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

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Abstract

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

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

1. INTRODUCTION

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

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

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

More recently, statistical models have also been proposed. Moreno, et al. (2013) developed a Poisson regression model to estimate the passing frequency for a 15-minute period in the subject direction combining geometric and traffic-related factors (more specifically, the length of the passing zone, the two-way traffic volume and the directional split in the subject direction). Later on, Mwesige, et al. (2016) included some other predictors to develop a passing rate per hour model (i.e., the absolute vertical grade, the 85^{th} percentile speed, and the percentage of heavy vehicles). In addition to the variables considered in the abovementioned studies, Karimi, Boroujerdian, et al. (2020) used the lane width and the proportion of motorcycles as variables in the passing rate model they developed. The model included geometric and traffic-related variables and did not consider any driver characteristic variables.

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

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

To address the limitations of earlier studies related to a prediction of the number of passing manoeuvres, the main goal of this study was to investigate the effects of driver characteristics, age, gender, level of self-reported aggressive driving scores, driving exposure, and nationality (Italian or Iranian) on the passing frequency along a two-lane rural highway. Hence, a predictive model for passing frequency (i.e., the number of passing manoeuvres per kilometre per driver) was developed with the aim of calculating the marginal effects of each variable. The model was calibrated on experimental data from a validated driving simulation with drivers coming from low/middle (Iran) and high-income (Italy) countries.

2. METHODOLOGY

2.1 Design

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

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

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

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

CPU, video card, RAM memory	Quad-core, NVIDIA GeForce® GTX 780 Ti, 8 Gb.
Monitor	Three 32-inch full HD (cover 130º of driver field of view).
Cockpit	Car seat, steering wheel, manual gearbox, pedals, and dashboard.
Vehicle and road interaction	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.
Software (SCANeR™studio)	Design tracks, manage the vehicle parameters, generate the experimental scenarios, run the simulations, collect and extract data.

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

Three factors including V_O, S_S, and S_O were considered in the experimental design. Table **2** shows the three levels of factors. Three Gamma distributions with parameters of (α=0.844, β=12.956), (α=0.814, β=19.405), and (α=1.146, β=24.591) were used to generate the headways between the vehicles for the three levels of the traffic flow rate of -1, 0, and 1 in the opposing direction, respectively. The traffic flow in the driver direction was assumed to be constant and was generated by an exponential distribution with a parameter of λ = 13.094 that truncated from 5 to 20 s intervals. The 15^{th}, 50^{th} and 85^{th} percentiles of speeds of oncoming vehicles and the passed vehicles (in the observed passing manoeuvres) from the field data used three levels of S_O and S_S. Based on the decision that each participant should complete three scenarios, a 3^3 confounded factorial design was applied (Wilkie, 1961). Hence, the 27 scenarios with 6 replications implied the involvement of 54 drivers.

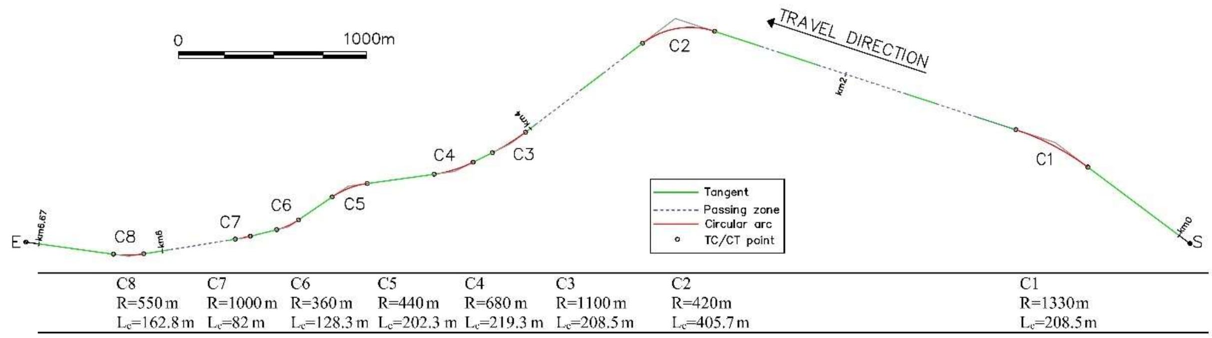

Figure 1: The distribution of passing zones along the test track (TC = tangent to curve, CT = curve to tangent)

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

2.2 Participants

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

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

2.3 Materials

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

2.4 Procedures

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

2.5 Statistical analysis

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

$$\lambda_i = E\left[N_{Pi} \mid X_i\right] = \exp\left(\beta X_i\right) \tag{1}$$

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

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

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

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

3. RESULTS

The physical condition and health of participants was checked through the pre-drive questionnaire. The pre and post driving cognitive status of drivers were examined by the *t-test* for auditory (*p-value* = 0.839) and visual (*p-value* = 0.705) perception and reaction time which implied that there were no significant differences. The results obtained from the post-drive questionnaire showed that the most reported simulator ailments affecting participants were eyestrain and sweating. However, the effects of reported sickness were limited (very low for some drivers) except for two participants who failed to complete the experiment. The participants also reported their feedback on the devices: they found the on-board equipment (i.e., acceleration, pedal, and gearbox) similar to what they experienced in the real world. However, they were not completely satisfied with the braking response. By removing the data of two participants who failed to complete the test, 156 observations were recorded from 52 participants and used in the analyses.

3.1 Dataset characteristics

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

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

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

There were statistically significant negative correlations (p-values < 0.05) between *ADBS* and the age, gender, and nationality of participants, which indicate that the younger participants, Iranians, and males reported more aggressive driving scores. The statistically significant correlation between nationality and age was because Iranian participants had a younger age range (i.e., 23-37 years old) than the Italian participants (21-61 years old). The significant negative correlation between *KM* and age implied that participants who drove fewer than 1000 km/year were novice drivers. This is also explained by the fact that the younger participants were mostly students, who generally drive less often than their non-student peers and also have a lower incidence of car ownership.

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			

Table 4. Pearson's correlation of explanatory variables with each other and their significance levels (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 (**0.000**)	1							
S_S	-0.500 (**0.000**)	0.030 (0.713)	1						
S_O	0.002 (0.984)	0.094 (0.243)	0.167 (**0.038**)	1					
Age	0.143 (0.075)	0.035 (0.667)	-0.038 (0.642)	0.043 (0.594)	1				
ADBS	0.202 (**0.012**)	-0.017 (0.834)	0.015 (0.851)	0.007 (0.932)	-0.434 (**0.000**)	1			
G	0.073 (0.367)	-0.029 (0.717)	-0.011 (0.888)	0.085 (0.294)	-0.022 (0.786)	0.164 (**0.041**)	1		
NAL	0.017 (0.831)	-0.003 (0.967)	-0.022 (0.790)	0.031 (0.701)	-0.450 (**0.000**)	0.567 (**0.000**)	0.136 (0.090)	1	
KM	-0.234 (**0.003**)	-0.002 (0.981)	0.033 (0.682)	-0.032 (0.688)	-0.384 (**0.000**)	-0.128 (0.110)	-0.086 (0.289)	-0.035 (0.668)	1

3.2 Model estimation

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

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

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

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

Variables	β-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 × *ADBS*	-0.0433297	-2.29	0.022
G × *Age*	0.0497212	4.07	0.000
constant	4.280753	4.31	0.000
Test		χ^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 α	$\alpha = 0.035$	$\bar{\chi}^2 = 0.60$	0.218
Cragg-Uhler R^2	0.73		
McFadden's R^2	0.28		
Sample size	156		

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

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

3.3 Sensitivity analysis

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

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

Table 6. Average marginal effects of explanatory variables on the number of passing manoeuvres 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)

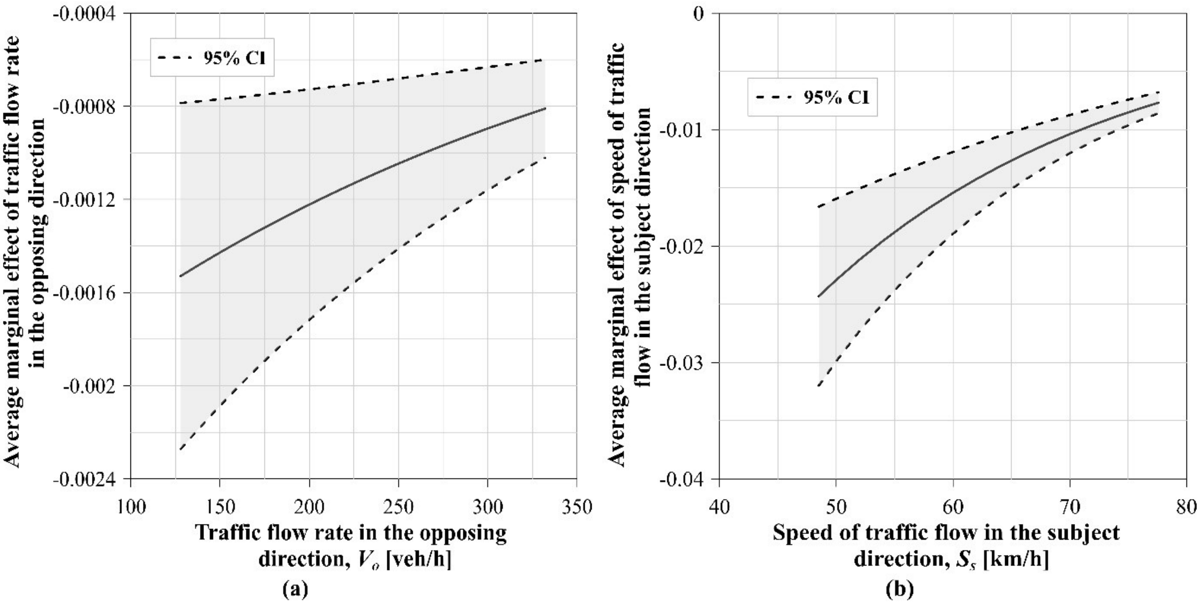

Figure 2. Average marginal effects of the opposing traffic-flow rate on the passing frequency at its various values (a). Average marginal effects of speed of traffic flow in the subject direction on the passing frequency at its various values (b).

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

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

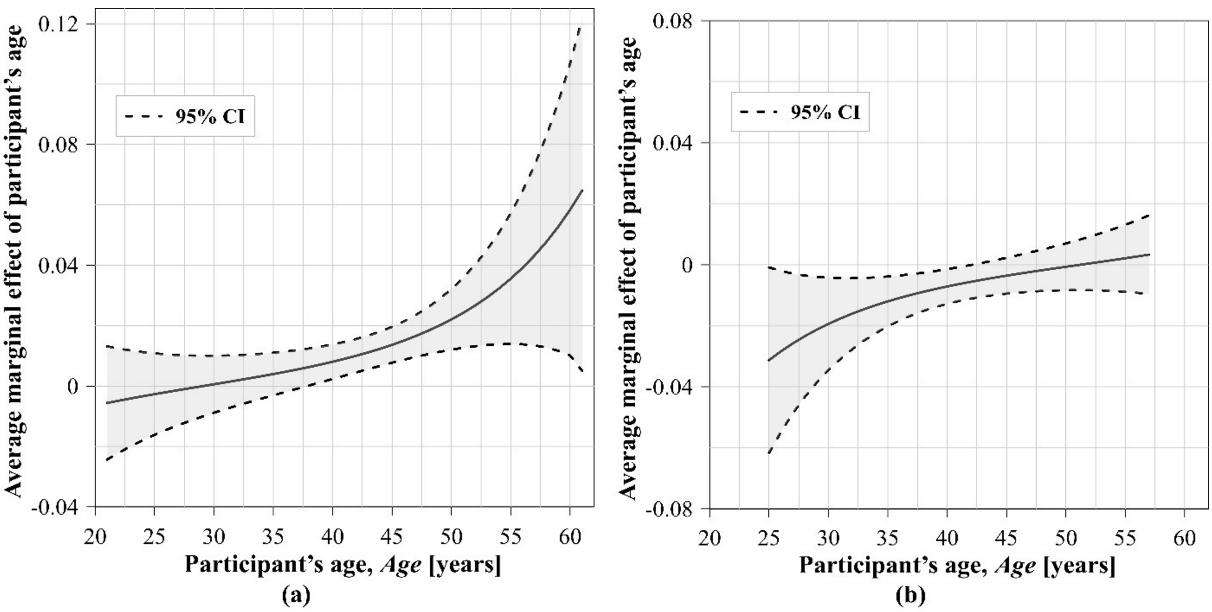

Figure 3: Average marginal effects of participant age on passing frequency at its various values for males (a) and females (b).

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

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

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

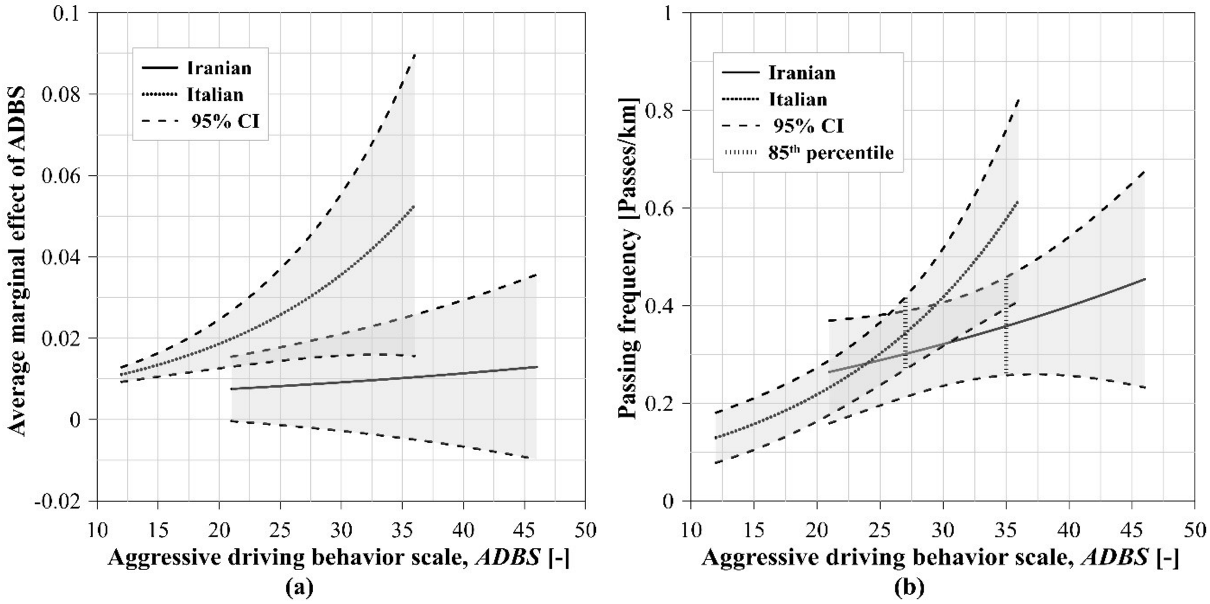

Figure 4. Average marginal effects of aggressive driving behaviour scale on the passing frequency at its various values for Iranian and Italian participants (a). Passing frequency at different levels of aggressive driving behaviour scales (b).

4. DISCUSSION

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

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

In this study, the age and gender of participants were found to be significant for the passing frequency, which increased as the age of males increased (38 to 61 years old range) and the age of females decreased (below the 42 years of age threshold). Farah (2011) found that the average number of overtaking manoeuvres for males is higher than females. However, in contrast to the evidence from this study, they found no significant differences between the age groups. The main shortcoming in Farah (2011) is the use of the ANOVA method to compare the count data samples. The two assumptions of ANOVA, normality and equality of variances, are violated for count data (Mai & Zhang, 2016). The passing gap acceptance models determine the probability that a driver accepts an available gap in oncoming traffic. The passing gap acceptance is directly related to the passing rate so that as drivers accept smaller available gaps, they are expected to have a higher passing frequency. Hassein, et al. (2017) showed that as age increases, the probability of accepting a specific gap decreases. Llorca, et al. (2013) found that although age and gender did not have statistically significant effects on the accepted gaps, their interaction term was significant. Toledo and Farah (2011) found that young drivers (i.e., between 21 and 25 years) accept statistically shorter gaps. Another study conducted by Farah, *et al.* (2009) divided participants into three age groups (i.e., ≤ 34 years, between 35 and 49 years, ≥ 50 years). They found that the two younger groups accept smaller gaps with respect to the aged 50 or older age group. A study conducted by Moghaddam, et al. (2017) found that the likelihood of being involved in at-fault accidents increases up to the 36 to 40 age category and decreases after that. This age threshold (36-40) is similar to the one that this study determined for the effectiveness of age on passing frequency. However, there were different effects in terms of gender so that as age increased for females younger than 42 years, the passing frequency decreased, while it increased as age increased for males older than 38 years. Analysing the frequency of aborted overtaking moves could also help us to achieve a greater understanding of possible driver errors during these manoeuvres. Farah (2016) found that age and gender are significant variables for the probability of aborting an overtaking manoeuvre. The author showed that males in general together with female participants belonging to the age groups of 25-45 years old were more likely to complete an already started passing manoeuvre.

The results showed that the *ADBS* has a significant positive effect on the passing frequency which is in line with previous works. Several studies showed that aggressive driving behaviours had a positive relation with the tendency to undertake dangerous overtaking manoeuvres (Atombo, et al., 2016), the incurrence of traffic violations (Harris, et al., 2014; Qu, et al., 2014), and the level of incidence of accidents (Marengo, et al., 2012; Qu, et al., 2014). The results of this study also suggested that the effect of *ADBS* on the passing frequency depends on the nationality of participants. Many studies reported cross-cultural differences in terms of driving behaviour (Lajunen, et al., 2004; Özkan, et al., 2006; Sârbescu, et al., 2014). In this study, Italian and Iranian participants were compared, with the Iranians reporting significantly higher aggressive driving scores with respect to their Italian counterparts. However, the results showed that the passing frequency depends on the *ADBS* level for Italians but not for Iranians. The Iranian participants were selected from among those who had recently come to Italy and, therefore, did not have any driving experience in the country. Uzondu, et al. (2020) explored the cross-cultural differences between UK participants and Nigerian participants with and without driving experience in the UK using a driving simulation and driver behaviour questionnaire. They found that the Nigerian participants with no driving experience in the UK reported more dangerous driving behaviours than two other participant groups. However, the authors did not note any significant improvements in the driving behaviour by improving the infrastructures in the simulation scenarios. Hence, using Iranian participants with driving experience in Italy could help to achieve a better understanding of the effects of cross-cultural differences on passing frequency.

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

5. CONCLUSION

Although the propensity of drivers to perform passing manoeuvres along two-lane highways has been investigated for several years, available models based on field data cannot capture and explain the dependence of this propensity on the behavioural and cultural characteristics of the driver population. This study aimed at filling this gap by investigating the influence of driver profile (i.e., age, gender, nationality, aggressive driving scores, driving exposure) and some traffic-related variables (i.e., the traffic-flow and speed in the opposing direction, and the speed in the subject direction) on the passing frequency using a simulation study. A Poisson regression model was used after appropriate comparisons with the negative binomial one.

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

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

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

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

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