently significance of parameters might be inconsistent (see Washington et al. 2010). Zuur et al (2009) have presented a series of potential variance structures that can be applied to account for heterogeneity in residual variance. The modification presented in the current section was applied in the "autoregressive" model resulting in the "autoregressive-heteroskedastic" model (or Model 3).

3.1.4 The "random autoregressive-heteroskedastic" model

Following Eq. 9, the correlation parameter $\rho$ assumes a constant effect of time correlation for all individuals. However, it is likely that the magnitude of correlation varies across drivers. To capture this effect, a random correlation parameter is suggested in the present paper. Given that

$|\rho| \leq 1$, it has been assumed that the correlation term follows a truncated normal distribution bounded between -1 and 1. The density function of such distribution is shown in Eq. 10:

$$f(\rho_n)=\frac{\frac{1}{\sigma_\rho}\varphi\left(\frac{\rho_n-\mu_\rho}{\sigma_\rho}\right)}{\Phi\left(\frac{1-\mu_\rho}{\sigma_\rho}\right)-\Phi\left(\frac{-1-\mu_\rho}{\sigma_\rho}\right)} \tag{10}$$

where $\Phi[.]$ is a cumulative normal distribution and $\mu_\rho$, $\sigma_\rho$ are the mean and standard deviation of the correlation term $\rho$ that need to be estimated. Following the assumption of a random autoregressive term, the likelihood function is conditional both on $\upsilon_n$ and $\rho_n$ as (Eq. 11):

$$f(Y_{ni2},Y_{ni3},\ldots,Y_{niT}|\upsilon_n)=\prod_{i=1}^{I}\prod_{t=2}^{T}f(Y_{nit}|\upsilon_n,\rho_n) \tag{11}$$

and the unconditional form is (Eq. 12):

$$L_n=f(Y_{ni2},Y_{ni3},\ldots,Y_{niT})=\int_\rho\int_\upsilon\prod_{i=1}^{I}\prod_{t=2}^{T}f(Y_{ni2},Y_{ni3},\ldots,Y_{niT}|\upsilon_n,\rho_n)f(\upsilon_n)\,f(\rho_n)\,du\,d\rho \tag{12}$$

To solve the integral in Eq. 12, 1000 draws were again used. However, the draws related to the correlation term should only produce values within the (-1,1) range. A draw from a truncated normal distribution can be obtained as shown in Eq. 13:

$$\rho=\Phi^{-1}\left(\Phi\left(\frac{-1-\mu_\rho}{\sigma_\rho}\right)+U\cdot\left(\Phi\left(\frac{1-\mu_\rho}{\sigma_\rho}\right)-\Phi\left(\frac{-1-\mu_\rho}{\sigma_\rho}\right)\right)\right)\sigma_\rho+\mu_\rho \tag{13}$$

where $\Phi^{-1}$ is the inverse of a normal cumulative, and U are uniform draws from the (0,1) range (Train, 2009). The approach presented in this section was applied as an extension of the "autoregressive-heteroskedastic" model. The new model will be mentioned as "random autoregressive-heteroskedastic" for the rest of the paper (or Model 4). It should be mentioned that this model specification assumes that time correlation varies across drivers but remains unchanged within the various drives of the same individual. Studies related to advances in unobserved heterogeneity (Pantangi et al., 2019; Jordan et al., 2019; Heydari et al., 2018; Fountas et al., 2018) have also suggested the estimation of different parameters (grouped random heterogeneity) for subsets of data i.e. for the different drives of an individual in the current case, however, this second level of heterogeneity has not been considered.

3.1.5 Incorporation of sensation-seeking – The "latent variable" model

Sensation-seeking was investigated via the AISS questionnaire. Hence, the incorporation of the AISS responses as direct explanatory variables would seem a reasonable approach, as it is also easy to implement while it may also produce expected and reasonable results. However, research in the field of econometrics and choice modelling (Ben-Akiva et al., 1999; Ben-Akiva et al., 2002; Bolduc and Daziano, 2010 to name a few) has shown that similar model specifications would be theoretically erroneous and could also lead to biased estimates. To be more concrete, the responses to the AISS statements are underlying indications of sensation-seeking rather than a direct measure of it. Thus, it is likely that the responses suffer from measurement errors, which can be magnified owing to the categorical-ordered format of the scale (Mariel et al., 2014), since they represent unitless values without a specific measurement unit. Moreover, the responses may be correlated with other unobserved factors which can lead to endogeneity between them and the disturbance terms of the model. To address the previous issues, sensation-seeking was introduced in the model specification as a latent variable using the sensation-seeking items as indicators.

Following the theoretical framework of the studies mentioned in the previous paragraph, a latent variable can be represented as (Eq. 15):

$$LV_n = \mathbf{h}(\mathbf{Z_n}, \boldsymbol{\delta}) + \omega_n \qquad (15)$$

where $\mathbf{h}(\mathbf{Z_n}, \boldsymbol{\delta})$ is a linear function of explanatory variables $\mathbf{Z_n}$ and $\boldsymbol{\delta}$ their parameters to be estimated while $\omega_n$ is a normally distributed disturbance. In the current work however, no explanatory variables were used in the latent variable specification. Moreover, it should be mentioned that for model identification purposes (Vij & Walker, 2014), the variance of the disturbance term was fixed equal to unity. After including sensation-seeking in the sets of explanatory variables, the model specification is taking the following form (Eq. 16):

$$Y_{nit} = \alpha_0 Y_{0nit} + \theta Y_{nit-1} + b_o + \mathbf{bX_{nit}} + \xi LV_n + a\upsilon_n + \rho\varepsilon_{nit-1} + \nu_{nit} \qquad (16)$$

where $\xi$ is a parameter to be estimated and represents the effect of the latent variable on the dependent variable.

As explained in previous paragraph, the responses to AISS were used as indicators of sensation-seeking. Given the ordered nature of the responses, the specification presented in Daly at al. (2012b) was used (see Eq. 17), rather than considering them as continuous variables with a normal disturbance term. Thus, the measurement equation of a K-level indicator, with levels $i_1, i_2, \ldots, i_K$ are specified as a function of $\tau_{l,1}, \tau_{l,2}, \ldots, \tau_{l,K}$ thresholds that need to be estimated:

$$I_{ln} = \begin{cases} i_1 & \text{if} \quad -\infty < LV_n \leq \tau_{l,1} \\ i_2 & \text{if} \quad \tau_{l,1} < LV_n \leq \tau_{l,2} \\ & \vdots \\ i_k & \text{if} \quad \tau_{l,(K-1)} < LV_n < \infty \end{cases}$$

The likelihood of an observed indicator value is given as (Eq. 17):

$$L_{I_{ln}} = I_{(I_{ln}=i_1)} \left[\frac{\exp(\tau_{l,i_1} - \zeta_l LV_n)}{1+\exp(\tau_{l,i_1} - \zeta_l LV_n)}\right] + \sum_{k=2}^{K} I_{(I_{ln}=i_k)} \left[\frac{\exp(\tau_{l,k} - \zeta_l LV_n)}{1+\exp(\tau_{l,k} - \zeta_l LV_n)} - \frac{\exp(\tau_{l,(k-1)} - \zeta_l LV_n)}{1+\exp(\tau_{l,(k-1)} - \zeta_l LV_n)}\right] + I_{(I_{ln}=i_K)} \left[1 - \frac{\exp(\tau_{l,(K-1)} - \zeta_l LV_n)}{1+\exp(\tau_{l,(K-1)} - \zeta_l LV_n)}\right] \qquad (17)$$

where $\zeta_l$ measures the effect of the latent variable on indicator $I_{ln}$. If Eq. 16 is combined with Eq. 10 and 15, then the likelihood function of the model is given as (Eq. 18):

$$L_n = f(Y_{ni2}, Y_{ni3}, \ldots, Y_{niT}) = \int_\omega \int_\rho \int_\upsilon \prod_{i=1}^{I} \prod_{t=2}^{T} f(Y_{ni1}, Y_{ni2}, Y_{ni3}, \ldots, Y_{niT} | \upsilon_n, \rho_n, \omega_n) \prod_{l=1}^{K} L_{I_{ln}} f(\upsilon_n) f(\rho_n) f(\omega_n)\, d\upsilon d\rho d\omega \qquad (18)$$

In previous research (Hoyos et al., 2012; Hess et al., 2018), factor analysis approaches have been applied to investigate whether the indicators used are representative of the latent variables they should reflect. With reference to Arnett (1994), the AISS is decomposed in two subscales namely, "intensity" and "novelty". The original decomposition of the scale is presented in Table A.1 of the Appendix. In the current work, the items of these two subscales were not directly used as indicators of sensation-seeking because they might not be representative of the sample (especially given the small sample size). Therefore, factor analysis approaches were used in order to identify the most representative items of sensation-seeking for the current sample. The results of this analysis are presented in Section 4.2. The model specification presented in this section will be reported as the "latent variable" model for the remainder of the paper (or Model 5).

### 3.2 Significance of additive shift parameters

The driving simulator scenario included two different road types (rural and urban) with different levels of road curvature and lateral furniture thus, different parameters were estimated for these variables based on the road type. In the model specification, some generic parameters were considered for both cases however, when a separate parameter needed to be introduced for the urban road, this was included as an additive shift to the generic respective parameter. In brief, the aforementioned specification can be generally described as (Eq. 19):

$$\omega = \omega_g + \omega_u \cdot (\text{road type} == \text{urban}) \tag{19}$$

where $\omega_g$ is the generic parameter which in this case captures the common effect value of both road types and $\omega_u$ is an additive shift to the generic parameter that differentiates the effect of urban road type from rural. This can be also seen similar to the interaction effect of some parameters with the road environment. Based on this model specification, the significance level of $\omega$ can be directly evaluated for rural roads however, this is not the case for urban roads as the significance level is the sum of two separate parameters. To address this issue and calculate the levels of significance for combination of parameters, the Delta method was applied, as described in Daly et al. (2012a). Based on this approach, the standard errors and thus the t-ratios for a series of parameters of interest can be calculated as a function of the parameter values and the covariance matrix of the estimates. The approach is based on Cramer's (1986) theorem. For further details, the reader is advised to read the work of Daly et al. (2012a). The authors provide a series of formulae for deriving standard errors for several cases including sum, difference, ratio and product however, the technique can be extended to further relationships among parameters.

### 3.3 Individual-level parameters for residual analysis

As shown in Eq. 15, the model specification assumes an i.i.d. normal disturbance term. This assumption can be confirmed by residual analysis i.e. by taking the difference between each observed and each predicted speed value. However, the model specification includes a series of random parameters which are the individual-level disturbance term, sensation-seeking and the random autoregressive disturbance. The parameter estimates related to these terms represent a set of distributions however, it is not known in which part of the distribution each individual lies. With reference to Thai et al. (2013) these individual values can be calculated based on the mean of the posterior distribution of each random variable. Following Train (2009) and according the Bayes' rule, individual level values are calculated as (Eq. 20):

$$\hat{\boldsymbol{\upsilon}}_{\mathbf{n}}(\boldsymbol{\theta})=E\left[\boldsymbol{\upsilon}_{\mathbf{n}}|y_n,\mathbf{x}_{\mathbf{n}},\boldsymbol{\theta}\right]=\int \boldsymbol{\upsilon} h\left(\boldsymbol{\upsilon}|y_n,\mathbf{x}_{\mathbf{n}},\boldsymbol{\theta}\right) d\upsilon=\frac{\int \boldsymbol{\upsilon} P\left(y_n|\mathbf{x}_{\mathbf{n}},\boldsymbol{\theta}\right)g(\boldsymbol{\upsilon}|\boldsymbol{\theta})\, d\upsilon}{\int P\left(y_n|\mathbf{x}_{\mathbf{n}},\boldsymbol{\theta}\right)g(\boldsymbol{\upsilon}|\boldsymbol{\theta})\, d\upsilon} \tag{20}$$

The quantity in the denominator is simply the value of the model likelihood. The numerator part is the integral of the density of $\upsilon$ in the sample, times the probability of observing a sequence of dependent variables $y_n$ under conditions $\mathbf{x_n}$ if an individual's parameter values were $\boldsymbol{\upsilon}$. The integrals in Eq. 19 do not have an analytical solution but can be simulated by drawing from the density of $\boldsymbol{\upsilon}$.

## 4. Estimation results

### 4.1 Explanatory variables

The explanatory variables used for model estimation were already introduced in Section 2.2. The current section presents the frequency table (Table 3) of the main independent variables and the reference category used in each case, given their categorical nature. In addition to the previously mentioned variables, a variable named "Transition tile" dummy variable was included. These tiles were used in the experiment for a smoother transition between urban to rural areas and vice versa.

**Table 3:** Explanatory variables frequency and reference categories

| Variable | Values | Frequency | Min | Max | Mean | Sd |
|---|---|---|---|---|---|---|
| Mean speed per tile (m/s) | - | - | 6.45 | 40.19 | 20.88 | 3.89 |
| Road type | Rural (reference) | 9632 | | | | |
| | Urban | 3414 | | | | |
| Radius | Straight (reference) | 2932 | | | | |
| (Rural) | 252m | 572 | | | | |
| | 170m | 5000 | | | | |
| | 100m | 1128 | | | | |
| Radius | Straight (reference) | 1956 | | | | |
| (Urban) | 750m | 1458 | | | | |
| Lateral furniture | Asphalt (reference) | 884 | | | | |
| (Rural) | Grass | 1420 | | | | |
| | Kerb | 3116 | | | | |
| | Hedge | 3146 | | | | |
| | Blockage | 1066 | | | | |
| Lateral furniture | Kerb | 1836 | | | | |
| (Urban) | Centre hatch | 189 | | | | |
| | Edge hatch | 600 | | | | |
| | Blockage (reference) | 789 | | | | |
| Lane width | Wide (reference) | 6322 | | | | |
| | Narrow | 6724 | | | | |
| Direction of curvature | Left (reference) | 3984 | | | | |
| | Centre | 4888 | | | | |
| | Right | 4174 | | | | |
| Risk persistence | Persistent – 250m (reference) | 8618 | | | | |
| | Non-persistent – 20m | 4428 | | | | |
| Oncoming traffic | No (reference) | 5510 | | | | |
| | Yes | 7536 | | | | |
| Transition tile | No (reference) | 12294 | | | | |
| | Yes | 752 | | | | |

## 4.2 Indicators of sensation-seeking latent variable

Based on the methodology described in Section 3.1.4, sensation-seeking was considered as a latent variable in the model specification, using the responses from AISS as indicators. Following similar approaches of latent variable models (Hoyos et al., 2012; Hess et al., 2018) an initial principal component analysis was applied to investigate whether the main constructs of novelty and intensity components of the AISS rise from the data, and consequently decide which indicators to include in the model specification. The results for eigenvalues greater than 0.9 indicated a 7-factor solution that each explained at least 5% of the variance however, these were not informative with respect to the indicators of sensation-seeking, since there was high dispersion of the questionnaire items, resulting in few of them in each factor. This finding can be an outcome of insufficient sample size.

The approach described in the previous paragraph did not yield satisfactory results thus, an exploratory factor analysis (EFA) with varimax rotation was applied forcing the number of factors to two, given that the original AISS is decomposed in two main sub-scales. The detailed results of the factor loadings are presented in Table A.2 of the Appendix. The resulted factors did not follow the original decomposition of the scale but the questionnaire items of both novelty and intensity were mixed in Factor 1. Moreover, the loadings of Factor 2 showed some inconsistencies with respect to the expected direction of the signs which could be another indication of small sample size. Thus, items with parameters above 0.5 in Factor 1 were selected as indicators of the sensation-seeking latent variables. Similar approaches to derive the most representative survey items can be also found in other studies related to driving behaviour (e.g. Danaf et al., 2015). It should be mentioned that in order to reduce computational time of the latent variable models, only items with all 4 possible answers being chosen in the sample were considered. The selected items together with their original sub-scale are outlined in Table 4.

**Table 4:** Selected sensation-seeking latent variable items

| | Item | AISS sub-scale |
|---|---|---|
| 1 | I can see how it would be interesting to marry someone from a foreign country | Novelty |
| 2 | I think it's fun and exciting to perform or speak before a group | Novelty |
| 3 | If I were to go to an amusement park, I would prefer to ride the rollercoaster or other fast rides | Intensity |
| 4 | I would have enjoyed being one of the first explorers of an unknown land | Novelty |
| 5 | It would be interesting to see a car accident happen | Intensity |
| 6 | I like the feeling of standing next to the edge on a high place and looking down. | Intensity |
| 7 | If it were possible to visit another planet or the moon for free, I would be among the first in line to sign up | Novelty |

*[Source: Arnett, 1994]*

## 4.3 Model evaluation and interpretation of parameter estimates

The current section presents the model estimation results. A series of models was initially estimated based on the specifications presented in Section 3.1. The results of this process are outlined in Table 6. The models were then compared via the likelihood ratio test to investigate whether the stepwise addition of new terms significantly improved model fit (Section 4.3.1). Finally, the model with the best fit was augmented with the sensation-seeking latent variable. The interpretation of this model is presented in Section 4.3.2.

### 4.3.1 Model evaluation

A set of different specifications was investigated in order to determine the most appropriate model to approximate speed choice decisions. The sequence of model estimation followed the formulations presented in Section 3.1 starting from the random heterogeneity and concluding at the latent variable model. With reference to Table 6, the gradual addition of extra terms resulted in the improvement of the log-likelihood (LL) scores. The significance of these improvements was evaluated via the likelihood ratio test. (e.g. Ben-Akiva and Lerman, 1985). In brief, the test can be defined as:

$$LR= -2(LL^R - LL^U)$$

where $L^R$ is the LL value of the restricted model (the one with fewer variables) and $L^U$ is the LL of the unrestricted model (the model that includes the extra variables). The resulting likelihood ratio (LR) statistic is asymptotically $\chi^2$-distributed and is compared with a critical value that depends on the degrees of freedom (difference in estimated parameters). If the LR statistic exceeds that threshold value, then the null hypothesis that both models perform equally is rejected.

It is worth mentioning that the latent variable model was not included in the LR analysis as the inclusion of latent variables is not expected to result in any improvement in the model fit. To better illustrate this, two different LL scores were calculated for the latent variable model (Table 6), including and excluding the contribution of the indicators to the final LL value. The results show that the LL of the speed model component only, is almost the same for both the random autoregressive-heteroskedastic and the latent variable model. This has been the case also in other studies that used similar latent variable specifications (Kløjgaard & Hess, 2014; Sanko et al., 2014). In brief, the inclusion of sensation-seeking in the model provides behavioural insights regarding its effect of speed without however further increasing model fit. Further details regarding this issue are provided by Vij & Walker (2016).

The results of the various likelihood ratio tests are presented in Table 5. In all cases, the null hypothesis is rejected at 99% level which implies that the newly added variables resulted in a significant improvement of goodness-of-fit. In particular, the improvement of model fit between the autoregressive (Model 2) and the random heterogeneity (Model 1) models implies a significant effect of past behaviour (i.e. mean speed at the previous tile) and correlation of disturbances across observations. This finding is expected given the time-series nature of the data and the short time distance between observation periods. The autoregressive model (Model 2) was then compared with the autoregressive-heteroskedastic (Model 3) model. The significant improvement that stemmed from the inclusion of the scale parameter in the standard deviation of the density function (see Eq. 14) is an indication of heteroskedasticity in the model residuals between urban and rural areas. Finally, the treatment of the autoregressive disturbance as a random parameter (Model 4) significantly improved model fit. This outcome suggests that residual correlation varies across individuals and should be considered to capture more accurately the dependency between the disturbance terms and hence obtain more accurate parameter estimate and standard errors.

**Table 5:** Likelihood ratio tests' results

| Models | LR | Degrees of freedom (df) | $\chi^2$(99%,df) | Null hypothesis |
|---|---|---|---|---|
| Model 2 vs Model 1 | 9660.28 | 3 | 11.34 | Rejected |
| Model 3 vs Model 2 | 125.32 | 1 | 6.63 | Rejected |
| Model 4 vs Model 3 | 454.42 | 1 | 6.63 | Rejected |

Based on the results presented this section, the random autoregressive-heteroskedastic was considered as the most preferred model for the analysis of speed choices. Thus, this model was re-estimated, including sensation-seeking via the process described in Sections 3.1.5 and 4.2, resulting in the latent variable model. The results of the latter were considered as the most representative and presented more detailed in Section 4.3.2.

4.3.2 Interpretation of parameter estimates

This section presents the interpretation of parameter estimates. Significance levels were examined with respect to the robust t-ratio values rather than the classical t-ratios. The rationale for this approach is explained in Section 4.4, where model validation is discussed.

Most of the parameter estimates were significant at the 0.05 level ($|\text{Robust t-ratio}| \geq 1.96$) and had expected signs. In particular, the parameter of the urban environment dummy variable had a strong negative effect on speed which is consistent with the speed limit decrease in those areas, compared to the rural roads. Also, the parameter of narrow lane yielded a negative impact on speed while segments with non-persistent risk were related to significant speed increase. The presence of oncoming traffic had a negative effect on speed however, this was not statistically significant.

The road radius and risk type parameters can be directly interpreted for the rural road environment based on the values in Table 6 however, this is not the case for the same parameters when they are related to the urban road areas, as they in fact represent the value of an additive shift to the respective parameters of the former (see Section 3.2). The actual values and significance of the latter parameter estimates were calculated via the Delta method and summarised in Table 7. The same table also includes all pairwise comparisons of radius and risk type parameters, together with the significance levels, as in the initial model estimation these values have been calculated with respect to a fixed reference category only.

On rural roads, the radius had a gradually higher negative effect as its value decreased. Based on the results of the Delta method (Table 7), the reduction of speed was always significant when a radius category was compared to the immediate smaller one (for instance 170m to 100m). The effect of road curvature for urban roads was also derived via the Delta method. More specifically, radius of 750m had a significant negative impact on speed, compared to straight road segments.

The interpretation of the lateral risk type parameters follows the same approach as the road radius case. In particular, on rural road areas, all risk types had a negative impact on speed, compared to the asphalt reference category. However, the parameters of grass and kerb were not significantly different from asphalt which may imply that drivers do not observe distinct differences for these three types of risk. On the other hand, the presence of hedge and lane blockage had a significantly negative impact on speed. It is worth mentioning that the lane blockage was related to an approximate decrease of 2m/s in speed, compared to asphalt condition. With respect to the urban environment, in areas with centre hatch speed was significantly higher, compared to kerb, however, cycle lane and lane blockage had a negative and significant impact compared to the latter. Moreover, the impact of the two aforementioned risk types was negative and significant also compared to centre hatch. Finally, areas with lane blockage resulted in significant speed decrease compared to areas with cycle lane.

Focusing on the non-road environment related parameters, a significant impact of the random heterogeneity term was found, which implies that apart from road and traffic characteristics,

**Table 6:** Parameter estimates of all speed choice models

| | Model1 Random heterogeneity model | | | Model2 Autoregressive model | | | Model3 Autoregressive-heteroskedastic model | | | Model 4 Random autoregressive-heteroskedastic model | | | Model 5 Latent variable model | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Estimate | t-ratio | Rob. t-ratio | Estimate | t-ratio | Rob. t-ratio | Estimate | t-ratio | Rob. t-ratio | Estimate | t-ratio | Rob. t-ratio | Estimate | t-ratio | Rob. t-ratio |
| Initial observation speed | - | - | - | 0.1093 | 12.91 | 7.80 | 0.1016 | 11.56 | 6.85 | 0.0938 | 9.60 | 4.18 | 0.0987 | 14.04 | 6.28 |
| Intercept | 25.234 | 161.69 | 203.08 | 11.1423 | 37.24 | 16.52 | 11.4038 | 48.07 | 30.70 | 12.7423 | 53.35 | 29.26 | 12.7303 | 122.27 | 45.30 |
| Transition area dummy | 0.637 | 4.53 | 3.89 | 0.0858 | 0.92 | 0.75 | 0.0841 | 1.04 | 0.79 | 0.2101 | 2.76 | 2.17 | 0.2087 | 2.75 | 2.31 |
| Urban road dummy | -4.1896 | -28.58 | -8.87 | -2.5446 | -23.06 | -9.52 | -2.5469 | -23.84 | -9.97 | -2.831 | -26.61 | -12.27 | -2.8202 | -26.75 | -13.20 |
| Narrow lane dummy | -0.5395 | -8.54 | -5.33 | -0.2536 | -4.64 | -4.43 | -0.248 | -4.36 | -4.65 | -0.2818 | -5.00 | -4.73 | -0.2802 | -4.94 | -4.13 |
| Radius 1: 252m | -2.3943 | -19.42 | -12.25 | -2.388 | -24.59 | -14.85 | -2.3573 | -23.15 | -14.18 | -2.3038 | -22.87 | -13.27 | -2.3 | -22.24 | -10.66 |
| Radius 2: 170m | -3.6828 | -56.16 | -18.96 | -3.1304 | -66.24 | -17.52 | -3.1099 | -63.59 | -17.19 | -3.0637 | -62.73 | -16.43 | -3.0585 | -61.43 | -14.82 |
| Radius 3: 100m | -5.7495 | -60.38 | -23.55 | -3.9898 | -53.92 | -19.37 | -3.9687 | -51.27 | -19.83 | -3.9657 | -52.14 | -20.41 | -3.964 | -52.04 | -20.10 |
| Radius urban dummy (750m) | 1.9963 | 12.79 | 10.56 | 1.8669 | 16.37 | 12.49 | 1.84 | 16.23 | 11.85 | 1.7737 | 16.06 | 11.06 | 1.7718 | 15.80 | 9.09 |
| Right curve dummy | 0.1316 | 2.25 | 2.46 | 0.1771 | 4.11 | 4.07 | 0.1689 | 3.92 | 3.88 | 0.1661 | 4.01 | 3.78 | 0.1657 | 4.01 | 3.82 |
| Risk 1 grass - rural | -0.3419 | -3.14 | -3.89 | -0.1037 | -1.25 | -1.73 | -0.1061 | -1.23 | -1.62 | -0.2008 | -2.33 | -2.25 | -0.1991 | -2.13 | -1.22 |
| Risk 2 kerb - rural | -0.1613 | -1.68 | -1.95 | -0.1774 | -2.39 | -3.10 | -0.1704 | -2.19 | -2.72 | -0.2119 | -2.71 | -2.50 | -0.2114 | -2.37 | -1.28 |
| Risk 3 hedge - rural | -0.8344 | -8.73 | -8.94 | -0.6621 | -9.13 | -8.34 | -0.6418 | -8.42 | -8.00 | -0.6703 | -8.77 | -6.68 | -0.6669 | -7.53 | -3.66 |
| Risk 4 blockage - rural | -2.524 | -19.66 | -11.44 | -1.9069 | -19.83 | -9.41 | -1.896 | -18.99 | -9.87 | -1.9229 | -19.45 | -9.25 | -1.9228 | -17.46 | -7.43 |
| Risk 1 kerb - urban | -1.0725 | -6.36 | -5.26 | -0.9904 | -8.45 | -5.73 | -0.9726 | -8.65 | -5.50 | -0.898 | -8.32 | -4.72 | -0.9007 | -8.25 | -4.23 |
| Risk 2 centre hatch - urban | -1.1284 | -5.01 | -5.16 | -0.4779 | -3.15 | -2.32 | -0.4933 | -3.60 | -2.43 | -0.5029 | -3.90 | -2.33 | -0.507 | -3.96 | -2.49 |
| Risk 3 cycle lane - urban | -0.8627 | -5.05 | -3.66 | -0.7239 | -6.31 | -3.54 | -0.736 | -6.87 | -3.64 | -0.723 | -7.13 | -3.50 | -0.7295 | -7.19 | -3.60 |
| Mid area dummy | 0.1979 | 3.21 | 2.47 | 0.2134 | 4.15 | 4.36 | 0.2028 | 3.97 | 4.28 | 0.1529 | 3.06 | 2.73 | 0.1485 | 2.94 | 2.36 |
| Oncoming traffic dummy | -0.5957 | -12.50 | -2.31 | -0.0364 | -0.77 | -0.34 | -0.0274 | -0.57 | -0.26 | -0.1596 | -3.09 | -1.31 | -0.1508 | -3.15 | -1.35 |
| Previous tile speed | - | - | - | 0.4953 | 51.83 | 20.79 | 0.4905 | 55.43 | 28.08 | 0.444 | 44.13 | 18.56 | 0.4427 | 55.82 | 19.04 |
| $\alpha$ | -1.7067 | -35.53 | -25.96 | -0.818 | -7.35 | -5.87 | -0.8575 | -9.27 | -10.03 | -1.068 | -7.69 | -4.16 | -0.8286 | -18.66 | -8.14 |
| $\rho$ | - | - | - | 0.2307 | 15.56 | 8.09 | 0.2559 | 17.75 | 7.65 | - | - | - | - | - | - |
| $\sigma$ | 2.5331 | 161.30 | 19.47 | 1.7527 | 161.31 | 22.32 | 1.8299 | 133.77 | 20.86 | 1.8136 | 134.66 | 20.91 | 1.813 | 135.55 | 21.17 |
| $\sigma^{urb}$ | - | - | - | - | - | - | 0.8323 | -12.59(1) | -3.76(1) | 0.7941 | -16.55 | -5.54 | 0.7949 | -16.86 | -5.71 |
| Sensation-seeking | - | - | - | - | - | - | - | - | - | - | - | - | 0.2354 | 8.98 | 10.88 |
| $\rho^{\mu}$ | - | - | - | - | - | - | - | - | - | 0.2539 | 8.47 | 8.14 | 0.3081 | 16.66 | 9.10 |
| $\rho^{\sigma}$ | - | - | - | - | - | - | - | - | - | 0.1867 | 12.79 | 14.20 | 0.1703 | 17.92 | 12.38 |
| LL - overall | -30731.94 | | | -25901.8 | | | -25839.14 | | | -25611.93 | | | -25873.62 | | |
| LL - speed component | -30731.94 | | | -25901.8 | | | -25839.14 | | | -25611.93 | | | -25610.59 | | |

speed choice is also influenced by unobserved individual heterogeneity. To this, it should be also added the significant impact of the sensation-seeking latent variable that indicates a positive correlation with speed choice; increased sensation-seeking is related to driving at higher speeds. This finding suggests that psychological traits may be able to provide insights with respect to observed driving behaviour in a modelling context that can be also extended to future autonomous vehicle controller preferences. Some potential implications of this outcome are discussed in the Conclusion section. Moreover, it should be mentioned that the parameter estimates of the measurement model (Table A.3), had expected positive signs and almost all of them significant at the 0.05 level (apart from item 5). This finding supports the use of the items presented in Section 4.2 as indicators of sensation-seeking.

Regarding the dynamic aspect of the model, the parameter of lagged speed had a positive impact which shows a correlation between past and current speed observation. Moreover, both the mean and the variance of the autoregressive disturbance were statistically significant which shows that i) the observations were serially correlated and ii) the level of serial correlation varies across individuals.

**Table 7:** Pairwise parameter comparisons and significance levels

| | | Risk0 rural | Risk1 rural | Risk2 rural | Risk3 rural | Risk4 rural |
|---|---|---|---|---|---|---|
| Risk 0 asphalt rural | Estimate | 0 | | | | |
| | Rob. t-ratio | - | | | | |
| Risk 1 grass rural | Estimate | -0.1991 | 0 | | | |
| | Rob. t-ratio | -1.22 | - | | | |
| Risk 2 kerb rural | Estimate | -0.2114 | -0.0124 | 0 | | |
| | Rob. t-ratio | -1.28 | -0.29 | - | | |
| Risk 3 hedge rural | Estimate | -0.6669 | -0.4678 | -0.4555 | 0 | |
| | Rob. t-ratio | -3.66 | -6.34 | -9.26 | - | |
| Risk 4 blockage rural | Estimate | -1.9228 | -1.7237 | -1.7113 | -1.2559 | 0 |
| | Rob. t-ratio | -7.43 | -7.70 | -8.28 | -6.39 | - |
| | | Risk1 urban | Risk2 urban | Risk3 urban | Risk4 urban | |
| Risk 1 kerb urban | Estimate | 0 | | | | |
| | Rob. t-ratio | - | | | | |
| Risk 2 centre hatch urban | Estimate | 0.3813 | 0 | | | |
| | Rob. t-ratio | 3.27 | - | | | |
| Risk 3 cycle lane hatch urban | Estimate | -0.2966 | -0.6779 | 0 | | |
| | Rob. t-ratio | -5.05 | -5.68 | - | | |
| Risk 4 blockage urban | Estimate | -0.823 | -1.2043 | -0.5264 | 0 | |
| | Rob. t-ratio | -7.14 | -6.97 | -4.18 | - | |
| | | Radius0 rural | Radius1 rural | Radius2 rural | Radius3 rural | |
| Radius 0 Straight rural | Estimate | 0 | | | | |
| | Rob. t-ratio | - | | | | |
| Radius 1 252m rural | Estimate | -2.3 | 0 | | | |
| | Rob. t-ratio | -10.66 | - | | | |
| Radius 2 170m rural | Estimate | -3.0585 | -0.7586 | 0 | | |
| | Rob. t-ratio | -14.82 | -8.03 | - | | |
| Radius 3 100m rural | Estimate | -3.964 | -1.664 | -0.9054 | 0 | |
| | Rob. t-ratio | -20.10 | -12.49 | -9.00 | - | |
| | | Radius0 urban | Radius1 urban | | | |
| Radius 0 Straight urban | Rob. t-ratio | 0 | | | | |
| | Estimate | - | | | | |
| Radius 1 750m urban | Rob. t-ratio | -0.5281 | 0 | | | |
| | Rob. t-ratio | -6.00 | - | | | |

4.4 Model validation

The assumption regarding the disturbance term of the speed model is that it is independent and identically normally distributed with a zero mean. Within an effort to ensure that these assumptions were met, the disturbance structure was decomposed introducing heterogeneity across individuals, autoregressive and heteroscedastic disturbance which all had a significant effect. Although the assumption of normality is not essential to be tested in mixed effects models (Gelman & Hill, 2006), heteroscedasticity needs to be considered as it may lead to inconsistent standard errors and thus significance levels of parameters.

The model specification included a series of random parameters that lead to the estimation of respective distributions. Thus, individual-level values were calculated from each distribution as described in Section 3.3. Residuals were then calculated as in Thai et al. (2013) as the difference between observed and fitted values. Heteroskedasticity was already considered in the model specification via the introduction of different variances of the i.i.d. disturbance for rural and urban environments that showed a significance difference between the two cases. Although the results in Table 6 did not always show large changes in the standard errors after the introduction of the scale term (as specified in Section 3.1.3), it was retained in the model specification as it significantly improved the overall model fit. The issue of heteroscedasticity was further investigated visually for these two road type cases, by plotting fitted values vs standardised residuals of the models (Figure 2). As shown in Figure 2 there is some indication of unequal spread of residuals across the fitted values and potentially heteroskedasticity. To that end, significance levels of parameters in all models were considered based on the robust (sandwich) standard errors (Freedman, 2006) that can also account for the effect of the panel nature of the data (Daly & Hess, 2010).

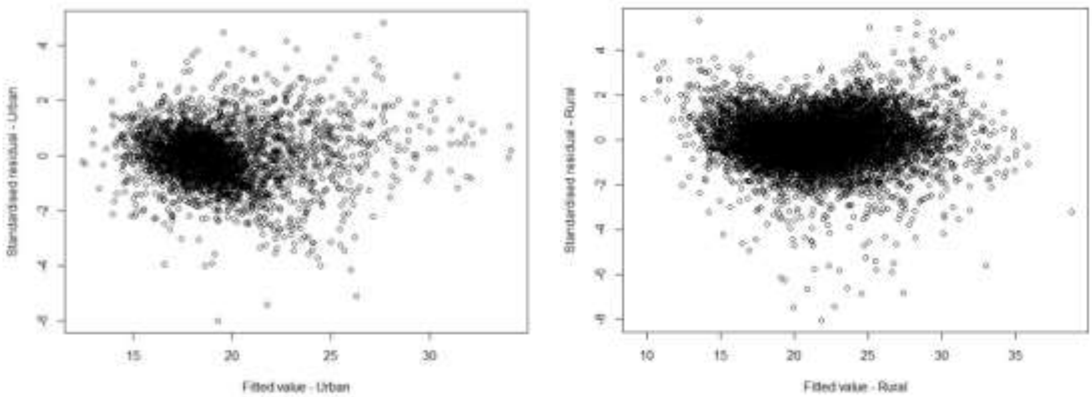


**Figure 2:** Standardised residuals vs fitted values plots

## 5. Conclusion

The results presented in this paper were a part of a comprehensive study that aims in investigating drivers' comfort within the context of autonomous vehicles. The development of human-like autonomous vehicle controllers, in terms of longitudinal and latitudinal behaviour, could increase drivers' comfort levels and consequently their trust, acceptance and intention to use. The current approach focused on deriving indications about comfort related to speed via the observation of driving behaviour in a driving simulator environment. Speed choices were investigated in various contexts, including different road types, road geometry, lateral risk context, and oncoming traffic. Moreover, sensation-seeking was considered as a factor that explains observed speed choice behaviour. The analysis included the development of a series of models, where speed was treated as the response variable, while different levels of heterogeneity and correlation were gradually included in order to obtain more insights regarding their effects. Every new model was compared with the previous via the likelihood ration test to investigate improvements of model fit. Model fit could be further improved via the introduction of more random parameters in the explanatory variables, and also allowing for the correlation among them. However, owing to specification complexity and computational cost, we decided to account for random heterogeneity only in the disturbance terms of the model, and no more random parameters were considered. This approach is possibly significantly limiting the capability of the model to capture unobserved heterogeneity and reducing the overall fit, however, in terms of model interpretation, the fixed parameters are still showing significance, and are consistent with expected results that provide useful insights.

With respect to the main findings, road environment had, as expected, a negative impact on speed, given that speed limit is lower in urban areas. Moreover, a significant impact of road radius was found; decrease of radius resulted in speed reduction in both rural and urban road environments. Also, narrower lanes had a negative impact on speed. Regarding the effects of lateral risk in rural roads, the negative effect of grass was very similar, and not significantly different from asphalt. However, the presence of hedge, and any type of partial lane blockage, resulted in gradual, and significant speed reduction. Similarly, in the urban environment, cycle lanes and partial lane blockage had the most negative, and significant, impact on speed. Finally, in areas where the lateral risk was not persistent (i.e. risk element covered only 20m out of the 250m of a tile), parameter estimates indicate a significant increase in speed, compared to the segments with persistent risk.

Given the panel nature of the data, the effects of several types of correlation and heterogeneity was considered, on top of the impact of the road environment. The results of the latent variable model (Model 5) suggested that there is a part of variance in speed that is related to unobserved drivers' characteristics. Moreover, average speed in the previous road segment and the autoregressive disturbance term also had a significant impact on speed. With respect to the latter, the introduction of a normally distributed autoregressive term improved model fit suggesting that time correlation varies across individuals. Finally, a part of the individual unobserved heterogeneity was explained via the sensation-seeking latent variable that had a significant and positive impact on speed. This finding implies that participants who determined themselves as higher sensation-seekers also drove faster in the driving simulator scenarios.

When summarising the findings of the current analysis, it becomes evident that comfort, as expressed through observed behaviour, is a function both of the road environment and individual preferences. This finding suggests that future autonomous vehicle controllers may need to adapt their behaviour based on the road context, in order to improve perceived comfort to the maximum feasible extent. Moreover, the significant impact of sensation-seeking and unobserved driver heterogeneity implies the potential need for personalised autonomous vehicle controllers in order to match vehicle behaviour with the preferences of the end user. For instance, high sensation-seekers may prefer or feel comfortable when using faster controllers, compared to other users. This approach is in line with findings in the existing relevant literature that show a preference of drivers for autonomous driving styles similar or close to what they perceive as their own (Basu et al., 2016; Hartwich et al., 2018; Yusof et al., 2016). However, the feasibility, practicality and necessity of the latter, together with its implications on the road networks, is yet to be investigated in future research.

Despite the promising and significant results, the driving simulator nature of the data needs to be considered before deriving any outcomes as secure and robust, as there might be fundamental incongruence in behaviour, compared to the real world. Some steps towards the future validation of the outcomes involve the development of dynamic driving simulator scenarios, with higher variance in the road environment and risk levels, and also the comparison of driving behaviour between a driving simulator and the real road. Another aspect that can be investigated is evaluation of the performance of autonomous vehicles with controllers developed as variants of the driving behaviour observed in the current study. These issues have since been investigated in the HumanDrive project, and will hopefully provide valuable insights, and a better understanding of users' preferences, that could assist the automotive industry in the design of autonomous vehicles in the future.

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**Declaration of interest**
None

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# Appendix

**Table A.1:** The original AISS decomposition

| | |
|---|---|
| Novelty subscale | |
| 1 | I can see how it would be interesting to marry someone from a foreign country. |
| 3 | If I have to wait in a long line, I'm usually patient about it.(-) |
| 5 | When taking a trip, I think it is best to make as few plans as possible and just take it as it comes. |
| 7 | I think it's fun and exciting to perform or speak before a group. |
| 9 | I would like to travel to places that are strange and far away. |
| 11 | I would have enjoyed being one of the first explorers of an unknown land. |
| 13 | I don't like extremely hot and spicy foods. (-) |
| 15 | I often like to have the radio or TV on while I'm doing something else, such as reading or cleaning up. |
| 17 | I think it's best to order something familiar when eating in a restaurant. (-) |
| 19 | If it were possible to visit another planet or the moon for free, I would be among the first in line to sign up. |
| Intensity subscale | |
| 2 | When the water is very cold, I prefer not to swim even if it is a hot day. (-) |
| 4 | When I listen to music, I like it to be loud. |
| 6 | I stay away from movies that are said to be frightening or highly suspenseful. (-) |
| 8 | If I were to go to an amusement park, I would prefer to ride the rollercoaster or other fast rides. |
| 10 | I would never like to gamble with money, even if I could afford it.(-) |
| 12 | I like a movie where there are a lot of explosions and car chases. |
| 14 | In general, I work better when I'm under pressure. |
| 16 | It would be interesting to see a car accident happen. |
| 18 | I like the feeling of standing next to the edge on a high place and looking down. |
| 20 | I can see how it must be exciting to be in a battle during a war. |

*[Source: Arnett, 1994]*

**Table A.2:** Rotated Component Matrix of 2-factor EFA solution

| | Factor | |
|---|---|---|
| | 1 | 2 |
| I can see how it would be interesting to marry someone from a foreign country | 0.522 | -0.609 |
| When the water is very cold, I prefer not to swim even if it is a hot day | | |
| If I have to wait in a long line, I'm usually patient about it | | 0.617 |
| When I listen to music, I like it to be loud | | |
| When taking a trip, I think it is best to make as few plans as possible and just take it as it comes | | 0.607 |
| I stay away from movies that are said to be frightening or highly suspenseful | | |
| I think it's fun and exciting to perform or speak before a group | 0.594 | |
| If I were to go to an amusement park, I would prefer to ride the rollercoaster or other fast rides | 0.637 | |
| I would like to travel to places that are strange and far away | 0.751 | |
| I would never like to gamble with money, even if I could afford it | | |
| I would have enjoyed being one of the first explorers of an unknown land | 0.722 | |
| I like a movie where there are a lot of explosions and car chases | | |
| I don't like extremely hot and spicy foods | | |
| In general, I work better when I'm under pressure | | |
| I often like to have the radio or TV on while I'm doing something else, such as reading or cleaning up | | |
| It would be interesting to see a car accident happen | 0.594 | |
| I think it's best to order something familiar when eating in a restaurant | | |
| I like the feeling of standing next to the edge on a high place and looking down. | 0.629 | |
| If it were possible to visit another planet or the moon for free, I would be among the first in line to sign up | 0.762 | |
| I can see how it must be exciting to be in a battle during a war | 0.685 | |

**Table A.3:** Measurement equations estimates with random autoregressive disturbance

| | Estimate | t-ratio | Rob. t-ratio |
|---|---|---|---|
| *Impact of the latent variable* | | | |
| $\zeta_1$ | 0.9259 | 2.34 | 2.13 |
| $\zeta_2$ | 1.0439 | 2.53 | 2.41 |
| $\zeta_3$ | 1.1361 | 2.81 | 2.92 |
| $\zeta_4$ | 1.9595 | 2.99 | 3.88 |
| $\zeta_5$ | 0.5687 | 1.60 | 1.58 |
| $\zeta_6$ | 1.3674 | 2.63 | 2.97 |
| $\zeta_7$ | 2.4207 | 2.41 | 2.31 |
| | | | |
| *Thresholds estimates* | | | |
| $\tau_{1,1}$ | -3.4933 | -3.84 | -3.72 |
| $\tau_{1,2}$ | -1.9509 | -3.35 | -4.40 |
| $\tau_{1,3}$ | 0.5272 | 1.29 | 1.23 |
| $\tau_{2,1}$ | -1.1107 | -2.30 | -2.26 |
| $\tau_{2,2}$ | 0.6145 | 1.43 | 1.49 |
| $\tau_{2,3}$ | 1.7339 | 3.33 | 3.42 |
| $\tau_{3,1}$ | -2.5976 | -3.79 | -3.41 |
| $\tau_{3,2}$ | -0.4041 | -0.90 | -0.99 |
| $\tau_{3,3}$ | 0.4588 | 1.04 | 1.12 |
| $\tau_{4,1}$ | -5.0969 | -3.45 | -4.97 |
| $\tau_{4,2}$ | -2.2326 | -2.96 | -3.44 |
| $\tau_{4,3}$ | 0.8044 | 1.39 | 1.53 |
| $\tau_{5,1}$ | -0.1417 | -0.38 | -0.36 |
| $\tau_{5,2}$ | 0.9691 | 2.35 | 2.46 |
| $\tau_{5,3}$ | 3.5912 | 3.48 | 3.45 |
| $\tau_{6,1}$ | -0.5224 | -1.11 | -1.09 |
| $\tau_{6,2}$ | 1.2440 | 2.34 | 2.55 |
| $\tau_{6,3}$ | 2.8512 | 3.72 | 3.72 |
| $\tau_{7,1}$ | -5.2138 | -2.59 | -2.76 |
| $\tau_{7,2}$ | -1.9145 | -2.11 | -2.28 |
| $\tau_{7,3}$ | 1.6997 | 2.32 | 2.24 |