

Who overtakes more? Explanatory analysis of the characteristics of drivers from low/middle and high-income countries on passing frequency

*Original*

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1 **Who overtakes more? Explanatory analysis of the characteristics of**  
2 **drivers from low/middle and high-income countries on passing**  
3 **frequency**

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7 **Karimi<sup>a</sup>, A., Boroujerdian, A.M., Catani<sup>b</sup>, L., Bassani<sup>\*,b</sup>, M.**

8 (<sup>a</sup>) Department of Civil and Environmental Engineering, Tarbiat Modares University, Tehran, Iran

9 (<sup>b</sup>) Department of Environment, Land and Infrastructure Engineering, Politecnico di Torino, Torino, Italy

10 (\*) Corresponding author

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12

13 Arastoo Karimi: E-mail: [arastookarimi@modares.ac.ir](mailto:arastookarimi@modares.ac.ir)

14 Amin Mirza Boroujerdian: E-mail: [boroujerdian@modares.ac.ir](mailto:boroujerdian@modares.ac.ir)

15 Lorenzo Catani: E-mail: [lorenzo.catani@polito.it](mailto:lorenzo.catani@polito.it)

16 Marco Bassani: +39 011 090 5635, +39 335 13 00 230 E-mail: [marco.bassani@polito.it](mailto:marco.bassani@polito.it)

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22 **Abstract**

23 The passing manoeuvre requires a driver to make decisions and take actions which are dependent  
24 on his/her behavioural characteristics and driving ability. However, previous works on passing rate  
25 models have exclusively considered geometric and traffic-related variables. This study aims at  
26 bridging this gap by investigating the influence of driver profile (i.e., age, gender, nationality -  
27 Italian or Iranian - aggressive driving scores, driving exposure) on passing frequency. A driving  
28 simulation experiment involving 54 drivers (36 Italians, 18 Iranians) was conducted along a  
29 6.67 km segment of a two-lane rural highway with passing manoeuvres permitted along 25% of  
30 its length. Controlled factors included traffic flow and speed in the oncoming direction, and speed  
31 in the driver direction, with a total of 27 scenarios assigned to drivers based on a 3<sup>3</sup> confounded  
32 factorial design. A Poisson regression model was used to investigate the significance of  
33 independent variables. Age and gender and their interaction term were significant, thus the effects  
34 of age and gender on the number of passing manoeuvres are mutually interdependent. Furthermore,  
35 drivers who drive less often completed fewer overtaking manoeuvres. Sensitivity analyses were  
36 carried out to understand the magnitude of change in passing frequency attributable to a variation  
37 in the explanatory variables. The findings suggest that driver characteristics have a significant  
38 effect on passing frequency and should be considered when conducting a performance and safety  
39 evaluation of two-lane roads.

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41

42 **Keywords:** driver behaviour; passing manoeuvre; aggressive behaviour scale; passing frequency;  
43 two-lane rural highway.

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45

46 **1. INTRODUCTION**

47 Along two-lane highways, drivers seeking to maintain their desired speed are only permitted to  
48 overtake slower vehicles along designated passing zones. Although the extension of passing zones  
49 may effectively increase average speed and reduce the percentage of total travel time spent  
50 following slower vehicles (HCM, 2016), the number of actual passing manoeuvres strongly  
51 depends on the propensity and desire of faster drivers to overtake slower ones (Farah, 2011). A  
52 passing manoeuvre is risky because it exposes drivers to dangerous interactions with oncoming  
53 vehicles and, to a lesser extent, with those proceeding in the same direction. It requires decisions  
54 and driving actions which are dependent on the behavioural characteristics and the driving ability  
55 of the individuals behind the wheel. A considerable number of works have been developed on  
56 passing rate models, all of which have focused exclusively on geometric and traffic-related  
57 variables.

58 In his pioneering work, Wardrop (1952) developed a theoretical model to estimate passing  
59 demand from the speed distribution while assuming ideal conditions with no oncoming traffic and  
60 no passing sight limitations. Other authors followed the theoretical approach while including other  
61 traffic-related factors like the traffic flow in both directions (Daganzo, 1975), traffic and sight  
62 distance limitations (McLean, 1989), speed, and density of vehicle distributions in traffic  
63 (Dommerholt & Botma, 1988).

64 Other studies focused on the regression analysis of field data to increase the predictability  
65 of passing demand. While earlier observational studies only included a limited number of field  
66 factors, recent contributions have included a larger number of regressors. Tuovinen and Enberg  
67 (2006) used only one-way traffic flows in a series of linear regression models to interpret the  
68 passing rates along individual road segments. Hegeman (2008) used a multivariate linear  
69 regression model separating the traffic flow in the subject direction from that in the opposing lane,  
70 with field data coming from segments where the passing manoeuvre was prohibited alternately in  
71 the two directions to improve safety (Wegman, et al., 2008).

72 More recently, statistical models have also been proposed. Moreno, et al. (2013) developed  
73 a Poisson regression model to estimate the passing frequency for a 15-minute period in the subject  
74 direction combining geometric and traffic-related factors (more specifically, the length of the  
75 passing zone, the two-way traffic volume and the directional split in the subject direction). Later  
76 on, Mwesige, et al. (2016) included some other predictors to develop a passing rate per hour model

77 (i.e., the absolute vertical grade, the 85<sup>th</sup> percentile speed, and the percentage of heavy vehicles).  
78 In addition to the variables considered in the abovementioned studies, Karimi, Boroujerdian, et al.  
79 (2020) used the lane width and the proportion of motorcycles as variables in the passing rate model  
80 they developed. The model included geometric and traffic-related variables and did not consider  
81 any driver characteristic variables.

82 Farah (2011) conducted an ANOVA to compare the average passing frequency between  
83 age and gender groups. Male participants conducted significantly more passing manoeuvres than  
84 females, with no significant differences being observed between the passing frequencies of the  
85 younger group (i.e., under 30 years old) and those of the older group (i.e., over 30 years old). The  
86 interaction term between age and gender was also not significant.

87 Studies on gap-acceptance behaviour reveal the probable effects of driver characteristics  
88 on passing frequency. In fact, by increasing the probability of accepting smaller gaps, an increment  
89 in passing frequency may be reasonably expected. Farah, et al. (2009) developed a logit model to  
90 evaluate the effects of variables on the probability that a driver may accept a certain gap. They  
91 found that driver characteristics like age, gender, and driving exposure were significant.  
92 Conversely, the driving style of the drivers investigated via questionnaires (e.g., angry and hostile,  
93 anxious, reckless, and/or careless) did not prove to be significant. In a recent simulation study,  
94 Toledo and Farah (2011) evaluated the effects of driver characteristics (i.e., age and gender) on  
95 gap acceptance behaviour. The conclusion was that gender resulted as being not significant. Of  
96 relevant interest is the work of Hassenin, et al. (2017) based on field data collected by instrumented  
97 vehicles. In the proposed gap acceptance behaviour model, driver characteristics like age and  
98 experience were found to be significant, thus confirming the evidence previously observed in  
99 simulated conditions. Finally, in the simulator study of Leung and Starmer (2005) the effect of  
100 blood alcohol concentration on gap-acceptance results was not significant for both young (18-21  
101 years) and more mature drivers (25-35 years).

102 To address the limitations of earlier studies related to a prediction of the number of passing  
103 manoeuvres, the main goal of this study was to investigate the effects of driver characteristics, age,  
104 gender, level of self-reported aggressive driving scores, driving exposure, and nationality (Italian  
105 or Iranian) on the passing frequency along a two-lane rural highway. Hence, a predictive model  
106 for passing frequency (i.e., the number of passing manoeuvres per kilometre per driver) was  
107 developed with the aim of calculating the marginal effects of each variable. The model was

108 calibrated on experimental data from a validated driving simulation with drivers coming from  
109 low/middle (Iran) and high-income (Italy) countries.

110

## 111 **2. METHODOLOGY**

### 112 **2.1 Design**

113 The dependent variable investigated in this study was the number of passing manoeuvres that a  
114 participant conducted along the test track in a given scenario ( $N_p$ ). Scenarios were based on three  
115 explanatory variables: (i) traffic flow rate in the opposing direction ( $V_O$ ), (ii) speed of traffic flow  
116 in the subject direction ( $S_S$ ), and (iii) speed of opposing traffic flow ( $S_O$ ).

117 Other explanatory variables related to driver characteristics include age ( $Age$ ) and gender  
118 ( $G$ , Male = 1, Female = 0) which are both expected to influence the passing frequency as they had  
119 significant effects in other passing behaviour studies (Farah, et al., 2009; Farah, et al., 2007; Llorca,  
120 et al., 2013; Toledo & Farah, 2011). Since overtaking is a complicated manoeuvre, it is expected  
121 that drivers with more driving experience will overtake more. Driving exposure ( $KM$ ) was,  
122 therefore, considered a dummy variable (Drives < 1000 km/year, if yes  $KM = 1$ , otherwise 0).  
123 Since participants were from two countries with one being a low/middle income country and the  
124 other being a high income one, nationality could have a significant effect. WHO (2018) reported  
125 that the risk of having a fatal accident is more than three times higher in low income countries than  
126 in high income countries. Hence, nationality ( $NAL$ , Iranian = 1, Italian = 0) was used as an  
127 explanatory variable to reflect the differences in driving behaviour due to cultural factors.  
128 Furthermore, as more aggressive drivers are much more likely to engage in more dangerous  
129 manoeuvres such as overtaking, the Aggressive Driving Behaviour Scale ( $ADBS$ ) was included as  
130 a variable.

131 The validated fixed-base driving simulator at the Politecnico di Torino (Bassani *et al.*,  
132 2018), the characteristics of which are synthesized in Table 1, was used in the experiments. A  
133 validation study for the simulator regarding overtaking behaviours along two-lane highways was  
134 conducted by Karimi, Bassani, et al. (2020). The authors found statistically similar behaviours in  
135 the simulator and real environments through different passing variables, achieving both relative  
136 and absolute validation.

137

138

139 **Table 1. Characteristics of the fixed-base driving simulator.**

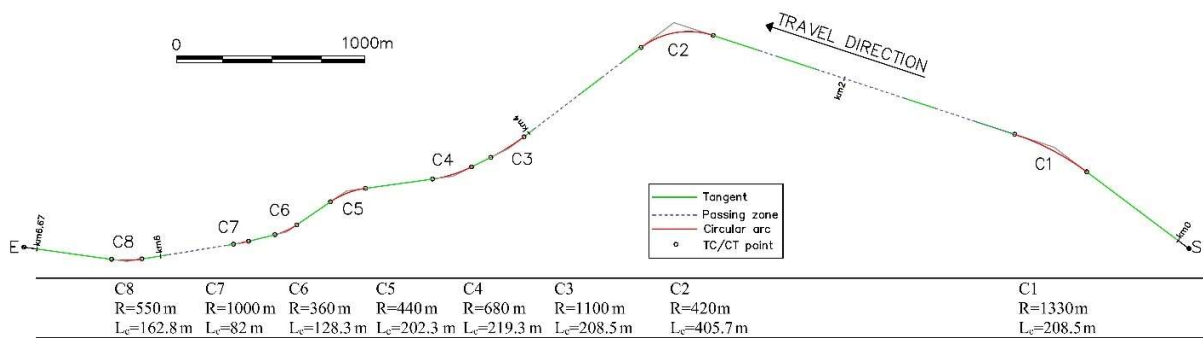
<b>CPU, video card, RAM memory</b>	Quad-core, NVIDIA GeForce® GTX 780 Ti, 8 Gb.
<b>Monitor</b>	Three 32-inch full HD (cover 130° of driver field of view).
<b>Cockpit</b>	Car seat, steering wheel, manual gearbox, pedals, and dashboard.
<b>Vehicle and road interaction</b>	Steering wheel returns active force feedback to the driver, simulating wheels' rolling, pavement roughness, and shocks. Vibration pads return vehicle vibrations to seat and pedals.
<b>Software (SCANeR™studio)</b>	Design tracks, manage the vehicle parameters, generate the experimental scenarios, run the simulations, collect and extract data.

140

141 In this experiment, the test track (6.67 km long, maximum absolute vertical gradient of  
 142 2.54%) was modelled from an existing flat road segment. There were passing zones along 25% of  
 143 the test track length with a discontinuous lane-marking, while other segments used a continuous  
 144 centreline marking (no-passing zones). The posted speed limit was 85 km/h which was displayed  
 145 by a traffic sign at the beginning of the road. Figure 1 shows the length and location of passing  
 146 zones along the test track.

147 Three factors including  $V_O$ ,  $S_S$ , and  $S_O$  were considered in the experimental design. Table  
 148 2 shows the three levels of factors. Three Gamma distributions with parameters of ( $\alpha=0.844$ ,  
 149  $\beta=12.956$ ), ( $\alpha=0.814$ ,  $\beta=19.405$ ), and ( $\alpha=1.146$ ,  $\beta=24.591$ ) were used to generate the headways  
 150 between the vehicles for the three levels of the traffic flow rate of -1, 0, and 1 in the opposing  
 151 direction, respectively. The traffic flow in the driver direction was assumed to be constant and was  
 152 generated by an exponential distribution with a parameter of  $\lambda = 13.094$  that truncated from 5 to  
 153 20 s intervals. The 15<sup>th</sup>, 50<sup>th</sup> and 85<sup>th</sup> percentiles of speeds of oncoming vehicles and the passed  
 154 vehicles (in the observed passing manoeuvres) from the field data used three levels of  $S_O$  and  $S_S$ .  
 155 Based on the decision that each participant should complete three scenarios, a 3<sup>3</sup> confounded  
 156 factorial design was applied (Wilkie, 1961). Hence, the 27 scenarios with 6 replications implied  
 157 the involvement of 54 drivers.

158



159  
160 **Figure 1: The distribution of passing zones along the test track (TC = tangent to curve, CT = curve**  
161 **to tangent)**  
162

163 **Table 2: Factors included in the experimental design.**

Factors	Levels		
	-1	0	1
Traffic flow rate in the opposing direction	128 veh/h	268 veh/h	332 veh/h
Speed of traffic flow in the subject direction	48.5 km/h	68.5 km/h	77.6 km/h
Speed of traffic flow in the opposing direction	65.2 km/h	81.5 km/h	96.4 km/h

164  
165 **2.2 Participants**  
166 The fifty-four licensed, volunteer drivers involved in the experiment adhered to the Code of Ethics  
167 of the World Medical Association (Williams, 2008). Italian participants were recruited by sending  
168 emails to those people who had participated in a previous simulation test. Those invited to  
169 participate were then randomly selected from the list of all possible candidates. Iranian participants  
170 were recruited through social media by posting a statement. All participants signed an informed  
171 consent form prior to the testing session.

172 Thirty-six Italians (22 males and 14 females) aged between 21 and 61 years old  
173 (M = 40.4 y, SD = 11.8 y), and eighteen Iranians (14 males and 4 females) aged between 23 and  
174 37 years old (M = 29.1 y, SD = 4.0 y) were involved. Since the experiment was conducted in Italy,  
175 Iranian drivers were chosen from among those who had recently arrived in Italy and had not yet  
176 driven in the country. Participants drove for more than 10 mins prior to the experiment to  
177 familiarize themselves with the simulator. In the experiment, each driver was involved in three  
178 randomly assigned scenarios out of the 27 designed for the study. One Iranian and one Italian out  
179 of fifty-four participants were unable to complete the experiment due to simulation sickness.

180

### 181 **2.3 Materials**

182 A pre-drive questionnaire was used to assess the physical condition and health of participants.  
183 Participant reaction times to visual and auditory stimuli were measured by means of an online  
184 platform (<http://www.cognitivefun.com/>) in order to check the levels of participant fatigue before  
185 and after the experiment was run. The fidelity of on-board devices and the simulator sickness issue  
186 were the focus of a post-drive questionnaire based on the method proposed in (Kennedy, et al.,  
187 1993). Finally, participants reported their aggressive driving behaviour using the aggressive  
188 driving questionnaire, which was designed by Houston, et al. (2003). The aggressive driving  
189 behaviour of participants was measured by an 11-item measure as per the Aggressive Driving  
190 Behaviour Scale (*ADBS*). The *ADBS* places emphasis on driver behaviour rather than their  
191 cognitive ability, emotions, or motivational states. Houston, et al. (2003) examined the reliability  
192 and validity of the *ADBS*, and they proposed it as a self-assessment instrument.

193

### 194 **2.4 Procedures**

195 The simulator experimental procedure included: (i) completion of the pre-drive questionnaire;  
196 (ii) performance of the pre-drive cognitive tests (visual and auditory); (iii) driving exposure in  
197 three scenarios with two-minute rest intervals; (iv) performance of the post-driving cognitive tests;  
198 and (v) completion of the post-drive and aggressive driving questionnaires. Before starting the  
199 simulation, participants were told to drive as they usually did in the real world and to pass slower  
200 vehicles if they wished to do so.

201

### 202 **2.5 Statistical analysis**

203 To predict the number of completed passing manoeuvres along the test track ( $N_P$ ) using traffic-  
204 and driver characteristic-related variables, the Poisson and the negative binomial regression  
205 models were considered. In fact, the number of passing manoeuvres is an integer, so the  
206 appropriate approach is based on count data regression models (Cameron & Trivedi, 2013). The  
207 Poisson regression model is one of the most popular methods for modelling count data. The  
208 number ( $N_{Pi}$ ) of completed passing manoeuvres along the test track in the run  $i$  of the simulator  
209 experiment is defined with the Poisson regression model as follows:

$$210 \quad \lambda_i = E[N_{Pi} | X_i] = \exp(\beta X_i) \quad (1)$$

211 where  $\lambda_i$  is the expected  $N_{Pi}$  for simulator run  $i$ ,  $X_i$  represents the vector of independent variables,  
212 and  $\beta$  denotes the vector of model parameters. The standard maximum likelihood method could be  
213 used to estimate the model parameters (Cameron & Trivedi, 2013).

214 The existence of overdispersion can be checked by testing the null hypothesis of  $\alpha = 0$   
215 through the likelihood ratio test, where  $\alpha$  is the overdispersion parameter. If  $\alpha$  is statistically  
216 nonzero, the Poisson regression is not suitable. The negative binomial regression model accounts  
217 for the overdispersion in the data. To assess the calibration of the selected model in this study, the  
218 Pearson goodness of fit test was used (Washington, et al., 2010).

219 The linear correlation between two variables measured by Pearson's correlation was used  
220 to understand the probable direction of effect between the dependent and explanatory variables,  
221 the probable significant variable, warning about multicollinearity, and possible interactions in the  
222 model. However, omitting an important variable from the model, which is known as  
223 misspecification, leads to bias in the model (Wooldridge, 2016).

224 To evaluate the overall significance of the model, the null hypothesis that all variable  
225 coefficients are concurrently equal to zero was tested using the Likelihood ratio test. The Pearson  
226 test was applied to determine whether the model statistically fits the data well. Also, the descriptive  
227 measures of Cragg-Uhler  $R^2$  (Cragg & Uhler, 1970) and McFadden's  $R^2$  (McFadden, 1973) were  
228 used to evaluate the goodness of fit (the closer the measures are to one, the better the model fits).  
229 To evaluate the effectiveness of variables, the Wald test was used to test the hypothesis that  $\beta_i = 0$   
230 against the alternative  $\beta_i \neq 0$  (Washington, et al., 2010).

231

### 232 3. RESULTS

233 The physical condition and health of participants was checked through the pre-drive questionnaire.  
234 The pre and post driving cognitive status of drivers were examined by the *t-test* for auditory  
235 (*p-value* = 0.839) and visual (*p-value* = 0.705) perception and reaction time which implied that  
236 there were no significant differences. The results obtained from the post-drive questionnaire  
237 showed that the most reported simulator ailments affecting participants were eyestrain and  
238 sweating. However, the effects of reported sickness were limited (very low for some drivers)  
239 except for two participants who failed to complete the experiment. The participants also reported  
240 their feedback on the devices: they found the on-board equipment (i.e., acceleration, pedal, and  
241 gearbox) similar to what they experienced in the real world. However, they were not completely

242 satisfied with the braking response. By removing the data of two participants who failed to  
243 complete the test, 156 observations were recorded from 52 participants and used in the analyses.

244

### 245 **3.1 Dataset characteristics**

246 Table 3 presents a summary of dependent and explanatory variables used to estimate the model.  
247 The range of completed passing manoeuvres along the test track was 0-10 passes with a mean of  
248 2.39 passes. The traffic-flow rate in the opposing direction and the speed of traffic flow in both  
249 subject and opposing directions were set at three levels and assigned to each scenario based on the  
250 design of the experiment. Participants reported values on the *ADBS* of between 12 and 46. The  
251 *ADBS* range reported by Italian and Iranian participants were 12-36 and 21-46, respectively.  
252 Around 13.4% of participants declared that they drove fewer than 1000 km/year.

253 Table 4 provides the Pearson's correlations among the dependent and explanatory  
254 variables. The values in the parentheses indicate the significance levels of the correlations. The  
255 traffic flow rate in the opposing direction ( $V_o$ ) and speed of traffic flow in the subject direction  
256 ( $S_s$ ) had significant correlations with the number of completed passing manoeuvres ( $N_p$ ) at the  
257 95% confidence level ( $p$ -values  $< 0.05$ ). Their negative correlations indicate that an increase in the  
258 oncoming traffic flow rate or in the speed of traffic flow in the subject direction results in a  
259 decrease in the number of passing manoeuvres.

260 No significant correlations were found between the number of passing manoeuvres and the  
261 age, gender, and nationality of participants ( $p$ -values  $> 0.05$ ). A statistically significant positive  
262 correlation was found between the number of passing manoeuvres and the aggressive driving  
263 behaviour scale (*ADBS*), which implied that drivers with higher *ADBS* values conducted more  
264 passing manoeuvres. The variable *KM* had a significant negative correlation at the 95% confidence  
265 level ( $p$ -values = 0.003), which indicates that participants who drive fewer than 1000 km per year  
266 completed fewer passing manoeuvres than those who drive more.

267 There were statistically significant negative correlations ( $p$ -values  $< 0.05$ ) between *ADBS*  
268 and the age, gender, and nationality of participants, which indicate that the younger participants,  
269 Iranians, and males reported more aggressive driving scores. The statistically significant  
270 correlation between nationality and age was because Iranian participants had a younger age range  
271 (i.e., 23-37 years old) than the Italian participants (21-61 years old). The significant negative  
272 correlation between *KM* and age implied that participants who drove fewer than 1000 km/year

273 were novice drivers. This is also explained by the fact that the younger participants were mostly  
 274 students, who generally drive less often than their non-student peers and also have a lower  
 275 incidence of car ownership.

276

277 **Table 3. Descriptive statistics of the dependent and explanatory variables**

Variable, Index [Unit]		Mean	Min.	Max.	SD
Number of completed passing manoeuvres along test track, $N_P$ [#]	total	2.39	0	10	2.44
	Italians	2.36	0	10	2.50
	Iranians	2.45	0	10	2.33
Age of Participant, $Age$ [years]	total	36.8	21	61	11.2
	Italians	40.3	21	61	11.9
	Iranians	29.7	23	37	3.8
Aggressive driving behaviour scale, $ADBS$ [-]	total	24.42	12	46	6.59
	Italians	21.83	12	36	5.05
	Iranians	29.77	21	46	6.17
Drives < 1000 km/year (Yes=1, NO=0), $KM$ [-]		0.13			
Gender (Male = 1, Female = 0), $G$ [-]		0.67			
Nationality (Iranian = 1, Italian = 0), $NAL$ [-]		0.33			

278

279 **Table 4. Pearson's correlation of explanatory variables with each other and their significance levels**  
 280 **(in parenthesis, and in bold when < 0.05).**

	$N_P$	$V_O$	$S_S$	$S_O$	$Age$	$ADBS$	$G$	$NAL$	$KM$
$N_P$	1								
$V_O$	-0.296 ( <b>0.000</b> )	1							
$S_S$	-0.500 ( <b>0.000</b> )	0.030 (0.713)	1						
$S_O$	0.002 (0.984)	0.094 (0.243)	0.167 ( <b>0.038</b> )	1					
$Age$	0.143 (0.075)	0.035 (0.667)	-0.038 (0.642)	0.043 (0.594)	1				
$ADBS$	0.202 ( <b>0.012</b> )	-0.017 (0.834)	0.015 (0.851)	0.007 (0.932)	-0.434 ( <b>0.000</b> )	1			
$G$	0.073 (0.367)	-0.029 (0.717)	-0.011 (0.888)	0.085 (0.294)	-0.022 (0.786)	0.164 ( <b>0.041</b> )	1		
$NAL$	0.017 (0.831)	-0.003 (0.967)	-0.022 (0.790)	0.031 (0.701)	-0.450 ( <b>0.000</b> )	0.567 ( <b>0.000</b> )	0.136 (0.090)	1	
$KM$	-0.234 ( <b>0.003</b> )	-0.002 (0.981)	0.033 (0.682)	-0.032 (0.688)	-0.384 ( <b>0.000</b> )	-0.128 (0.110)	-0.086 (0.289)	-0.035 (0.668)	1

281

282 **3.2 Model estimation**

283 To estimate the number of completed passing manoeuvres, the Poisson was used to fit the data  
 284 using the STATA statistical software (StataCorp, 2017). A number of model forms with different  
 285 combinations of traffic- and driver-related variables were developed and compared to each other  
 286 using the statistical test to assess the performance of each model. The variables explored in this  
 287 process included those presented in Table 3. Finally, the model reported in Table 5 was found to  
 288 be superior. The results of the Likelihood ratio test in Table 5 shows that  $\alpha$  was statistically not  
 289 significant at the 95% confidence level ( $\bar{\chi}^2 = 0.60, p\text{-value} = 0.218$ ). Since  $\alpha$  is statistically equal  
 290 to zero, the Poisson regression model was deemed appropriate.

291 Table 5 presents the results. The Likelihood ratio test implied that, from an overall point  
 292 of view, the model was significant at the 95% confidence level ( $\chi^2 = 199.69, p\text{-value} < 0.0001$ ).  
 293 The results of the Pearson test reveal that model fitting was significant at the 95% confidence level  
 294 ( $p\text{-value} > 0.05$ ). Cragg-Uhler  $R^2$  and McFadden's  $R^2$  were equal to 0.73 and 0.28 respectively.

295 Table 5 provides the Z-values of the Wald test and the corresponding  $p$ -values for parameter  
 296 coefficients. The significant variables were kept in the model and shown in Table 5.

297

298 **Table 5: Model estimation results of passing frequency along the test track**

Variables	$\beta$ -Estimate	Z-value	$p$ -value
$V_o$	-0.0031106	-5.28	0.000
$S_s$	-0.0395426	-9.30	0.000
$Age$	-0.1152502	-2.35	0.019
$Age^2$	0.0497212	1.90	0.057
$ADBS$	0.0649896	5.15	0.000
$G$	-1.83914	-4.07	0.000
$NAL$	1.038673	1.86	0.062
$KM$	-0.8536231	-3.34	0.001
$NAL \times ADBS$	-0.0433297	-2.29	0.022
$G \times Age$	0.0497212	4.07	0.000
$constant$	4.280753	4.31	0.000
Test		$\chi^2$	$p$ -value
Overall model evaluation, Likelihood ratio test		199.69	0.0000
Goodness-of-fit, Pearson test		172.43	0.0597
Overdispersion, LR test of $\alpha$	$\alpha = 0.035$	$\bar{\chi}^2 = 0.60$	0.218
Cragg-Uhler $R^2$	0.73		
McFadden's $R^2$	0.28		
Sample size	156		

299 The speed of traffic flow in the opposing direction was statistically not significant at the  
300 confidence level of 95%. However, two other traffic-related variables (i.e.,  $V_O$ , and  $S_S$ ) were  
301 statistically highly significant ( $p$ -value  $< 0.001$ ). The negative sign of the traffic flow rate in the  
302 opposing direction implied that an increase in this variable leads to a decrease in the number of  
303 passing manoeuvres. As the speed of traffic-flow in the subject direction decreased, the number of  
304 passing manoeuvres increased.

305 The age and gender of participants were found to be statistically significant at the 95%  
306 confidence level. Since the interaction terms between age and gender were significant  
307 ( $p$ -value  $< 0.001$ ), their effects on the number of passing manoeuvres depend on each other. The  
308 significant positive coefficient of  $ADBS$  at the 95% confidence level implied that participants with  
309 higher reported  $ADBS$  values conducted more passing manoeuvres along the road. However, since  
310 the interaction between the  $ADBS$  and indicator variable representing nationality ( $NAL$ ) was  
311 significant at the 95% confidence level, the effect of  $ADBS$  values on the number of passing  
312 manoeuvres was different for Iranian and Italian participants. The  $KM$  variable had a statistically  
313 significant effect on the number of passing manoeuvres at the 95% confidence level  
314 ( $p$ -value = 0.001), which showed that participants who drive fewer than 1000 km/year conducted  
315 fewer passing manoeuvres than those who drive more.

316

### 317 **3.3 Sensitivity analysis**

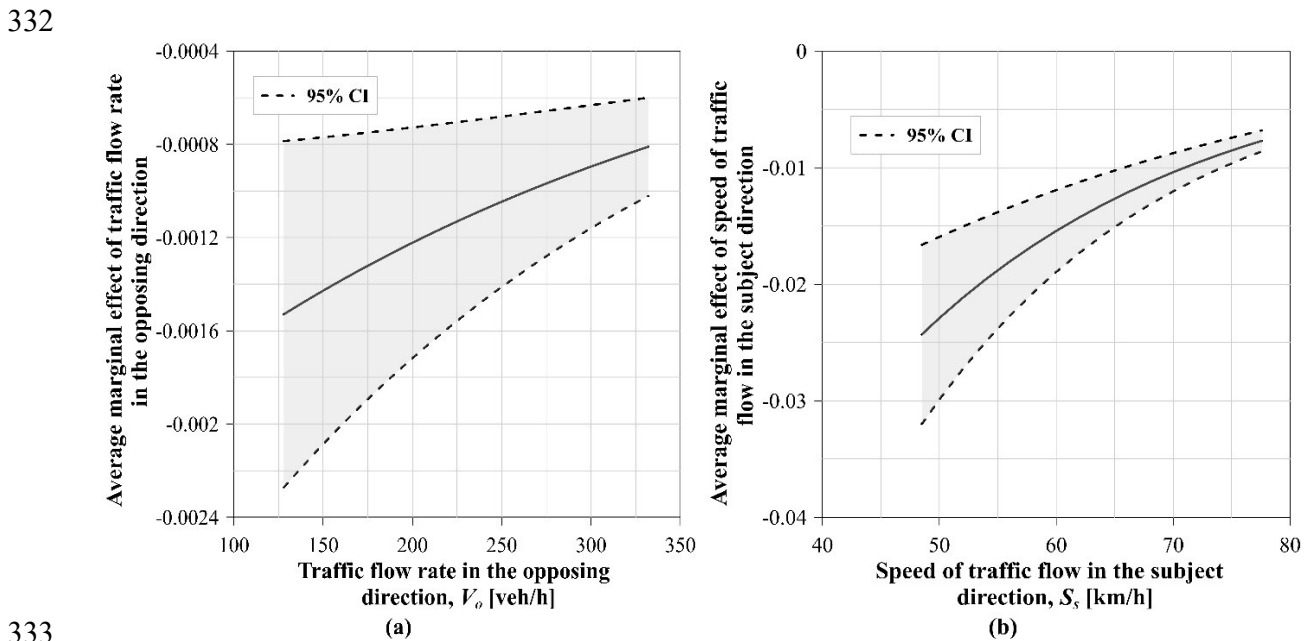
318 A sensitivity analysis of the various model explanatory variables was conducted to demonstrate  
319 their relative contribution to passing frequency (i.e., the number of passing manoeuvres per  
320 kilometre). Table 6 exhibits the average marginal effects of explanatory variables on the passing  
321 frequency. Figure 2a shows the average marginal effects of  $V_O$  on passing frequency at different  
322 values of  $V_O$ . The figure indicates that there was a negative marginal effect at different values of  
323  $V_O$ , which was significant at the 95% confidence level. The figure also implies that there was a  
324 smaller reduction in passing frequency at the higher level of  $V_O$  due to an increase in the  $V_O$ .

325 Figure 2b shows how average marginal effects change for different values of  $S_S$ . The figure  
326 shows that the average marginal effect of  $S_S$  on passing frequency was significant at the 95%  
327 confidence level for different values of  $S_S$ . The negative effects of  $S_S$  on the passing frequency  
328 decreased as  $S_S$  increased.

329

330 **Table 6. Average marginal effects of explanatory variables on the number of passing manoeuvres**  
 331 **per km (i.e., the passing frequency) [passes/km/one-unit change in the explanatory variable]**

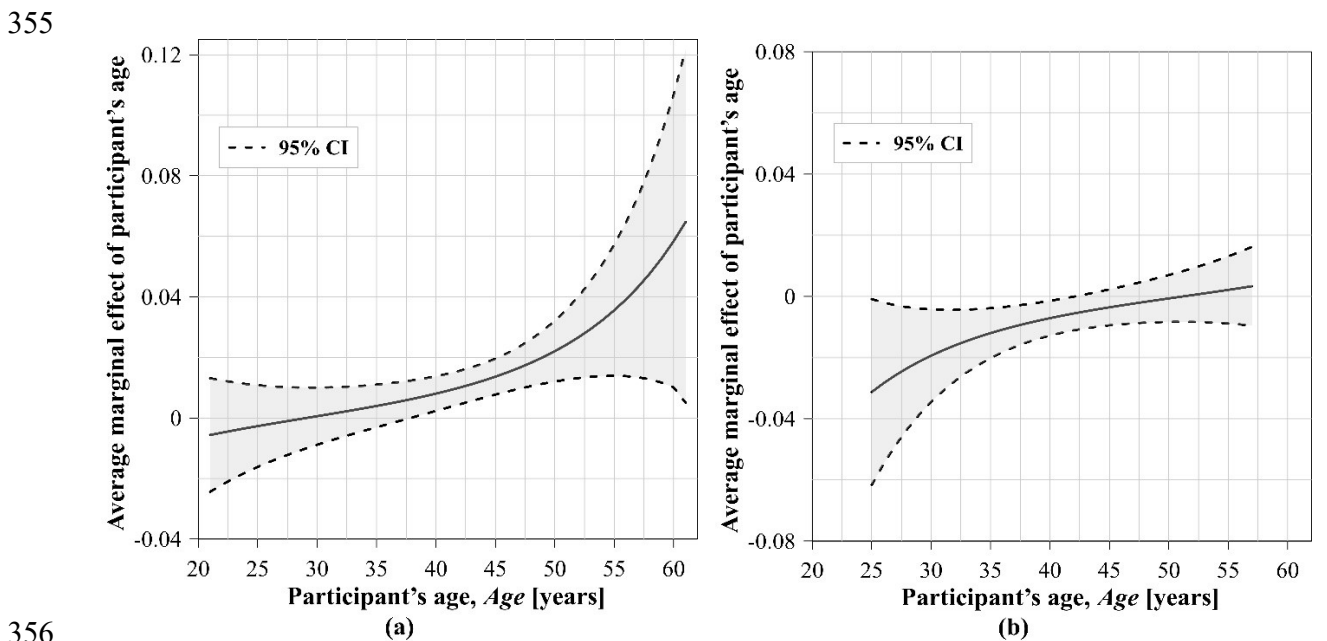
Variables	Average marginal effects	z	p-value	Confidence interval (95%)
$V_o$	-0.001115	-5.09	0.000	(-0.001544, -0.000686)
$S_s$	-0.014175	-8.38	0.000	(-0.017490, -0.010860)
Age	0.002332	0.76	0.448	(-0.003695, 0.008359)
G (males vs. females)	0.025951	0.57	0.572	(-0.063964, 0.115865)
Age (for males)	0.008763	2.79	0.005	(0.002614, 0.014913)
Age (for females)	-0.013953	-2.43	0.015	(-0.025199, -0.002707)
ADBS	0.018092	4.94	0.000	(0.010917, 0.025267)
NAL (Iranians vs. Italians)	-0.027928	-0.50	0.616	(-0.137149, 0.081292)
ADBS (for Iranians)	0.008084	1.69	0.091	(-0.001282, 0.017453)
ADBS (for Italians)	0.026431	4.07	0.000	(0.013713, 0.039149)
KM	-0.220689	-4.70	0.000	(-0.312642, -0.128158)



333 **Figure 2. Average marginal effects of the opposing traffic-flow rate on the passing frequency at its**  
 334 **various values (a). Average marginal effects of speed of traffic flow in the subject direction on the**  
 335 **passing frequency at its various values (b).**  
 336

337 As shown in Table 6, the average marginal effect of *Age* on the passing frequency for all  
 338 participants was not significant at the 95% confidence level ( $p$ -value = 0.448). The average  
 339 marginal effect for all males compared with that for all females was not also significant at the same  
 340 confidence level ( $p$ -value = 0.572). However, the significant interaction term between *Age* and  
 341 *Gender* in the estimated model (Table 5) implied that the effect of *Age* depends on *Gender*. Hence,  
 342 the average marginal effect of *Age* was calculated for the two groups of males and females. The  
 343 results show that, on average, a one-year increase in the *Age* of females corresponded to a 0.014  
 344 decrease in the passing frequency for females, which was significant at the 95% confidence level  
 345 ( $p$ -value = 0.015). However, in the case of males, a one-year increase in *Age* corresponded on  
 346 average to an 0.0088 increase in their passing frequency, which was significant at the same  
 347 confidence level ( $p$ -value = 0.005).

348 Figure 3a and Figure 3b show the average marginal effects of *Age* on the passing frequency  
 349 and their 95% confidence intervals over various *Age* values for males and females, respectively.  
 350 Figure 3a indicates that the average marginal effects of *Age* for males were only statistically  
 351 significant in the 38 to 61 years old range, which had positive effects. No significant average  
 352 marginal effect was found for the *Age* of males in the 21 to 37 year-old range. However, the  
 353 negative average marginal effect of *Age* for females was statistically significant below the 42 years  
 354 of age threshold.



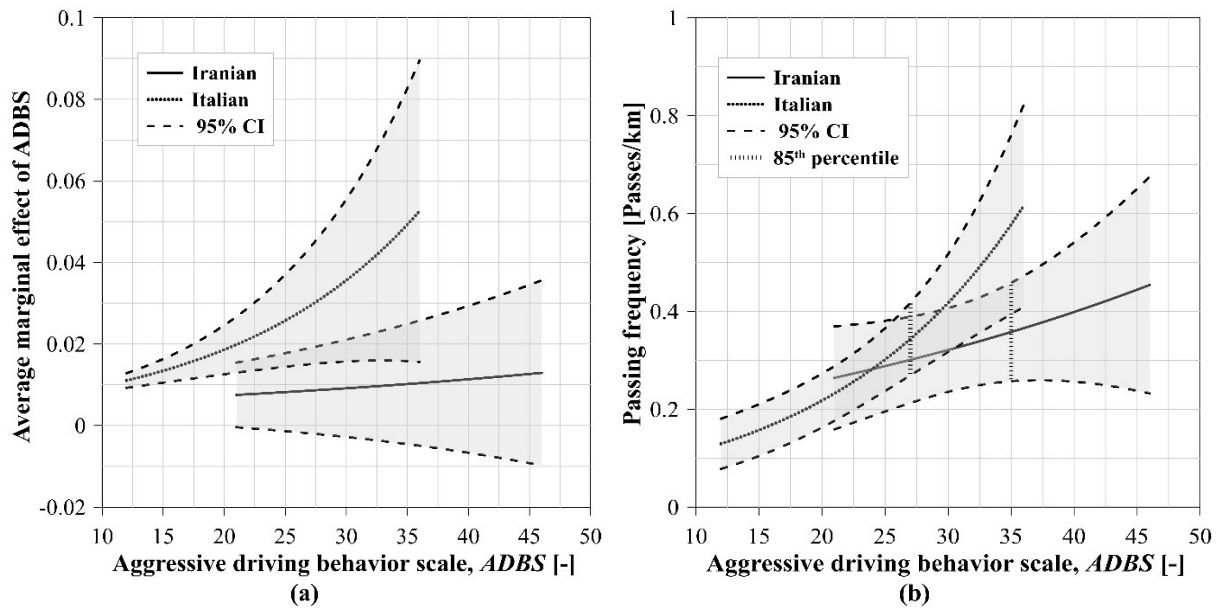
356  
 357 **Figure 3: Average marginal effects of participant age on passing frequency at its various values for**  
 358 **males (a) and females (b).**

359 Table 6 indicates that the average marginal effect of *ADBS* on passing frequency was  
360 significant at the 95% confidence level ( $p$ -value  $< 0.001$ ). The results showed that a one-unit  
361 increase in the self-reported *ADBS* value by participants corresponded to an average increase of  
362 0.018 in the passing frequency. The average marginal effect of the nationality of participants  
363 (Iranian and Italian) was not significant at the 95% confidence level ( $p$ -value = 0.616). However,  
364 the significant interaction term between *ADBS* and *NAL* implied that the effect of *ADBS* on the  
365 passing frequency depends on the nationality of participants. Figure 4 shows that although the  
366 average marginal effect of *ADBS* for Iranians was not significant at the 95% confidence level  
367 ( $p$ -value = 0.091), it is highly significant for Italian participants ( $p$ -value  $< 0.001$ ). Figure 4 also  
368 illustrates that Iranian participants reported higher *ADBS* values compared to the Italians  
369 (i.e., 21-46 vs 12-36). However, Figure 4a shows that the average marginal effects of *ADBS* for  
370 Iranians at different *ADBS* values were not significant at the 95% confidence level. The average  
371 marginal effect of *ADBS* for Italians was statistically significant and increased in line with their  
372 self-reported aggressive driving scores.

373 In Figure 4b, the passing frequency was estimated using the model for Iranian and Italian  
374 males with a driving exposure of greater than 1000 km/year across the different *ADBS* levels, while  
375 the mean values of other variables were used. The figures suggest that, although Iranians reported  
376 higher *ADBS* values, there was no statistically significant variation in the passing frequency  
377 attributable to self-reported aggressive driving scores. However, a significant variation in passing  
378 frequency exists among Italians with respect to their self-reported aggressive driving scores. As  
379 shown in Figure 4b, 85% of Italian participants reported an *ADBS* value equal to or less than 27;  
380 while the same value for Iranians was 35. Italians with an *ADBS* value lower than their 85<sup>th</sup>  
381 percentile of *ADBS* had a passing frequency almost equal to or lower than their Iranian  
382 counterparts. However, 15% of Italian participants with the highest self-reported *ADBS* value pass  
383 more frequently than their corresponding Iranian participants.

384 Table 6 indicates that participants who drove fewer than 1000 km/year conducted 0.221  
385 fewer passing manoeuvres per km compared to those drivers who drove more than 1000 km/year  
386 on average, which is significant at the 95% confidence level ( $p$ -value  $< 0.001$ ).

387



388  
 389 **Figure 4. Average marginal effects of aggressive driving behaviour scale on the passing frequency**  
 390 **at its various values for Iranian and Italian participants (a). Passing frequency at different levels of**  
 391 **aggressive driving behaviour scales (b).**  
 392

#### 393 4. DISCUSSION

394 While previous passing rate models failed to consider the effects of driver characteristics, the  
 395 effects of manipulated variables in this study (i.e.,  $V_O$ ,  $S_S$ ,  $S_O$ ) were assessed by previous research  
 396 works. In most previously developed theoretical (Daganzo, 1975; Dommerholt & Botma, 1988;  
 397 McLean, 1989) and empirical (Hegeman, 2008; Mwesige, et al., 2016; Tuovinen & Enberg, 2006)  
 398 passing rate models, the opposing traffic-flow rate variable was included. Some other field studies  
 399 (Moreno, et al., 2013; Mwesige, et al., 2016) considered the effect of this variable indirectly using  
 400 directional split incorporating the traffic flow in both directions. In the simulator study conducted  
 401 by Farah (2011), the opposing traffic-flow rate had a significant effect on the number of passing  
 402 manoeuvres completed by participants.

403 Wardrop (1952) used the average of space mean speeds in the subject direction in a  
 404 theoretical passing rate model so that increases in the average of space mean speeds correspond to  
 405 decreases in the passing rate. A simulator study conducted by Farah (2011) showed that the speed  
 406 of vehicles in front had a significant effect on the number of passing manoeuvres conducted by  
 407 participants.

408 In this study, the age and gender of participants were found to be significant for the passing  
 409 frequency, which increased as the age of males increased (38 to 61 years old range) and the age of

410 females decreased (below the 42 years of age threshold). Farah (2011) found that the average  
411 number of overtaking manoeuvres for males is higher than females. However, in contrast to the  
412 evidence from this study, they found no significant differences between the age groups. The main  
413 shortcoming in Farah (2011) is the use of the ANOVA method to compare the count data samples.  
414 The two assumptions of ANOVA, normality and equality of variances, are violated for count data  
415 (Mai & Zhang, 2016). The passing gap acceptance models determine the probability that a driver  
416 accepts an available gap in oncoming traffic. The passing gap acceptance is directly related to the  
417 passing rate so that as drivers accept smaller available gaps, they are expected to have a higher  
418 passing frequency. Hassein, et al. (2017) showed that as age increases, the probability of accepting  
419 a specific gap decreases. Llorca, et al. (2013) found that although age and gender did not have  
420 statistically significant effects on the accepted gaps, their interaction term was significant. Toledo  
421 and Farah (2011) found that young drivers (i.e., between 21 and 25 years) accept statistically  
422 shorter gaps. Another study conducted by Farah, *et al.* (2009) divided participants into three age  
423 groups (i.e.,  $\leq 34$  years, between 35 and 49 years,  $\geq 50$  years). They found that the two younger  
424 groups accept smaller gaps with respect to the aged 50 or older age group. A study conducted by  
425 Moghaddam, et al. (2017) found that the likelihood of being involved in at-fault accidents  
426 increases up to the 36 to 40 age category and decreases after that. This age threshold (36-40) is  
427 similar to the one that this study determined for the effectiveness of age on passing frequency.  
428 However, there were different effects in terms of gender so that as age increased for females  
429 younger than 42 years, the passing frequency decreased, while it increased as age increased for  
430 males older than 38 years. Analysing the frequency of aborted overtaking moves could also help  
431 us to achieve a greater understanding of possible driver errors during these manoeuvres. Farah  
432 (2016) found that age and gender are significant variables for the probability of aborting an  
433 overtaking manoeuvre. The author showed that males in general together with female participants  
434 belonging to the age groups of 25-45 years old were more likely to complete an already started  
435 passing manoeuvre.

436 The results showed that the *A DBS* has a significant positive effect on the passing frequency  
437 which is in line with previous works. Several studies showed that aggressive driving behaviours  
438 had a positive relation with the tendency to undertake dangerous overtaking manoeuvres (Atombo,  
439 et al., 2016), the incurrence of traffic violations (Harris, et al., 2014; Qu, et al., 2014), and the level  
440 of incidence of accidents (Marengo, et al., 2012; Qu, et al., 2014). The results of this study also

441 suggested that the effect of *ADBS* on the passing frequency depends on the nationality of  
442 participants. Many studies reported cross-cultural differences in terms of driving behaviour  
443 (Lajunen, et al., 2004; Özkan, et al., 2006; Sârbescu, et al., 2014). In this study, Italian and Iranian  
444 participants were compared, with the Iranians reporting significantly higher aggressive driving  
445 scores with respect to their Italian counterparts. However, the results showed that the passing  
446 frequency depends on the *ADBS* level for Italians but not for Iranians. The Iranian participants  
447 were selected from among those who had recently come to Italy and, therefore, did not have any  
448 driving experience in the country. Uzongu, et al. (2020) explored the cross-cultural differences  
449 between UK participants and Nigerian participants with and without driving experience in the UK  
450 using a driving simulation and driver behaviour questionnaire. They found that the Nigerian  
451 participants with no driving experience in the UK reported more dangerous driving behaviours  
452 than two other participant groups. However, the authors did not note any significant improvements  
453 in the driving behaviour by improving the infrastructures in the simulation scenarios. Hence, using  
454 Iranian participants with driving experience in Italy could help to achieve a better understanding  
455 of the effects of cross-cultural differences on passing frequency.

456 The results show that drivers who drove less than 1000 Km/year conducted fewer passing  
457 manoeuvres than drivers with higher levels of driving exposure. The data analysis also revealed  
458 that most of the drivers with lower exposure levels were novice drivers. Previous studies showed  
459 that one of the main problems with such drivers is their relative lack of skill (McGwin & Brown,  
460 1999). The visual search strategies adopted during passing manoeuvres is related to the level of  
461 accidents involving inexperienced drivers (Zhang, et al., 2016) since inexperienced drivers are less  
462 skilled at employing visual scan strategies than experienced drivers (Zheng, et al., 2020). Farah,  
463 et al. (2009) also confirmed that driving exposure affects the passing gap-acceptance.

464

## 465 **5. CONCLUSION**

466 Although the propensity of drivers to perform passing manoeuvres along two-lane highways has  
467 been investigated for several years, available models based on field data cannot capture and explain  
468 the dependence of this propensity on the behavioural and cultural characteristics of the driver  
469 population. This study aimed at filling this gap by investigating the influence of driver profile (i.e.,  
470 age, gender, nationality, aggressive driving scores, driving exposure) and some traffic-related  
471 variables (i.e., the traffic-flow and speed in the opposing direction, and the speed in the subject

472 direction) on the passing frequency using a simulation study. A Poisson regression model was used  
473 after appropriate comparisons with the negative binomial one.

474 Drivers who drive less often overtake less. On average, Italians (from a high-income  
475 country) and Iranians (from a low/medium income country) had statistically similar passing  
476 frequencies. However, there was a significant variation in passing frequency between Italian  
477 drivers due to self-reported *ADBS* values (i.e., aggressive driving scores), suggesting that  
478 aggressive drivers overtake more frequently. In the case of Iranian drivers, although the variation  
479 in passing frequency attributable to aggressive driving scores was in line with that for Italians, it  
480 was not statistically significant.

481 This study serves to widen the spectrum of subjective factors useful for depicting driver  
482 characteristics, while also confirming that gender, nationality (Italian or Iranian) and self-reported  
483 aggressive driving scores (which varies between drivers within the same restricted group) have an  
484 impact on the passing frequency along highways.

485 Different countries, especially those with different income levels, show differences in  
486 aggressive driving scores, driver age distribution, and gender composition of driver population  
487 especially on rural roads. All these factors significantly affect the passing frequency. The main  
488 implication of this investigation pertains to the transferability of behavioural insights and models  
489 across countries with different income levels. The results of this study can be used to reduce the  
490 heterogeneity of driver behaviours and bias in the transferability of passing rate models from one  
491 country to another.

492 Future investigations should extend and generalize the results obtained here. Previous  
493 studies have revealed that route familiarity can affect driving behaviour and can lead to distraction,  
494 over-confidence, and dangerous behaviour (Intini, et al., 2019). Hence, the number of influencing  
495 factors should also take the familiarity of drivers with the particular road segment into account,  
496 which may influence their confidence levels vis-à-vis their tendency to adopt risky passing  
497 manoeuvres. Passing zones provide passing opportunities for vehicles behind slow vehicles when  
498 there is a sufficient gap(s) in oncoming traffic. Drivers are likely to become frustrated if they are  
499 unable to overtake (Kinnear, et al., 2015). Hence, the number of passing zones and their  
500 distribution along the road are important variables, which were considered constant in this study.  
501 From an experimental point of view, drivers from other countries should also be included to  
502 understand the effects of driver population heterogeneity on passing behaviour.

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510

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