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HOW USUAL BEHAVIOUR CAN AFFECT PERCEIVED DRIVERS' PSYCHOLOGICAL STATE WHILE DRIVING

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Abstract. Road accidents have a relevant impact in terms of economic and social costs. As a consequence, many research studies have focused on identifying the key factors affecting accident severity. Traditionally, these factors can be included in the infrastructural, human and vehicle groups. Among these, human factors have a relevant impact on accident severity, which depends on driving experience, driver's socio-economic characteristics, and driving behaviour, but also on the driver's psychological state while driving. In this paper we investigate on the relationships between driving behaviour usually taken by the driver and his/her perceived psychological state while driving. In order to achieve this goal we adopt an Ordered Probit (OP) model formulation calibrated on the basis of experimental data collected by a sample survey. We demonstrate that the adopted methodology accounts for the differential impacts of certain human factors on driver's psychological state.

Keywords: road accident; driving behaviour; psychological state while driving; ordered probit model.

Introduction

Road accidents cause direct impact on the social and physical environment. In Italy, during the past few years road accidents produced about 30 billion EUR per year, corresponding to 2% of the national Gross Domestic Product (GDP) (ACI 2008, 2009, 2010).

Many researchers investigated the key factors having an impact on accident severity. Traditionally, these factors can be included in the infrastructural, human and vehicle groups (Wang *et al.* 2002). The first one include road and traffic characteristics, like road geometry and surface condition, traffic flow, vehicle speed, and weather condition. Human factors concern driver characteristics, like driving experience and attitude, physiological and psychological state, personal trait. Vehicles can be considered in terms of type and conditions.

Among these, human factors have a relevant impact on accident severity. The findings obtained by Wang *et al.* (2013) indicate that driver's behaviour plays a far greater role in the occurrence of crashes than do vehicle, environmental or geometric factors. In Italy, it has been quantified that 80% of the road accidents were caused by fault of the drivers, and this percentage, as everyone knows, is quite the same in most of the developed Countries of the world.

By taking into account this evidence, in this paper we investigate on the relationships between the behaviour that the driver usually takes and his/her psychological state while driving. In order to achieve this goal we adopt an Ordered Probit (OP) model formulation, which we retain a suitable methodology for modelling categorical dependent variables as psychological state of the driver was captured according to the questionnaire used for conducting a survey addressed to a sample of drivers.

In the following, we report a section concerning a literature review of some works analysing the factors having an impact on road accident severity, and specifically human factors; we focused, also, on how psychological state of the driver can be described. Some remarks are highlighted about works proposing different modelling methodology on accident severity. The methodological section is about the conceptual structure at the basis of this work and the theoretic fundamentals of the OP. The third section is about the sample survey supporting the research; specifically, we describe the collected data and the survey outcomes. The paper ends with the description of the results of the proposed models, the discussion about the main findings, and a brief conclusive section.

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1. Literature Review

The factors having an impact on road accident severity were widely investigated in the scientific literature. Traditionally, researchers distinguished among environment or road factors, characteristics of the vehicles involved in an accident, and human factors.

Many efforts were made in order to deeply analyse the human factors affecting accident severity. Researchers have found that accident severity depends especially on driving experience (in terms of licence status, years that respondent has been driving, accident involvement in the last few years, distance in mile/km driven), drivers' socio-economic characteristics (in terms of gender, age, personal or family income, commuter status, educational level, current marital status), and driving behaviour (in terms of traffic offence in the last few years, physical condition of the driver, usage of alcohol and drugs, usage of silt-belt, driving in excess of posted speed limit, failure to keep in proper lane, passing where prohibited by posted signs, usage of the cell phone, etc.) (Wang *et al.* 2002; Dissanayake 2004; Yannis *et al.* 2005; Clarke *et al.* 2006; Lambert-Bélanger *et al.* 2012; Tractinsky *et al.* 2013).

In addition, the psychological state of the driver while driving was investigated. Particularly, we focus this review on how psychological state of the driver can be described. As an example, Wang *et al.* (2002) introduce in their investigation a respondent's self-description of his/her psychological state in most situations while driving. They choose five categories: an aggressive driver; an impatient driver; a hesitant driver; a slow driver; a very cautious driver. Clarke *et al.* (2006) reported intentions and behaviours of drivers as interpreted by the attending police officer, in terms of aggressive recklessness or not. Jamson *et al.* (2008) focus on driver awareness, distinguishing from poor (when driver is cognitively distracted) to excellent (when driver is fully concentrating on the driving task). Finally, Scott-Parker *et al.* (2009) introduce a self-reported risky driving behaviour expressed via a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Many works reported in the scientific literature investigated the relationships between road accidents and the factors affecting accident severity. Since accident data are categorical in nature, discrete models have been used to identify these factors. Some researchers have relied on logistic regression (e.g., Al-Ghamdi 2002; Bédard *et al.* 2002; Dissanayake 2004; Yau *et al.* 2006), while others have used multinomial logit models (e.g., Malyshkina, Mannering 2009; Manner, Wünsch-Ziegler 2013), nested logit models (e.g., Patil *et al.* 2012) or mixed logit models (Milton *et al.* 2008; Kim *et al.* 2013). Given the discrete ordinal nature of severity, several researchers have considered the Ordered Probit (OP) or Ordered Logit (OL) models to be more suitable (e.g., O'Donnell, Connor 1996; Duncan *et al.* 1998; Khattak *et al.* 2002; Yamamoto, Shankar 2004; Rifaat, Chin 2007; Xie *et al.* 2009).

Most of the works reported in the literature are based on survey data gathered by means of 'self-reported risky driving behaviour'. More recently, drivers' behaviour have been indirectly investigated also by means of Stated Preference (SP) experiment where some driving situations are ranked or chosen according to the perceived risk level. As an example, driver's perception of safety was investigated through an SP experiment designed for evaluating the complex interactions among drivers in the context of a roundabout (Wang *et al.* 2002); the authors proposed an OP model. In Eboli and Mazzulla (2008) some logit models to estimate Willingness-To-Pay (WTP) for reducing road accident risk were proposed. Similar SP experiments were conducted by Rizzi and Ortúzar (2003), and Iragüen and Ortúzar (2004). In addition, Svensson and Johansson (2010) proposed the use of an SP survey to investigate on the WTP for risk reductions. Yannis *et al.* (2005) proposed a logistic regression for identifying driver behavioural parameters influencing user's choices in order to reduce the accident risk; also, in this case, an SP experiment was used to develop the explanatory model. Jamson *et al.* (2008) developed a driving safety index using a Delphi SP experiment in which road safety professionals make judgments about drivers' safe or unsafe behaviour. The study is aimed to establish safety thresholds, i.e. the point where behaviour can be considered unsafe.

2. Methodology

2.1. Preliminary Remarks

In order to well model how drivers' behaviour can affect their psychological state while driving, and decide the methodology which can well-fit our data, we preliminarily analyse the nature of the variable which we defined as response, sometimes called as dependent variable.

Our intent was to focus on how to describe the psychological state the driver usually has meantime he/she is driving, as perceived by him or herself. We thought that the topic was quite delicate so, before deciding on which criterion to follow, we studied if and who else had done some similar kinds of work. At least, we decided to follow the categories that Wang *et al.* (2002) used in their work.

Therefore, our dependent variable is a categorical variable, because it has measured with a scale consisting of a set of categories. Categorical variables have two main types of measurement scales. Many categorical scales have a natural ordering and, for this reason, categorical variables are called ordinal variables. Categorical variables having unordered scales are called nominal variables; for nominal variables, the order of listing the categories is irrelevant, and the statistical analysis should not depend on that ordering (Agresti 2007).

When dependent variables are measured according to an ordinal scale, there are many options for their analysis: firstly, treating the variable as though it were continuous, and then use Ordinary Least Square (OLS) regression techniques for continuous variables; secondly, ignoring the ordering of the variable and treating it as nominal, by using multinomial logit techniques; thirdly, treating the variable as though it was measured according to an ordinal scale, representing measurement of an underlying interval/ratio scale; OL or probit models can be used in such cases (Borooah 2001).

Our dependent variable is not perfectly an ordinal variable, because it is not expressed by a scale from a more aggressive state to a less aggressive one, but it is a categorical variable defined on five unordered levels, named as 'careful', 'slow', 'hesitant', 'impatient' and 'aggressive'. These levels are not exactly equal to different levels of 'aggressiveness'. Despite this, we choose to treat the variable as though it was measured on a 'true' ordinal scale, and we decide to adopt ordered models methodology, as assumed by some of the researchers in the cited studies regarding accident severity analysis (e.g. Duncan *et al.* 1998).

The choice between OP and OL model lies in the assumption regarding the distribution of errors; nevertheless, since many years ago, several researchers (e.g. O'Donnell, Connor 1996; Renski *et al.* 1999) have indicated that the results from the OP and OL are similar. However, there is no consensus on which model is the best (Xie *et al.* 2009). Several researchers argued that categorical models such as the multinomial logit model may be better than the OL and the OP models in that the ordered models restrict the effect of variables across outcomes (Khorashadi *et al.* 2005). In this case, we choose an OP model.

OP model is especially appropriate because, like OLS regression, it identifies statistically significant relationships between variables explanatory of the driver's usual behaviour, and a dependent variable like psychological state while driving. However, unlike OLS regression, OP discerns unequal differences between ordinal categories in the dependent variable. For example, it does not assume that the difference between 'aggressive' (level 5) and 'impatient' (level 4) is the same as the difference between 'impatient' (level 4) and 'slow' 'hesitant' (level 3), given a unit change in the explanatory variable. Here, OP model captures the qualitative difference between the different levels of driver aggressiveness or psychological state while driving.

2.2. Modelling Methodology

The modelling methodology used to analyse relationships between the behaviour that the driver usually takes and their perceived psychological state while driving is the OP model. The OP model was originally developed by McKelvey and Zavoina (1975).

In the OP there is an observed ordinal variable Y, which is, in turn, a function of another variable Y^* that is not measured (Borooah 2001). Specifically, in the ordered model there is a continuous unmeasured latent variable Y^*, whose values determines what the observed ordinal variable Y matches.

The continuous latent variable Y^* has various threshold points. The value Y_i of the observed variable depends on whether or not the value of Y^* crossed a particular threshold, as showed by the following Eqs (1):

$$\begin{aligned}
&Y_i = 1,\ \text{if}\ \ Y_i^* \le \mu_1;\\
&Y_i = 2,\ \text{if}\ \ \mu_1 < Y_i^* \le \mu_2;\\
&\ldots;\\
&Y_i = j,\ \text{if}\ \ \mu_{j-1} < Y_i^* \le \mu_j;\\
&\ldots;\\
&Y_i = m,\ \text{if}\ \ Y_i^* > \mu_{m-1}.
\end{aligned} \tag{1}$$

In the population, the continuous latent variable Y^* is equal to (Eq. 2):

$$Y_i^* = \sum_{k=1}^{K} \beta_k X_{ki} + \varepsilon_i = Z_i + \varepsilon_i, \tag{2}$$

where: β_k is the coefficient of the X_{ki} independent variable, Z_i is the linear combination of both coefficients and independent variables; it represents the deterministic portion, while ε_i is a random disturbance term normally distributed. The error term reflects the fact that the variables may not be perfectly measured, and some relevant variables may be not introduced in the equation.

By means of the OP we can estimate the expected average value of the Y_i^* (Eq. 3):

$$E\left(Y_i^*\right) = Z_i = \sum_{k=1}^{K} \beta_k X_{ki}. \tag{3}$$

Once we have estimated β coefficients and the $(m-1)$ kk cutoff terms, we can estimate the probability that Y will have a particular value. The formulas are the following (Eqs 4):

$$\begin{aligned}
&\mathrm{P}\left(Y_i = j\right) = \Phi\left(\mu_j - x_i\beta\right) - \Phi\left(\mu_{j-1} - x_i\beta\right);\\
&P\left(Y_i = m\right) = \Phi\left(\mu_m - x_i\beta\right) -\\
&\Phi\left(\mu_{m-1} - x_i\beta\right) = 1 - \Phi\left(\mu_{m-1} - x_i\beta\right).
\end{aligned} \tag{4}$$

Finally, the OP model can be used to estimate the probability that the unobserved variable Y^* falls within the various threshold limits.

3. Sample Survey

3.1. Data

Data used as a support of this research study were collected on the occasion of a project named Mobile-To-Mobility (M2M), which was finalized to make personal device software for smartphones able to acquire automatically kinematic and performance information of the vehicle and also with active users' involvement, information concerning road and traffic functional characteristics.

A face-to-face survey was addressed to a sample of 516 drivers (Cardamone *et al.* 2016, 2014a, 2014b); the interviews were conducted during April–May 2012. The drivers were approached near the major shopping centre of the urban area of Cosenza (in the South of Italy), when they were arriving from the parking area. For selecting the sample of drivers, we used an accidental non probabilistic technique, based on a casual consecutive selection of the statistical unit.

The sample survey was structured in three different levels:

1) investigation 'in depth';
2) pilot survey;
3) 'sample' survey.

The 'in depth' survey was directed to a sample of few persons and targeted to test and verify the 'basic interview form' in the preliminary phase of the investigation. Based on a critical analysis of the findings from this survey, we arrived to formulate the pilot survey questionnaire version, addressed to a sample of 100 students attending the University of Calabria, placed in the urban area of Cosenza (in the South of Italy). The results from the pilot survey gave useful information about the suitability of the questionnaire. Indeed, it was considered appropriate to make some further changes to the interview form obtaining the final investigation form used to conduct the sample survey.

The questionnaire consists of five sections. The first section is targeted for the collection of data regarding socio-economic characteristics of the interviewed: age, gender, employment (status, sector and occupational status), monthly net income of the household, number of members of the household. The second section of the questionnaire concerns the respondent's driving behaviour, and it is composed of multiple-choice questions asking for information about the possible suspension or revocation of the driving licence, any point reduction of the licence, the driver's perception about his/her tendency to be distracted while he/she is driving, including the use of alcohol, drugs or medicines. The section contains also questions related to the compliance to driving rules (seat-belt use, safety distance, speed limits, and rules of overtaking) and the driving style. The third section aims to collect information concerning potential car crashes caused by the respondent during the last 3 years. He/she may indicate the consequences of the worst accident choosing among 4 options of severity: 'no harm to things or to persons', 'only material damage', 'injured', and 'dead persons'. The fourth section concerns the use of device with web connection, and specifically, information about the possession of one of these devices by the interviewee, its' operating system, the kind of internet rate payment the customer have chosen, the frequency of the software use, if the device has a built-in GPS system and the usage frequency of it. The last section is about the willingness to receive/send information by using an information system, which in our case is represented by the M2M platform. In this section, the questionnaire proposes to the interviewee to choose among five levels depending on the grade of his/her willingness to receive information from the platform and to send them to it.

3.2. Survey Outcomes

The first section, whose results are summarized in Table 1, represents the approach between interviewers and interviewed people in the face-to-face survey. This section is characterized by having interviewed 21.9% of youngsters (age between 18 and 25 years), while 78.1% of people are more than 26 years old. 58.2% of interviewees are employed, 23.6% consists of university students and the remaining 18.2% consists of housewives, unemployed, never been employed, and pensioners.

Table 1. Sample's socio-economic characteristics

Socio-economic characteristics	Class	Percentage
Age	from 18 to 25	21.9%
	from 26 to 40	44.2%
	from 41 to 65	33.7%
	over 65	0.2%
Sex	male	55.0%
	female	45.0%
Occupational status	employed	58.2%
	unemployed	5.0%
	never been employed	2.1%
	housewife	9.5%
	high school student	0.0%
	university student	23.6%
	pensioner	1.6%
	other	0.0%
Occupational sector	agriculture, hunting and fishing	1.0%
	industry and constructions	9.3%
	electric energy, gas and water	1.7%
	trade, reparations, hotels, restaurants	24.3%
	transportation and storage	3.7%
	other private services	28.7%
	public administration, education, health, other public services	31.0%
	other	0.3%
Professional condition	entrepreneur	10.3%
	freelancer	20.3%
	manager	3.7%
	employee	46.0%
	worker	17.3%
	artisan	1.7%
	other	0.7%
Income level	up to 1000 EUR	20.7%
	from 1001 to 2000 EUR	44.2%
	from 2001 to 3000 EUR	20.4%
	from 3001 to 4000 EUR	8.9%
	from 4001 to 5000 EUR	2.7%
	over 5000 EUR	3.1%
Number of family members	singles	5.6%
	2	14.1%
	3	25.3%
	4	38.4%
	5	14.1%
	more than 5 members	2.5%

The prevalent occupational sectors are public (31.0%) and private services (28.7%). The sample is spread between male (55.0%) and female (45.0%), prevalently belonging to a family with a monthly net income between 1000 and 2000 EUR (44.2%). The average number of family members is 3.5.

The second section is about driver's behaviours and gives a hint of how people assess themselves (Table 2). As matter of fact, 30.2% of interviewed people are 'never' distracted while they are driving. Though, they often make other activities connected to guide while driving (37.4%), and sometimes they use mobile while driving (41.1%) and sometimes are drink-drivers (33.3%). The last question of this section is targeted to know the psychological state that respondents have while they drive. 58.9% answered that they are careful but it happens that paying attention to the responses they gave before the last question, it results that 11.5% of careful drivers had an accident in the last three years.

Table 2. Driving behaviour

Drivers' behaviour	Class	Percentage
Driving licence disqualification	yes	4.1%
	no	95.9%
Driving licence points reduced by the police	yes	22.1%
	no	77.9%
Distracted while driving	always	1.4%
	often	3.5%
	sometimes	64.9%
	never	30.2%
Making other activities connected to guide while driving	always	19.6%
	often	37.4%
	sometimes	36.8%
	never	6.2%
Using mobile while driving	always	3.9%
	often	11.0%
	sometimes	41.1%
	never	44.0%
Drink-driving	always	0.6%
	often	1.9%
	sometimes	33.3%
	never	64.2%
Driving in not optimal psychophysical conditions	always	1.0%
	often	1.9%
	sometimes	47.8%
	never	49.3%
Using safety belts	always	70.8%
	often	11.2%
	sometimes	12.2%
	never	5.8%
Respecting safety distance	always	51.0%
	often	28.9%
	sometimes	15.9%
	never	4.2%
Respecting speed limits	always	27.5%
	often	40.2%
	sometimes	26.9%
	never	5.4%
Respecting overtaking rules	always	62.8%
	often	26.6%
	sometimes	8.9%
	never	1.7%
Getting informed about road conditions before going on a trip	always	41.5%
	often	10.1%
	sometimes	17.8%
	never	30.6%
Driving usual psychological state	aggressive	9.7%
	impatient	24.2%
	hesitant	3.3%
	slow	3.9%
	careful	58.9%

Section 3 investigates on driver's experience. The results are reported in Table 3. Most of the interviewees (75.4%) have a long driving experience owning the licence since more than seven years; in fact, 80.0% of the interviewees did not have any accident in the last three years. The remaining 20.0% of the drivers who had at least one accident indicated only material damages in 68.9% of the cases.

Table 3. Drive experience

Drivers' experience	Class	Percentage
Years of driving licence	from 0 to 7	24.6%
	from 8 to 22	44.0%
	from 23 to 47	31.2%
	over 47	0.2%
Annual km covered on average in the last three years	up to 10000 km	44.4%
	from 10001 to 30000 km	40.1%
	from 30001 to 50000 km	10.7%
	over 50001 km	4.8%
Car accident in last three years	yes	20.0%
	no	80.0%
Consequences of most dangerous	no damages to persons or things	5.8%
	only material damages	68.9%
	injures	25.3%
	dead persons	0.0%

The following part examines data about the use of devices with web connection possibility and users' willingness to receive/give information through the M2M platform. This was done testing the interviewees approach towards M2M system in general and in specific critical events.

Questions were addressed to interviewees considering five different levels in order to receive and give information: very low, low, medium, high, and very high. Although these data were deeply analysed in other works (e.g. Cardamone *et al.* 2014a), it is worth to remind that the total opinion about M2M system reports that a 'very high' level is approved by more than a half sample (55%). The comparison of the percentage values shows how users for all events are more incline to receive information instead of giving it.

For the fifth section, concerning device possession and use, data processing response was: 43% web connection device owners, 42% of these have Android operating system and 20% Symbian system. The only rate options commercially available are the ones at consumption (with a cost depending on the length of time on web connection) and flat (with a fixed cost, usually monthly, independent from the length of time on web connection).

4. Model Specification and Results

As previously introduced, the model was specified by taking into account the psychological state while driving as dependent variable, and by adopting an OP ordered formulation.

The explanatory variables were selected on the basis of the analysis of the theoretical reasoning linking some factors to psychological state while driving. Each factor was treated making a priori hypotheses about the theoretical reasoning link to the dependent variable, and estimating an expected relationship between themselves. Selected factors are presented in Table 4.

The factors were divided into two groups. The first one contains driving behaviour factors, such as making other activities connected to guide, using mobile phone while driving, driving after an alcoholic drink, driving in not optimal conditions, using safety belts, respecting safety distance, speed limits, and overtaking rules. The second group includes socio-economic characteristics such as driver's age and gender.

Each factor was defined by two explanatory variables; factors about driving behaviour have a first variable (with value 'yes') defined by grouping 'always', 'often' and 'sometimes' class, and a second one (with value 'no') corresponding to the 'never' class. The factor 'Age' has a first variable assuming a value 'from 25 to 65', and a second variable grouping 'under 25' and 'over 65' class. Finally, the variables 'male' and 'female' relate to the factor 'Gender'. Definitively, we have a total of 10 factors and 20 variables.

In order to calibrate the coefficients for each variable, the model was based on a particular reference case. The 'reference case' correspond to a driver who does not make other activities connected to guide and does not use mobile while driving; a driver who does not use to drive after an alcoholic drink and in not optimal conditions; a driver who respects the rules about the use of safety belts, safety distance, speed limits and overtaking; and a driver who is a male 'under 25' or 'over 65' years old.

The results of the calibrated model are shown in Table 5.

Based on the p-values of the Wald tests, 16 variables are found to be significant, with $p < 0.1$.

The measures used to evaluate the overall goodness-of-fit of the model are pseudo ρ^2 and the log likelihood ratio index. For ordinal regression models it is not possible to compute the same R^2 statistic as in linear regression, so three approximations are computed instead: Cox's and Snell's, Nagelkerke's and McFadden's pseudo ρ^2. O'Donnell and Connor (1996) suggested that the usual practice is to ignore such goodness-of-fit measure in models of ordered multiple choice since sometimes the value of the log-likelihood ratio index is substantially less than one.

Although the ρ^2 values seem low, they are comparable with the values obtained in other studies about accident severity where OP model was employed.

Table 4. A priori hypothesis regarding the psychological state while driving

Factor	Reasoning	Expected relationship
Making other activities connected to guide while driving	When the driver make other activities connected to guide, as reading speed, temperature or fuel level, his attention to guide decreases	Driver's psychological state more aggressive
Using mobile while driving	The driver who uses mobile when driving has to guide using only a hand. This could cause driving style less comfortable. In addition, using mobile causes distraction even with the headset	Driver's psychological state more aggressive
Drink-driving	Driving after drinking booze could reduce the capacity to drive a vehicle. The driver pays less attention to the vehicle and to the street	Driver's psychological state more aggressive
Driving in not optimal psychological conditions	If driver is not in optimal psychophysical conditions, he could guide worse	Driver's psychological state more aggressive
Using safety belts	The use of safety belts is to consider as the compliance to driving rules. If driver uses safety belts, his driving behaviour could be less aggressive. However, the driver could use safety belts because he wants to go fast and needs a protection system	Driver's psychological state more/less aggressive
Respecting safety distance	The respect of safety distance is usual behaviour when the driver has not an aggressive driving	Driver's psychological state more careful
Respecting speed limits	The driver who respects speed limits maintains the vehicle speed under a certain value. This could lead to maintain constant speed without hard accelerations	Driver's psychological state more careful
Respecting overtaking rules	The respect of overtaking rules assumes a driving behaviour, which does not contemplate risky manoeuvres	Driver's psychological state more careful
Age	Drivers who are 'from 25 to 65' years old have different driving behaviour than younger ('under 25') and elderly ('over 65')	Driver's psychological state more/less aggressive
Gender	Gender could be impact the driving psychological state. A male could have a driving psychological state more aggressive than a female or otherwise	Driver's psychological state more/less aggressive

Table 5. Model results

Variables	Estimated coefficient, β	Wald	*p*-value	Estimated probability (ratio relative to reference case)				
				Aggressive	Impatient	Hesitant	Slow	Careful
Reference case				0.0858	0.2236	0.0318	0.0377	0.6212
Making other activities connected to guide while driving (relative to 'no')	–0.618	5.425	0.020	0.1013 (1.18)	0.2485 (1.11)	0.0341 (1.07)	0.0400 (1.06)	0.5761 (0.93)
Using mobile while driving (relative to 'no')	–0.275	6.054	0.014	0.1277 (1.49)	0.2750 (1.23)	0.0355 (1.12)	0.0411 (1.09)	0.5206 (0.84)
Drink-driving (relative to 'no')	–0.202	2.917	0.088	0.1270 (1.48)	0.2703 (1.21)	0.0350 (1.10)	0.0407 (1.08)	0.5270 (0.85)
Driving in not optimal psychological conditions (relative to 'no')	–0.300	7.345	0.007	0.1270 (1.48)	0.2759 (1.23)	0.0356 (1.12)	0.0413 (1.10)	0.5201 (0.84)
Using safety belts (relative to 'yes')	0.154	0.389	0.533	0.1248 (1.45)	0.2198 (0.98)	0.0299 (0.94)	0.0354 (0.94)	0.5902 (0.95)
Respecting safety distance (relative to 'yes')	–0.215	0.563	0.453	0.2440 (2.84)	0.2934 (1.31)	0.0316 (0.99)	0.0356 (0.95)	0.3953 (0.64)
Respecting speed limits (relative to 'yes')	–0.699	8.662	0.003	0.3206 (3.74)	0.3409 (1.52)	0.0321 (1.01)	0.0349 (0.93)	0.2715 (0.44)
Respecting overtaking rules (relative to 'yes')	–0.822	4.389	0.036	0.3617 (4.21)	0.3150 (1.41)	0.0291 (0.92)	0.0317 (0.84)	0.2625 (0.42)
Age (relative to 'under 25' and 'over 65')	0.328	6.199	0.013	0.0779 (0.91)	0.2247 (1.00)	0.0326 (1.03)	0.0387 (1.03)	0.6261 (1.01)
Gender (relative to 'male')	–0.219	3.455	0.063	0.0881 (1.03)	0.2391 (1.07)	0.0336 (1.06)	0.0396 (1.05)	0.5997 (0.97)
Number of observations	516	–	–	–	–	–	–	–
k_1 (threshold)	–2.272	–	–	–	–	–	–	–
k_2 (threshold)	–1.310	–	–	–	–	–	–	–
k_3 (threshold)	–1.213	–	–	–	–	–	–	–
k_4 (threshold)	–1.103	–	–	–	–	–	–	–
Pseudo ρ^2 (Cox and Snell)	0.113	–	–	–	–	–	–	–
Pseudo ρ^2 (Nagelkerke)	0.126	–	–	–	–	–	–	–
Pseudo ρ^2 (McFadden)	0.054	–	–	–	–	–	–	–
log likelihood	–896.29	–	–	–	–	–	–	–

For example, Duncan *et al.* (1998) developed two models and obtained values of ρ^2 of 0.075 for the first model and 0.067 for the second one. For a model discussed in Khattak (2001) the value of ρ^2 is 0.057. In another work where two models were proposed (Rifaat, Chin 2007) the values of ρ^2 are 0.0322 and 0.095.

5. Discussion about the Main Results

After evaluating the goodness-of-fit of the model, interesting observations can be made on the signs of the estimated β coefficients for each variable. In fact, the signs can be used to evaluate the impact of each independent variable on the driver usual psychological state.

The negative value of the coefficient means to tend toward an aggressive psychological state while driving, whereas the positive value indicates the opposite.

From the calibrated model, the effect of the identified psychological state factor was studied by examining the psychological state probabilities against the reference case. In the columns corresponding to the probability values (Table 5), the numbers in brackets are the variation of probabilities calculated with respect to the probabilities of the reference case.

The variable 'Making other activities connected to guide while driving' has a negative sign (β = –0.618) relative to 'Not making other activities connected to guide while driving'. This means that if the driver makes other activities, his psychological state tends to become 'aggressive'. In fact, the probability to have a psychological state defined as 'careful' decreases of about 7% whereas the other probabilities increase compared to the reference case. A possible interpretation is that making other activities connected to guide while user is driving, as checking the fuel level, speed, GPS, temperature, could influence the driver's psychological state because the attention paid to guide decreases and driver tends to became aggressive. This result confirms the assumption made about the relationship between independent and dependent variables.

The same trend is followed by the variable 'Using mobile while driving'. The coefficient has a negative sign (β = –0.275) and the probability to have 'careful' as psychological state decreases related to the reference case. Even in this case, the hypothesis is verified by this result.

The variable 'Drink-driving' has a negative sign (β = –0.202). If user drives after an alcoholic drink, the probability to have 'careful' as psychological state decreases (of about 15%) and the probabilities to have the other alternatives grow, as we considered a priori.

A negative sign for the estimated coefficient (β = –0.300) of the variable 'Driving in not optimal psychological conditions' means that the probability to have 'careful' as psychological state while driving decreases when driver is not in optimal psychological condition.

The independent variables 'Using safety belts' and 'Respecting safety distance' are not are significant at a level $p < 0.1$. In our model, these variables do not impact the psychological state while driving.

The negative sign (β = –0.699) of the variable 'Respecting speed limits' is referred to the case when the response is 'no'. Therefore, when driver does not respect speed limits his psychological state is quite likely towards 'aggressive'. In fact, the results showed that the probabilities to have 'aggressive' and 'impatient' increase compared to the reference case. Conversely, the respect of speed limits presupposes a psychological state tending toward 'careful'.

The analysis of the results obtained for the variable 'Respecting overtaking rules' indicates that the non-compliance of overtaking rules could impact the dependent variable producing the raise of probability to have 'aggressive' and 'impatient' against the reduction of the probability of 'hesitant', 'slow' and 'careful'.

About the variable 'Age', the results suggest that when driver is between 25 and 65 years old the probability to have 'hesitant', 'slow' and 'careful' is higher than the reference case, whereas the probability of 'aggressive' and 'impatient' decreases.

Finally, the results show that the psychological state while driving is influenced by gender, and when the driver is female, the probability to have 'careful' is lower than the case in which the driver is a male.

Conclusions

In this work, OP model methodology was used to investigate the factors affecting the psychological state while driving. OP model was chosen to carry out the analysis because it is a flexible model and allows the psychological state probability to vary differently across categories, based on the explanatory variable.

The analysis was based on data collected by a face-to-face survey conducted in the urban area of Cosenza (in the South of Italy). The model was specified by considering 'psychological state while driving' as dependent variable, whereas the explanatory variables were selected on the basis of the analysis of the theoretical reasoning linking with the dependent variable. The explanatory variables are driving behaviour variables, such as making other activities connected to guide, using mobile phone while driving, driving after an alcoholic drink, driving in not optimal conditions, using safety belts, respecting safety distance, speed limits, and overtaking rules; and socio-economic characteristics, as driver's age and gender.

The results of the model appear congruent with the statistics about the driving behaviour, suggesting some considerations reported in the following:

1. Several factors play major roles in affecting the psychological state while driving. Among these, the respect of overtaking rules and speed limits have a considerable impact on the driver's psychological state, as well as bad habits such as making other activities connected to guide while driving, or driving in not optimal psychological conditions. As expected, the respect of the rules is indicative of a relatively careful psychological state, while driving bad habits are peculiar to aggressive drivers.
2. People in general adopt a safe driving behaviour, but there is a not insignificant part of drivers who are impatient and adopt dangerous and risky manners while driving. This part of users represents potential causes of road accidents, and consequently of serious injuries in terms of economic and social costs. The results of the statistics, as well as the results of the model, suggest that there is a certain correlation between driving behaviour and habits and the psychological state of the drivers. Being psychological state affected by driving behaviour, just psychological state can influence the happening of a road accident and its severity.
3. Investigating on the human factors affecting road accident severity and specifically on the complex interaction between driver's behaviour and accident risk is very important. The application of OP models to investigate the impacts (driving behaviour, compliance to the road rules, and drivers' characteristics) on driver's psychological state can provide interesting implications in the study of human factors affecting accident severity. To this end, our findings can represent a useful contribution to the scientific literature of the sector, and can have relevant implications in road safety decisions and policy.

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