Understanding risky driving among motorized two-wheeler drivers
The role of time-related anxiety and impunctuality

Gupta, Monik; Velaga, Nagendra R.; Oviedo-Trespalacios, Oscar

DOI
10.1016/j.tranpol.2023.10.022

Publication date
2023

Document Version
Final published version

Published in
Transport Policy

Transport Policy 145 (2024) 199–210

Contents lists available at ScienceDirect

Transport Policy

journal homepage: www.elsevier.com/locate/tranpol

Understanding risky driving among motorized two-wheeler drivers: The role of time-related anxiety and impunctuality

Monik Gupta [a], Nagendra R. Velaga [a,*], Oscar Oviedo-Trespalacios [b]

[a] Transportation Systems Engineering, Department of Civil Engineering, Indian Institute of Technology Bombay, Powai, Mumbai, 400076, India
[b] Faculty of Technology, Policy and Management, Delft University of Technology, Delft, the Netherlands

ARTICLE INFO

Keywords:
Motorized two-wheeler
Red light running
Lane sharing
Decision tree
Anxious driving

ABSTRACT

Motorized Two-Wheeler (MTW) drivers significantly contribute to road fatalities due to their vulnerability and the higher severity of crashes. Risky driving behavior, such as violations and errors, is a key precursor to road crashes. Understanding the factors that influence such risky behavior can shed light on opportunities for risk management. In this investigation, data from 460 motorized two-wheeler drivers were collected through an online questionnaire, exploring Red Light Running (RLR), lane sharing, and turning without indicating driving tendencies, latent psychological factors, and demographic attributes of the participants. The analysis was conducted in two steps: (a) decision trees were developed to classify risky driving behavior, and (b) binary logistic regression models were developed to quantify risky driving choices based on demographic and latent psychological variables, as well as interaction variables. The results showed that as driver anxiety increased, the probability of lane sharing rose from 76.3% to 87.9% in normal driving situations and from 80.3% to 96.6% in time-pressure driving situations, respectively. Furthermore, the results revealed that the odds of running red lights and lane sharing decreased to 0.57 and 0.68, respectively, for older drivers compared to young drivers. Overall, this study quantified the impact of underlying psychological factors and demographic parameters, as well as their combined effects, on assessing traffic violations, traffic errors, and non-illegal dangerous driving behaviors among motorized two-wheeler drivers. Additionally, the study discusses the implications and policy interventions related to the legalization of lane sharing and the risks associated with time-pressure driving in online food delivery systems. These findings can inform evidence-based policymaking to achieve road safety goals.

1. Introduction

Road crashes cause approximately 13.5 million fatalities worldwide annually (World Health Organization, 2020). In south Asian countries, 44% of these road fatalities were among Motorized Two-Wheeler (MTW) drivers (Ministry of Road Transport and Highways, 2020). MTWs are popular because they have a higher power-to-weight ratio, easy maneuverability, and are significantly cheaper than cars. However, MTWs are single-track vehicles, which makes them laterally unstable and vulnerable to road crashes. The drivers' error, deliberate violation, or non-illegal dangerous driving behavior can lead to severe road crashes while driving MTWs (Ayuso et al., 2010; G. Zhang et al., 2013). Traffic errors including misjudging the speed of other vehicles, failing to notice pedestrians, turning without indicating, etc. can create a sudden hazardous driving situation for the other road users as well (Castillo-Manzano et al., 2019; Staubach, 2009). However, some driving errors are intentional and are considered traffic violations such as speeding beyond the posted limit, red light running, alcohol-impaired driving, avoiding protective equipment such as helmets, seatbelts, child constraints, etc (Reason James et al., 2011). The drivers also get involved in some non-illegal dangerous driving maneuvers such as lane splitting or lane filtering. Lane filtering refers to a driver moving in between two lanes of traffic that is either stopped or moving very slowly (e.g., slower than 30 km/h), whereas lane splitting refers to a driver passing between two lanes of moving traffic, and lane sharing is used as a term encompassing both filtering and splitting (Myra Sperley & Amanda Joy Pietz, 2010).

Traffic errors, violations, and non-illegal dangerous driving

* Corresponding author. Transportation systems engineering, Department of civil engineering, Indian Institute of Technology Bombay, Powai, Mumbai, 400076, India.
E-mail addresses: monikgupta@iitb.ac.in (M. Gupta), n.r.velaga@iitb.ac.in (N.R. Velaga), O.OviedoTrespalacios@tudelft.nl (O. Oviedo-Trespalacios).

https://doi.org/10.1016/j.tranpol.2023.10.022
Received 14 March 2023; Received in revised form 9 October 2023; Accepted 29 October 2023
Available online 31 October 2023

behaviors majorly contributed to both the risk and crash severity of motorized two-wheeler drivers (Castillo-Manzano et al., 2019; Gupta et al., 2021; Lin and Kraus, 2009). A study analyzing traffic errors revealed that turning without indicating was the fourth leading cause of traffic crashes (1.6%–4.1%) in Vietnam (Nguyen-Phuoc et al., 2020). Red Light Running (RLR) is a very frequent traffic violation that causes two million crashes annually at intersections in the USA (Limanond et al., 2010; NHTSA, 2021; Wong et al., 2008). According to NHTSA (2021) report, 17% of road fatalities are a consequence of driving beyond the speed limit. Non-illegal dangerous driving maneuvers such as lane sharing is a very common practice, especially in dense traffic conditions. The RIDER report studied 360 traffic crashes involving MTW users and revealed that 4.4% of these crashes occurred while lane sharing (Aupetit et al., 2015).

These risky driving maneuvers are generally performed to reach the destination faster or to fulfill the sensation-seeking, especially by younger drivers. The government of India increased the traffic penalties by approximately ten times in the Motor Vehicle Amendment Act 2019; Ministry of Road Transport and Highways (2020). However, several studies highlighted that driver violated the traffic rules despite accepting the risk of penalties and crashes while violating the traffic rules (Prat et al., 2017; Walsh et al., 2008). The risky driving behaviors are often controlled by the driver's own road safety perceptions, acceptance among other road users, and driving situations (Castillo-Manzano et al., 2015). The driving situations compelling the drivers to be anxious while driving can further incentivize the short-term gain of risky driving and motivate them to make unsafe driving decisions. The impact of such psychological factors on traffic violation actions also depends on individual characteristics such as age group, marital status, education, and income levels (Forward, 2009; Yang et al., 2018). Thus, to reduce traffic violations, it is important to explore the underlying psychological causes of traffic violations, traffic errors, and dangerous driving behavior among various socio-demographic groups. Therefore, in the present study, the risky driving choices of the drivers are explained by the combined effect of their psychological and demographic factors which can further help in policy making for improving the road safety on Indian roads.

2. Literature review

The risky driving behaviors are most common cause of the road crashes. Therefore, a vast literature has explored the causes of traffic violation, error and dangerous driving and their effect on the road safety (Shahar, 2009; Stephens et al., 2017; Nguyen-Phuoc et al., 2020; Yang et al., 2018). Table 1 summarizes the studies conducted in several countries exploring the effect of psychological factors and individual demographic variables on choices of risky driving behaviors. Table 1 also categorizes the existing literature based on their explored psychological variables such as self-efficacy, time anxiety, perceived risks, and subjective norms. Existing literature showed that subjective norms (i.e., the importance of the influence of other people in surroundings) can significantly affect the drivers' decision of violating the traffic rules or rash driving (Cestac et al., 2011a; Forward, 2009). Similarly, the effect of self-efficacy (confidence in driving skills) and perceived risks were found to affect risky driving decisions. Moreover, anxious driving in time pressure situations can also increase the risk-taking tendencies of the drivers. Therefore, this study considered several psychological factors in combination with individual demographic factors to evaluate the decision making of risky driving behaviors. The following subsections describe the findings of existing literature exploring the influence of individual characteristics, anxiety, impunctuality, and other psychological factors on risk taking tendencies of drivers. Further, the objectives of this study are formulated to overcome the potential research gaps in the existing studies.

2.1. Time-related anxiety and impunctuality as risk factors

Driving in time-constrained situations can compel the drivers to take higher risks on the roads. Existing studies revealed that driving performance parameters such as speed, acceleration, jerk, and harsh braking behaviors become prevalent in time pressure driving situations (Fitzpatrick et al., 2017; Oviedo-Trespalacios et al., 2019; Pawar and Velaga, 2020, 2021; Rendon-Velez et al., 2016). Fitzpatrick et al. (2017) found that the risk of crash under time pressure can increase up to 3–6 times, however, the time saved is very little especially when driving on higher posted speed limit roads. Hence it is very relevant to consider the risk-taking tendencies of the drivers who are generally late to reach their destination. Drivers having a tendency to be late are more likely to be under time-constrained driving situations and therefore, are more likely to be indulged in risky driving behavior. Therefore, this study considered the impunctuality of the riders as the explanatory variable for their risky driving decisions. Previous research also revealed that drivers with higher anxiety were more involved in aggressive driving (C. and Mallia, 2019; Shahar, 2009). However, several researchers investigated the clinical features of driving anxiety and the more severe fear of driving and phobia (C. and Mallia, 2019; M et al., 2006; Mackett, 2021). The influence of anxiety among normal drivers was not studied thoroughly (Shahar, 2009). Therefore, it is important to explore the influence of non-clinical panic driving behavior along with other psychological factors on traffic errors, violations, and risky driving tendencies.

2.2. Risky driving choices, psychological factors, and individual characteristics

The risky driving choices have been widely used to study the underlying intentions of dangerous driving behaviors, such as red light running (Abdul Manan et al., 2019; Nguyen-Phuoc et al., 2020; Satiennam et al., 2018; Wong et al., 2008; Yan et al., 2016) speeding (Cestac et al., 2011b; Chorlton et al., 2012), drinking and driving (Chan et al., 2010; Moan and Rise, 2011; Yadav and Velaga, 2019), seat belt use (Okamura et al., 2012; Şimşekoğlu & Lajunen, 2008), lane sharing ((Aupetit et al., 2015; Clabaux et al., 2017)), and traffic errors such as

Table 1
Summary of studies exploring the effect of psychological, and demographic factors on risky driving decision.

Author	Sample Size	Country	Analysis Technique	MTW	Psychological Factors				Demographic Factors
					SE	TA	PR	SN	
Yang et al. (2018)	160	China	Hierarchical Regression	✓	✓			✓	✓
Stephens et al. (2017)	470	Australia	Principal Axis Factoring	✓					✓
Okamura et al. (2012)	381	Japan	SEM		✓			✓	
Chorlton et al. (2012)	4929	United Kingdom	Multiple Regression	✓	✓		✓	✓	
Cestac et al. (2011)	3002	France	Hierarchical regression				✓	✓	✓
Elliott & Thomson (2010)	1403	United Kingdom	Hierarchical Regression		✓		✓	✓	✓
Forward (2009)	275	Sweden	Descriptive Statistics					✓	✓
Shahar (2009)	120	Israel	Multiple Regression			✓			
Şimşekoğlu & Lajunen (2008)	277	Turkey	SEM				✓	✓	✓

SE: Self-Efficacy; TA:Time Anxiety; PR: Perceived Risk; SN: Subjective Norm; SEM: Structural Equation Modeling; MTW: Motorized Two-Wheeler.

turning without indicating (Micucci et al., 2019; Nguyen-Phuoc, D. et al., 2020; Rusli et al., 2020; Wei et al., 2021) among car drivers. However, the motivations regarding motorized two-wheeler drivers' intentions of risky driving were not thoroughly explored in the previous studies. Existing studies found that psychological factors such as the presence of another person (Chorlton et al., 2012; Okamura et al., 2012; Şimşekoğlu & Lajunen, 2008), confidence in driving skills (Elliott and Thomson, 2010; Yang et al., 2018), and perceived risks (McBride et al., 2020; Y. Zhang et al., 2020) can significantly influence the road users' traffic violation decisions. Therefore, this study considered the effect of presence of other people while riding motorized two-wheeler and riders' confidence in their driving skills as an explaining factor for the risky driving choices on the road. However, the influence of psychological parameters might not be equal for all the demographic groups. The demographic parameters such as age, gender, income, education, marital status, etc. can significantly influence the drivers' risky driving decisions (Forward, 2009; Yang et al., 2018). Existing studies showed that young drivers had more inclination toward sensation seeking and violating the traffic rules (Forward, 2009). It had also been found that males were more often involved in risk-taking behavior and hence were more likely to violate the traffic rules (Yang et al., 2018). McBride et al. (2020) also revealed that drivers with several years of experience were more confident in their skills and were more often involved in risky driving behavior. White et al. (2010) revealed that drivers who drive on a daily basis were less hesitant to take risks while driving despite having less experience. Therefore, in this study the combined effect of psychological factors and demographic variables is considered using the interaction variables along with their main effect.

2.3. Research gap and objectives

The existing literature explained the intentions of risky driving among car drivers. However, Motorized Two-Wheeler (MTW) drivers' behavior under dangerous driving situations has not been thoroughly explored in lower middle-income countries such as India (Table 1). This study presents a comparative analysis of traffic violations (i.e., red light running), traffic error (i.e., turning without indicating), and non-illegal dangerous driving (i.e., lane sharing) among MTW drivers. Another research gap is that existing literature has only focused on evaluating the impact of clinical or severe fear of anxiety on traffic violation tendencies. However, anxiety can happen to the general population and can significantly affect driving behavior and choices (C. and Mallia, 2019; M et al., 2006; Shahar, 2009). We anticipate that in the road traffic environment time-related anxiety may play an important role on MTW drivers' dangerous behavior. Additionally, this study considers the impact of potential interaction between driver demographic attributes and psychological parameters on risky driving behaviors. The present study aims to overcome the limitations of existing literature by addressing the following objectives:

i. To quantify the risk-taking tendencies of MTWs drivers based on traffic related psychological factors, anxiety, and demographic variables.
ii. To compare decision making factors while violating traffic rules (i.e., red light running), traffic error (i.e., turning without indicating), and non-illegal dangerous driving (i.e., lane sharing) among motorized two-wheeler drivers.

The rest of the paper is organized as follows: Section 3 presents the methodology employed in the study, Section 4 presents the analysis and results of the study, further in Section 5, the inferences from this study are discussed, Section 6, describes the policy implications from this study, and finally the study is concluded along with highlighting the limitations of the study.

3. Methods

We conducted an online survey in India. Fig. 1 shows the process followed in this study to identify the underlying causes of drivers' tendencies towards risky driving decisions. An online questionnaire was prepared to collect the data regarding drivers' risky driving tendencies, their attitudes and perceptions, and individual demographic details. The dependent variables in this study are tendencies a) To violate the traffic rules, b) To make a traffic error, and c) To perform the non-illegal dangerous driving maneuver. The independent variables are the psychological latent variables (i.e., anxious driving and impunctuality etc.) and individual characteristics (i.e., experience, age, etc.). Initially, three decision tree models were developed to classify risky driving decisions based on psychological variables and individual demographic attributes. Interaction variables were defined from the results of the developed decision tree (Castillo Sierra et al., 2015; Elmitiny et al., 2010a; Scott-Parker and Oviedo-Trespalacios, 2017a). These interaction variables are combination of psychological latent variables and individual characteristics. The psychological latent factors such as anxious driving or impunctuality can significantly affect the drivers' risky driving choices when combined with individual characteristics such as age or experience. However, the decision trees are non-parametric hierarchical classification method which has type I error and hence a reduced ability to make inferences. Therefore, this study adopted a previously extensively used combined approach of decision tree and binary logistic regression (Haque et al., 2016; Washington, 2000). The interaction variables obtained from decision tree explained the non-linear relation of psychological latent factors and individual attributes in addition to their main effects on drivers' risky driving choices using binary logistic regression.

3.1. Questionnaire design

The questionnaire was designed to capture the dangerous driving frequency of the motorized two-wheeler drivers in India. The survey was designed into five sections to collect the different aspects of the information regarding the participants. The first section enquired regarding the likeliness of being involved in a) Red Light Running (RLR) i.e., crossing the signal at the red time, b) Turning without indicating, and c) Lane sharing in normal and time pressure driving conditions. The time pressure constraint was mentioned in the online questionnaire by providing situations such as getting late to reach the railway station. The self-reported risky driving tendency was higher in time pressure driving situations than in normal driving situations (Fig. 2). In the second section, the drivers' responses to time anxiety were captured. In this section, drivers were put under five different situations, and their response of the anxiety level on a 5-point Likert (1: Low to 5: High) scale was recorded. Further, In the third section, drivers' frequency of traffic violation was investigated in case they are driving in the presence of the pillion rider who are important to them (such as parents, spouse, or friends). The last section collected information regarding the importance of skill and impunctuality of the drivers. In this section, drivers were enquired regarding the importance of the driving skills over the risk of traffic violation by three measurement indicators. The details of the measurement indicators are also given in Table 2.

3.2. Data collection and participants

The data for this study was collected through an online questionnaire from April to June 2021. Before conducting the survey, approval was taken from the Institutional Review Board of the Indian Institute of Technology Bombay (Proposal No. IITB-IRB/2021/022). In this study, a total of 460 responses were obtained from several states in India. The participation was voluntary, and the snow-ball sampling method was used to collect the responses (Y. Zhang et al., 2020). The reported time of filling out the survey information was approximately 8–10 min. The

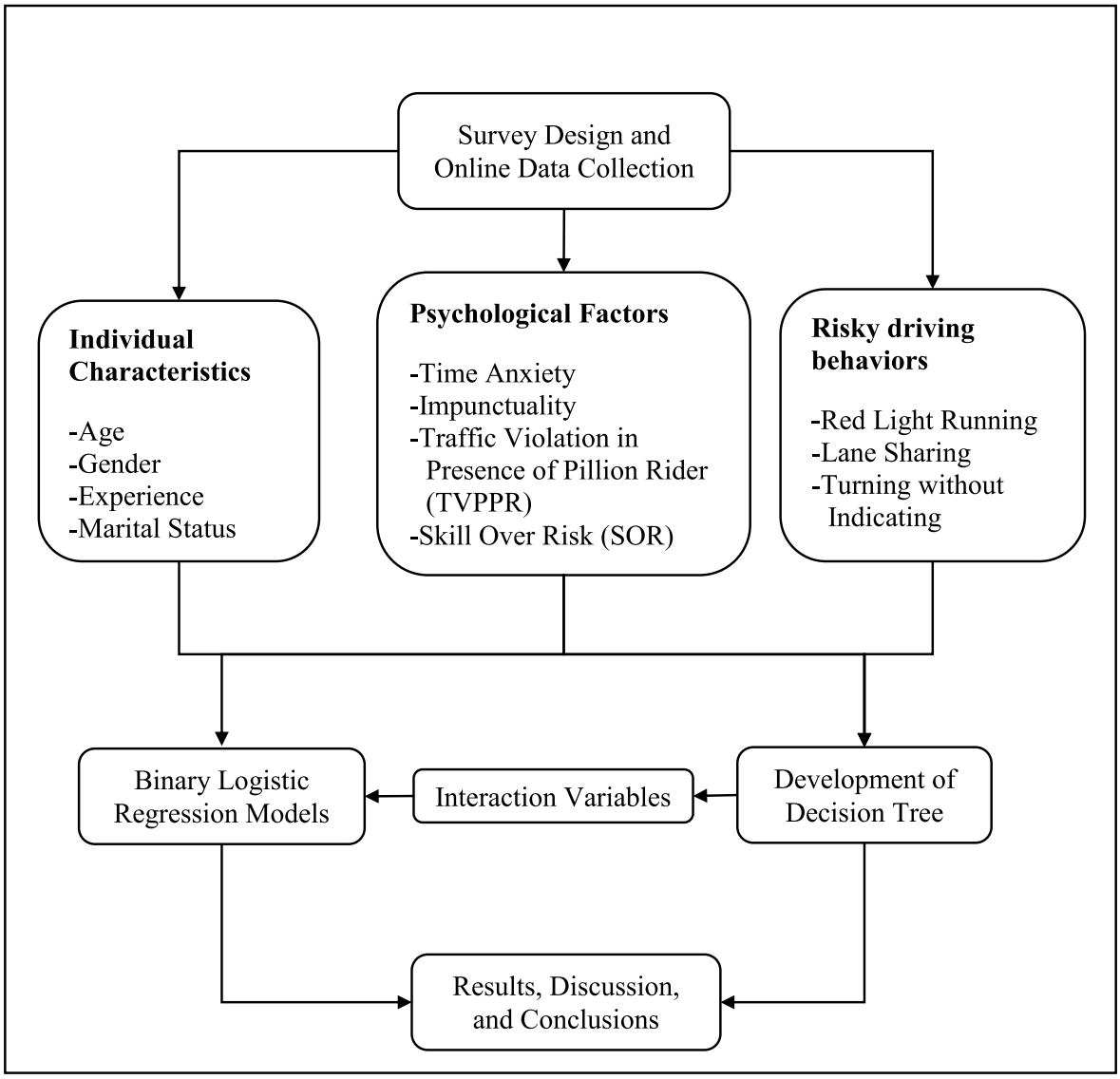

Fig. 1. Methodology adopted for the present study.

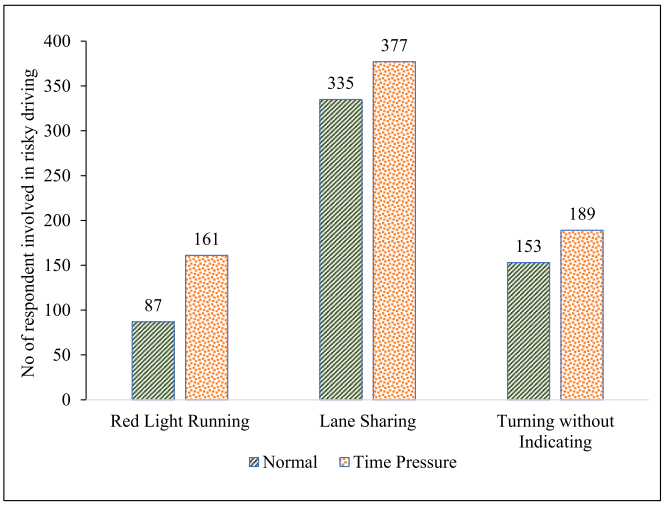

Fig. 2. Risky driving choices in normal and time pressure situations.

respondents were from different age categories (Mean = 27.1, Standard deviation = 8.4). The variation of participants' demographics, vehicle characteristics, and driving habits is presented in Table 3. The proportion of the female respondents in the sample is 19.2 % which is representative of the gender proportion of Indian driver population as in India, 72.5% of the driving registration holder's population are male (Ministry of Road Transport and Highways, 2016). In India the usage of low-powered engine capacity motorized two-wheeler are in majority. More than 85% of motorized two-wheelers have less than 150 CC engine capacity (Sunitha, 2021) which is similar to the vehicle usage of the survey respondent (84%). Also, the usage of manual transmission two-wheeler is approximately 65% in India (Marklines Automotive Industry, 2019) which is again close to the survey respondent geared two-wheeler usage (51%).

3.3. Statistical analysis

3.3.1. Decision tree development

The decision tree is a nonparametric hierarchical segmentation analysis technique that classifies the observations by partitioning the predictor space in a recursive manner. The Exhaustive CHAID algorithm is designed by G.V.Kass (1980) was used for developing the decision tree

Table 2
Details of measurement indicators in the questionnaire.

Measurement Indicator	Factor Loading	Cronbach's alpha
Traffic Violation in Presence of Pillion Rider (TVPPR)		0.86
SN1: How likely are you to violate traffic rules if you are traveling with parents?	.80	
SN2: How likely are you to violate traffic rules if you are traveling with spouse/partner?	.82	
SN3: How likely are you to violate traffic rules if you are traveling with a child?	.82	
SN4: How likely are you to violate traffic rules if you are traveling with a friend?	.72	
SN5: How likely are you to violate traffic rules if you are traveling with a colleague?	.83	
Self-reported experiences of Time-related Anxiety (TA)		0.79
TA1: Do you feel anxious if you get late for a movie?	.66	
TA2: Do you feel anxious if you get late for an office meeting?	.82	
TA3: Do you feel anxious if you get late for a doctor's appointment?	.73	
TA4: Do you feel anxious if you get late to reach airport?	.80	
TA5: Do you feel anxious if you get late for a meeting with a friend?	.56	
Skill Over Risk (SOR)		0.73
SE1: If someone is skilled, it is safe to move through the gaps available in the vehicles.	.83	
SE2: If someone drives with attention, it is alright to quickly overtake the vehicles.	.85	
SE3: There should be no penalty for using earphones while driving.	.70	
Impunctuality (IP)		0.61
HU1: My friends/colleagues complain that I always make them wait.	.75	
HU2: How often does it happen that you are getting late to reach the destination?	.75	

in the IBM SPSS software. The cross-validation method (10-folds) was used to assess the tree structure (Elmitiny et al., 2010b).

3.3.2. Binary logistic regression

Binary logistic regression models the dichotomous choices using the logit function. In the present study, the parameters were estimated using the Maximum Likelihood Estimation (MLE) approach. The mathematical formulation of the binary logistic model is as follows:

$$\ln\left(\frac{P(Y=1)}{1-P(Y=1)}\right)=\alpha-\beta X \quad (1)$$

Where, P (Y = 1) is the probability of violating the traffic rules. α represents the intercept, β is the estimate vector and X is the vector of explanatory variables.

4. Results

4.1. Development of decision tree to assess dangerous driving choices

Three decision trees were developed to identify the critical factors determining the red light running violation, lane sharing, and turning without indicating. The explanatory variables were (a) the four latent psychological variables, and (b) demographic factors of the respondents. In total, four latent variables were constructed using the 15 measurement items (Table 2). All the measurement items had factor loading greater than 0.4 (J. Hair, 2009), indicating a good measurement of the latent constructs. The obtained values of Cronbach's alpha for all the extracted factors were higher than 0.6 (J. J. Hair et al., 2015) suggesting the reliability of the measurement (Table 2). The decision tree correctly classified 81.1%, 72.8%, and 68% of the cases for red light running violation, lane sharing, and turning without indicating respectively. The first note in the decision tree is most decisive in deciding the particular risky driving behavior. For example, the presence of pillion rider is the most influencing factor in decision making of red-light running by the rider (Fig. 3). However, the belief in skills over risk (SOR) is the most significant factor in determining the lane sharing behavior of the riders. The decision tree helps in the assessment of the non-linear relationship between explanatory variables and dangerous driving choices (Choudhary and Velaga, 2019a). The terminal nodes of the decision tree, as represented by numbered circles in Fig. 3, can be defined as interaction variables. The interaction variables having a combination of psychological and demographic factors were further considered as explanatory variables in binary logistic models. The explanation of each interaction variable is provided in Table 4. For example, the interaction variable 1 depicts drivers who have a) five or more years of driving experience, b) do not prioritize risky driving behavior even when skillful, and c) do not violate the traffic rules in the presence of others. Fig. 3 shows the structure of the developed decision trees. 88.7% of the experienced and overconfident drivers drove their motorcycles by sharing in between the lanes (Interaction Variable 5).

Table 3
Summary of descriptive details of the participants (Gupta et al., 2022).

Parameters	Description	Level	% Sample
Driver Demographics			
Age	Age of the drivers in the years	Continuous (18–65)	
Gender	Driver's Gender	Male	80.8
		Female	19.2
Experience	Number of years the person is driving.	>5 years	59.4
		5 years or less	40.6
Marital Status	Driver's Marital Status	Married	18.7
		Unmarried	81.3
Vehicle Details			
Engine Size	Power of MTW's engine in Cubic Centimetres (CC).	150 CC or more	16.2
		<150 CC	83.8
Vehicle Type	Motorized two-wheeler torque transmission type	Geared	50.9
		Non-Geared	49.1
Driving Habits			
Travel Frequency	Frequency of travel using MTW	At least once a week	85.1
		Less than once a week	14.9

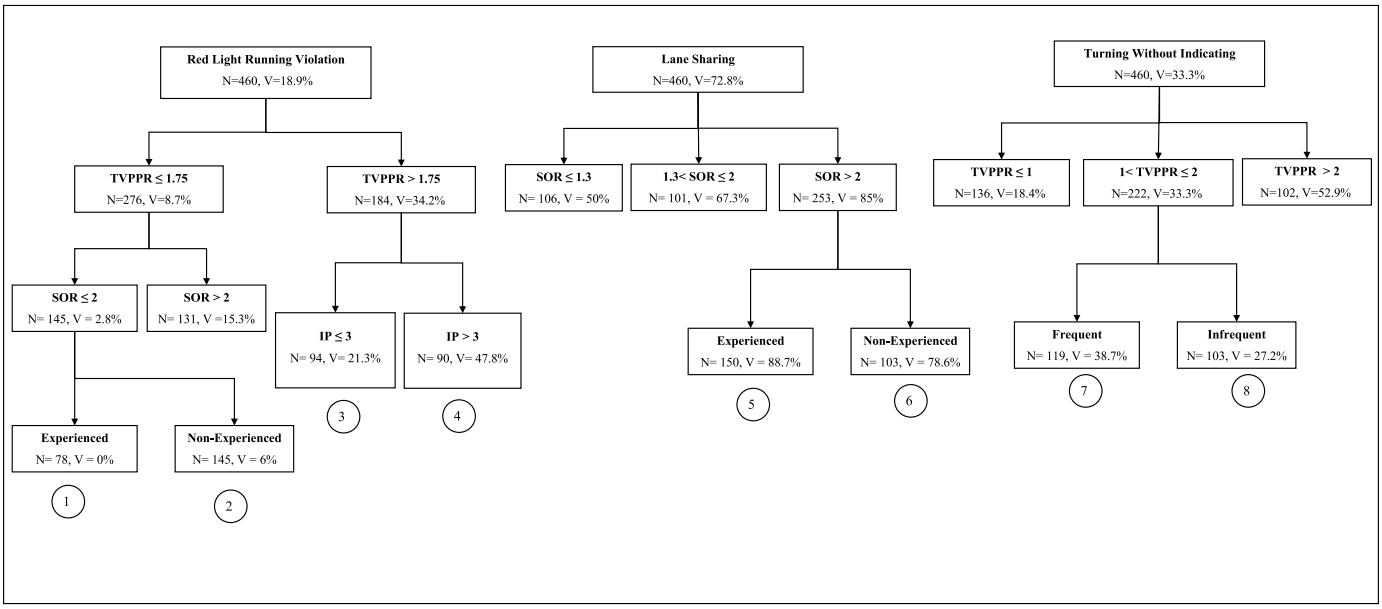

Fig. 3. Decision tree model for the traffic violation decision. Circled numbers represent the terminal node (interaction variables).

Table 4
List of interaction variables obtained from the decision tree model.

Variable	Description
Interaction Variable 1	Experienced drivers prioritizing safety over skills and having lesser acceptance for traffic violations from pillion rider.
Interaction Variable 2	Non-Experienced drivers prioritizing safety over skills and having lesser acceptance for traffic violations from pillion rider.
Interaction Variable 3	Punctual drivers encouraged for violating the traffic rules even in the presence of others
Interaction Variable 4	Impunctual drivers encouraged for violating the traffic rules even in the presence of others
Interaction Variable 5	Experienced drivers prioritizing skills over risk
Interaction Variable 6	Non- Experienced drivers prioritizing skills over risk
Interaction Variable 7	Frequent Drivers rarely violating traffic rules in the presence of others
Interaction Variable 8	Infrequent Drivers rarely violating traffic rules in the presence of others

***N = Number of cases; V = Percentage of Violators; TVPPR: Traffic Violation in Presence of Pillion Rider; SOR: Skill Over Risk; IP: ImPunctuality**.

4.2. Quantifying psychological and demographic attributes of dangerous driving decisions using binary logistic models

To quantify the impact of various psychological and demographical factors in determining the dangerous driving behavior three binary logistic models were developed in normal and time pressure driving situations. The binary dependent variables were a) Red light running, b) Lane sharing, and c) Turning without indicating. The explanatory independent variables were a) the psychological variables, b) the interaction variables obtained from the developed decision tree, and c) demographic variables. The results of all three binary logistic models are given in Table 5, Table 6, and Table 7. Results show that the odds of running the red light, and lane sharing decreased to 0.57, and 0.68 for the older drivers compared to the young drivers in normal driving situations. Results also revealed that acceptance from pillion rider (TVPPR) positively influenced all three traffic behaviors. Drivers' odds of lane sharing increased up to 1.23 and 1.62 times under normal and time pressure driving situations respectively. Results also indicated that drivers having the habit of being late to their destinations were more inclined towards running the red light and not indicating before turning.

Table 5
Results of binary logistic regression estimating red light running behavior.

Parameters	Normal			Time Pressure		
	Estimates	SE	Exp(b)	Estimates	SE	Exp(b)
Intercept	−4.30	0.58	0.01	−3.17	0.49	0.04
Age	−0.57*	0.40	0.57	−0.72**	0.30	0.49
Skill Over Risk (SOR)	0.18*	0.12	1.20	0.21*	0.10	1.23
TVPPR	0.69***	0.18	1.99	0.76***	0.17	2.14
Impunctuality	0.41***	0.12	1.51	0.29***	0.10	1.34
I1	−2.06**	1.04	0.13	−0.69*	0.43	0.50
Goodness of fit	AIC	BIC	LL	AIC	BIC	LL
	2376.6	2401.4	−1182.3	2110.2	2135.5	−1049.4

TVPPR: Traffic Violation in Presence of Pillion Rider; AIC: Akaike information criterion; BIC: Bayesian Information Criterion; LL: Log Likelihood; b = estimates; SE: Standard Error; *p < 0.10; **p < 0.05; ***p < 0.01, I1 (refer Table 4).

Table 6
Results of binary logistic regression estimating lane sharing behavior.

Parameters	Normal			Time Pressure		
	Estimates	SE	Exp(b)	Estimates	SE	Exp(b)
Intercept	−1.61	0.46	0.20	−2.02	0.55	0.13
Age	−0.38*	0.29	0.68	−1.15***	0.32	0.32
Time Anxiety (TA)	0.20*	0.11	1.23	0.48***	0.13	1.62
Skill Over Risk (SOR)	0.48***	0.13	1.61	0.54***	0.17	1.72
TVPPR	0.44**	0.19	1.56	0.69**	0.25	1.98
I5	0.94*	0.35	2.56	0.90*	0.46	2.46
Goodness of fit	AIC	BIC	LL	AIC	BIC	LL
	2206.7	2231.5	−1097.4	2481.5	2506.2	−1234.7

TVPPR: Traffic Violation in Presence of Pillion Rider; AIC: Akaike information criterion; BIC: Bayesian Information Criterion; LL: Log Likelihood; b = estimates; SE: Standard Error; *p < 0.10; **p < 0.05; ***p < 0.01, I5 (refer Table 4).

Table 7
Results of binary logistic regression estimating turning without indicating behavior.

Parameters	Normal			Time Pressure		
	Estimates	SE	Exp(b)	Estimates	SE	Exp(b)
Intercept	−2.94	0.39	0.05	−2.17	0.35	0.11
TVPPR	0.57***	0.15	1.78	0.54***	0.15	1.71
Impunctuality (IP)	0.38***	0.09	1.46	0.28***	0.09	1.33
I7	0.46*	0.23	1.58	0.28*	0.22	1.32
Goodness of fit	AIC	BIC	LL	AIC	BIC	LL
	2064.9	2081.5	−1028.5	2002.6	2019.1	−997.2

AIC: Akaike information criterion; BIC: Bayesian Information Criterion; LL: Log Likelihood; b = estimates; SE: Standard Error; *p < 0.10; **p < 0.05; ***p < 0.01, I7 (refer Table 4).

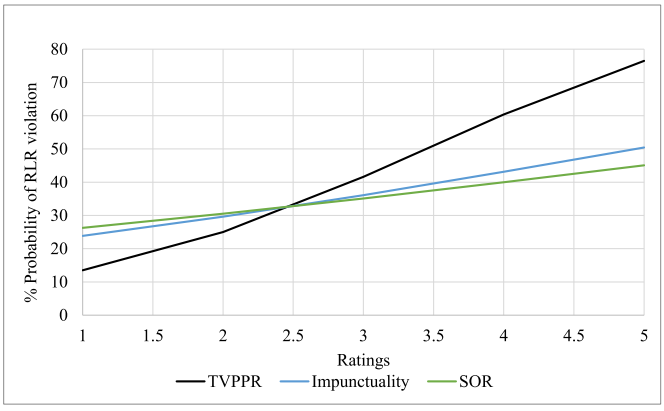

Fig. 4. Probability of Red light Running (RLR) based on psychological factors. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

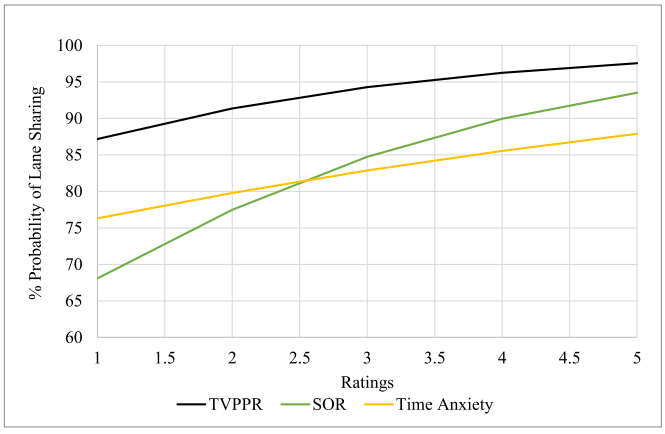

Fig. 5. Probability of lane sharing based on psychological factors.

5. Discussion

5.1. Psychological factors underlying traffic violations, errors, and non-illegal dangerous driving tendency

Driving is a complex process involving multiple activities simultaneously. The behavior of violating traffic rules, making traffic errors, and dangerous driving is often driven by underlying psychological factors (Castillo-Manzano et al., 2015). The results from this study revealed that the red light running violation tendency was influenced by characteristics such as impunctuality (IP), believing in skills under risky driving situations (SOR), and presence of pillion rider (TVPPR) (Fig. 4). The lower rating of TVPPR means that the driver do not prefer to violate the traffic rules in the presence of the pillion rider. As the rating of TVPRR increases, the acceptance for violating the traffic rule in presence of pillion rider increases, and therefore the actual probability of running the red light also increases. Fig. 4 also shows that presence of pillion rider (TVPRR) explained the highest variation of red light running violations among all the psychological factors. This indicates that the driver's traffic violation tendency often gets promoted when they are accepted for such behaviors by others (Alver et al., 2014; Cestac et al., 2011a). However, the lane sharing behavior of the drivers was better explained by the characteristic of believing in skills (SOR) in risky driving situations (Fig. 5). A higher rating of SOR represents drivers believing that with better driving skills risky driving is safe, and such drivers are more likely to perform dangerous driving maneuvers such as lane sharing (Fig. 5). This finding was also consistent with the previous studies which suggested a higher risk-taking tendency was observed when drivers were more confident regarding their driving skills (Elliott and Thomson, 2010; Yang et al., 2018). Fig. 6 reveals that drivers often turn without indicating, this traffic error often gets promoted when

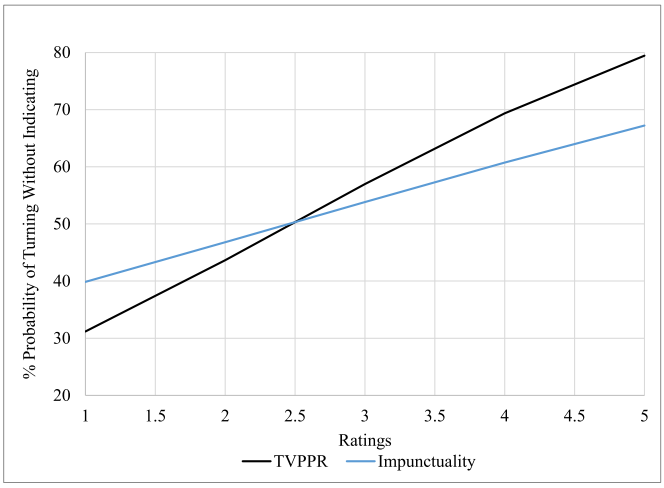

Fig. 6. Probability of turning without indicating based on psychological factors.

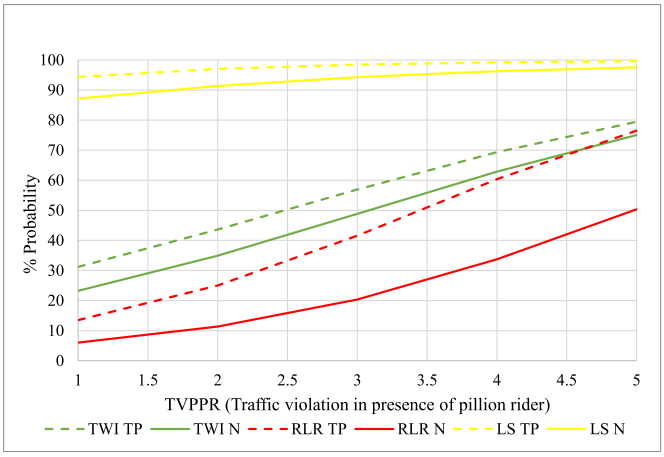

Fig. 7. Probability of Red Light Running (RLR), Turning Without Indicating (TWI), and Lane Sharing (LS) in Normal (N) and Time Pressure (TP) driving situations. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

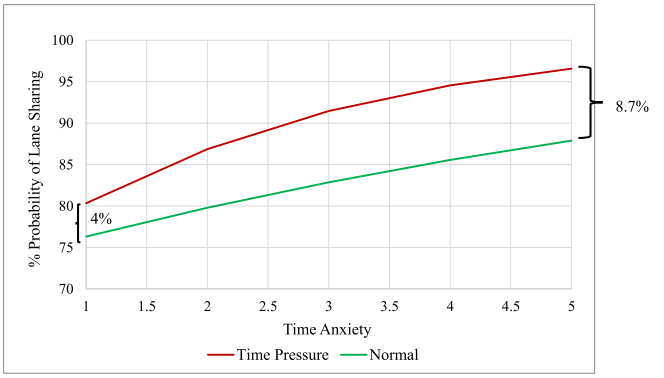

Fig. 8. Probability of lane sharing in normal and time pressure driving situations.

other people in the surroundings also do the same or accept other drivers' such inappropriate behaviors. Fig. 6 also indicates that for impunctual drivers, it is more common to not indicate before turning while driving, than the drivers who are generally punctual for their meetings.

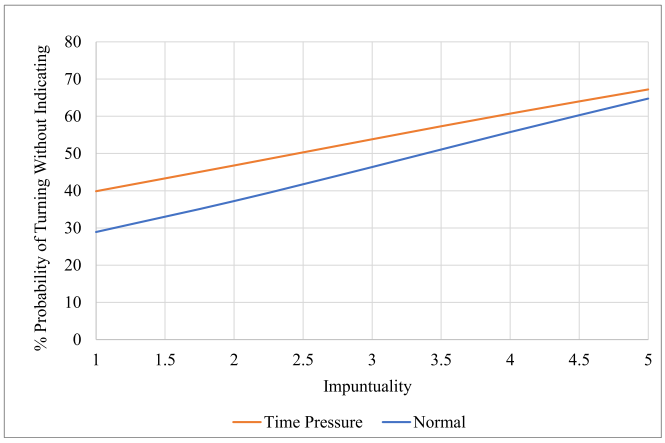

Fig. 9. Probability of turning without indicating by varying Impunctuality.

5.2. Time pressure and impunctuality

The time-constrained driving situation puts excessive pressure on drivers and may result in risky driving behaviors. Fig. 7 revealed that the probability of red light running, lane sharing, and turning without indicator is higher in case of time pressure driving situations than the normal driving situations. This might be because the primary objective of running the red light or sharing a lane while driving is to reduce the travel time spent in reaching the destination (Paul and Ghosh, 2020). Also, the probability of the traffic errors also increases when drivers are under time pressure driving situations (Fitzpatrick et al., 2017; Pawar and Velaga, 2020). Fig. 8 shows the probability of the lane sharing under normal and time pressure driving situations. The lowest value of time anxiety represents the group of drivers who do not get anxious at all while running out of time to complete the driving task. As the time anxiety increases among the drivers the probability of lane sharing increased from 76.3% to 87.9%, and 80.3% to 96.6 % in normal and time pressure driving situations respectively. Highly time anxious drivers (time anxiety = 5) had 8.7% higher probability of choosing a dangerous driving situation whereas less time anxious drivers (time anxiety = 1) had only 4% higher probability of dangerous driving in time pressure situation in comparison to normal driving situations. Fig. 9 also shows that punctual drivers are less likely to make traffic errors in normal driving situations than time constrained driving situations, however, drivers who are impunctual, make traffic errors more frequently in both normal and time pressure driving situations.

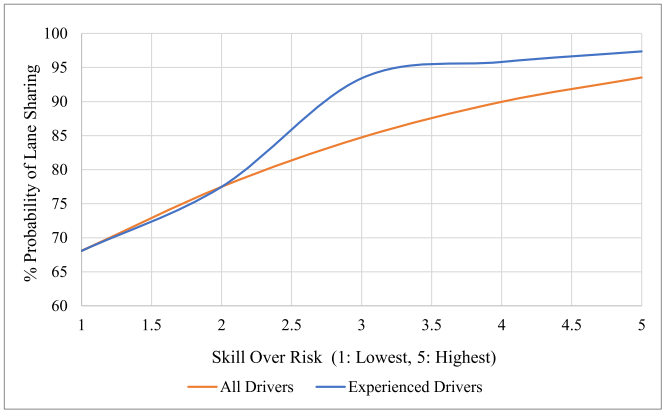

Fig. 10. Probability of lane sharing by varying perceptions of Skill Over Risk (SOR).

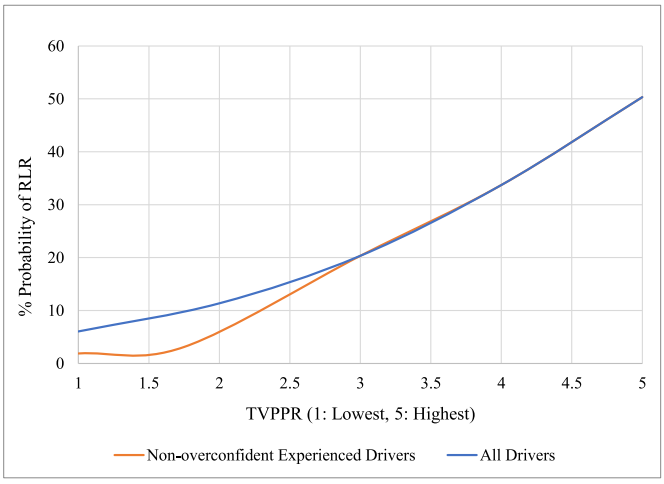

Fig. 11. Probability of red light running by varying tendency of traffic violation in presence of pillion rider. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

5.3. Combined effect of psychological and demographic variables on traffic violations

The study found that older drivers are less likely to be involved in red light running and lane sharing behavior. However, drivers did not improve their tendency to indicate before turning with age (see Tables 5 and 6). The previous studies also showed that traffic errors are not intentional and are less likely to be reduced even in the older drivers (Classen et al., 2010; Reason et al., 2011; Wang, 2022). Driving is a multitasking process and puts mental and visual workload on the drivers (Choudhary and Velaga, 2019b; Strayer and Drews, 2004). Drivers are aware that traffic violations and risky driving can save travel time but can also lead to a road crash. Therefore, making traffic violation choices while driving becomes a complex process to investigate. To capture and simplify this complex process, three decision trees were developed, and obtained interaction variables were further incorporated in binary logistic model. Fig. 10 shows the probability of the lane sharing by varying the individual perception of importance of skill over risk (SOR) i.e., confidence on the driving skills. It shows that experienced drivers having high confidence on driving skills (Interaction Variable 5) are more likely to drive by sharing in between the lanes. Fig. 11 also indicates that experienced drivers who are modest about importance of driving skills and are less accepted for violating the traffic rules (Interaction Variable 1), had significant lower tendency towards running the red light.

6. Policy and practice implications

6.1. Drivers' acceptance for performing non-illegal dangerous driving maneuvers

This study analyzed both the drivers' red light running and the lane sharing tendency while driving motorized two-wheelers. In India, the red light running is considered as a traffic violation whereas there is no specific penalty for lane sharing in the Motor vehicle Act 2019 (Ministry of Road Transport and Highways, 2020). Lane sharing is legal in most of the Asian, and European countries, however, it is illegal in the USA, and in many states of Australia (Beanland et al., 2015). The present study further discusses the requirement of the policy interventions in both the cases of legal ban and legal clearance of lane sharing maneuver.

6.1.1. Scenario 1: the legal ban on the lane sharing behavior

Driving is a complex process, and it becomes very difficult for a car driver when motorcycle drivers maneuver through the narrow available gaps in between the cars. Thus, the lane sharing behavior can lead to a road crash involving severe injuries as well (Aupetit et al., 2015; Clabaux et al., 2017). Therefore, it is important to control lane sharing behavior, however the acceptance of the legal ban among the public would be very difficult to achieve since as shown in the present study, more than 90% of people get indulged in this and especially when they are in hurry (Fig. 7). In the scenario of a legal ban, it is important to provide alternatives for the faster commute of motorized two-wheeler riders. One possible solution could be to provide alternative exclusive MTW lanes in congested traffic road networks, and near to the important city centers such as transit stations or medical facilities. This study showed that when drivers are under time constraint situations, they were willing to take higher risks, this indicates the possibility that if drivers are in hurry, they might even be interested in paying some additional charges to avail the high-speed access. However, such interventions need a large amount of capital investment in infrastructure. Also, it needs additional efforts to monitor the lane sharing violations because lane sharing occurs over a larger mid-block section unlike red light running violations at intersections.

6.1.2. Scenario 2: the legalization of the lane sharing behavior

The legalization of lane sharing facilitates easy maneuverability in the congestion of the city traffic. However, if lane sharing is legal, it further promotes the drivers to make dangerous driving maneuvers. In the present study, the interaction variable 1 represented the experienced drivers having confidence in the driving skills. Fig. 10 showed that almost 95% of such experienced confident drivers choose to move through the narrow available gaps. If lane sharing is legalized, it is of utmost importance to train even experienced drivers about the required precautions while performing lane sharing. The drivers must be trained for identifying the potential hazards involved in lane sharing. For example, a major hazard in lane sharing is the failure to understand that the leading car driver is about to take a turn. Certain cues such as the angle of leading car wheels, the lateral movement of the car, or the driver's head movement can give a prior indication to the MTW driver about the risky event (Aupetit et al., 2015). Also, before lane sharing MTW drivers shall use horns or flashlights at the night to make sure that the leading car driver has seen the MTW driver. Therefore, if lane-sharing behavior remains legalized, comprehensive training of novice, as well as experienced drivers, is essential to reduce the crash risks on the roads.

6.2. Avoiding crashes under time constrained driving situations

With a rapid surge in e-commerce, the demand for online food and goods delivery has increased immensely especially in the pandemic (Sanchez-Diaz et al., 2021). There have been so many food delivery platforms and with increased competition, the requirement for delivering the food items faster has been in the recent trends. The food is generally delivered using motorized two-wheelers by the delivery valets, they are often under time pressure since their monetary benefits are dependent on the number of completed deliveries (Dong et al., 2021; Nguyen-Phuoc et al., 2023; Verheyen and Kołacz, 2022). Also, they tend to get higher ratings from the customers if they deliver the food faster, which in turn decides the deliveries they get through the online platform. This study showed that drivers are more likely to indulge in risky driving and more prone to traffic errors when they feel time constrained to reach their destination. These dangerous driving behaviors can result in severe traffic crashes and severe injuries. Therefore, to reduce the time pressure on delivery valets, either incentives based on the number of deliveries shall be removed or the delivery valets could be incentivized for driving safer on the road.

6.3. Driving license and training

This study also highlighted that driver forget to use indicators while taking a turn or changing lanes while driving. This might be because

drivers are relying on the sound of the vehicle instead of actually looking for them before turning. However, electric vehicles have very low engine sound, and relying on the sound of the other surrounding vehicles before making a turn could become a severe problem with a rapid increase in the popularity of electric vehicles. Therefore, it is very important to bring the change in drivers' behavior to develop the habit of indicating before turning. It is also required to develop driver licensing and training modules specific to electric vehicle drivers about new possible hazardous driving situations considering the mixed traffic conditions.

7. Conclusions

Traffic violation, error, and non-illegal dangerous driving behaviors are the major contributing factor to road crashes. Despite several studies revealing drivers are well-aware of the risk involved in ignoring the traffic safety, risky driving is a very frequent practice among MTW drivers. In this study, decision tree models were developed to identify the possible interaction among various psychological and demographic factors. Further, binary logistic models were developed to quantify the effect of underlying psychological factors, demographic attributes, and their combined interaction effects on the risky driving behavior of MTW drivers. The following findings provide insights into the motivations behind risky driving:

i. Drivers were more likely to be involved in risky driving behavior if they were anxious under time pressure driving situations.
ii. Drivers were more inclined to violate the traffic rules if they were accepted for such behaviors in the presence of the pillion rider who was important to them.
iii. Impunctual drivers were more prone to turning without indicating while driving a motorized two-wheeler.
iv. Older drivers were less likely to violate the traffic law and involve in risky driving, however, age had no significant effect on the traffic errors.

8. Limitations and future scope

The traffic violation, traffic errors, and risky driving tendencies were collected through an online questionnaire in this study. The participants are often reluctant to reveal the actual information about their wrongdoings and hence their responses are often biased toward the socially desirable outcomes. However, in the present study, participants were informed about the anonymity of their responses, and no traceable personal information was collected in the questionnaire. The present study collected only 460 responses through online questionnaire across the country. Therefore, the samples do not represent the entire population that had limited access or was incapable of online communication. It is also difficult to capture full attention of the participants cannot be ensured while responding to the survey. To minimize the inattentive surveys, the responses having zero variance in their responses were omitted manually during the analysis (Brühlmann et al., 2020). The present study considered red light running as a deliberate traffic violation however the riders may sometimes cross the red-signal due to driving errors. In the present study, the responses were collected from various geographical regions of the country which may vary in terms of traffic legislation and enforcement levels. Further studies can be conducted to capture the impact on traffic violation choices across different geographic locations by considering the variations in traffic penalties, and enforcement levels. The findings of this study can be extended for the other low-middle income countries having similar conditions of heterogeneous traffic with poor lane discipline. These driving conditions increase the workload on the drivers making them prone to error and incentivize the riders to indulge in risky driving behaviors such as lane sharing or running the red light (Gupta et al., 2022; Pawar and Velaga, 2020). Many South Asian countries such as Cambodia, the Lao People's Democratic Republic, Malaysia, and Viet Nam have 51–95% motorized two-wheeler users as well as mixed traffic conditions like India (World Health Organization, 2020). Hence, the findings related to risky driving tendencies can be used as inferences and hypotheses for other developing countries that are often neglected in the academic literature (Haghani et al., 2022).

Author contributions

The authors confirm contribution to the paper as follows: study conception and design: Monik Gupta, Nagendra R. Velaga, Oscar Oviedo Trespalacios; data collection: Monik Gupta; analysis and development of models: Monik Gupta; interpretation of results: Monik Gupta, Nagendra R. Velaga, Oscar Oviedo Trespalacios; draft manuscript preparation: Monik Gupta; Review and Editing: Monik Gupta, Nagendra R. Velaga, Oscar Oviedo Trespalacios. All authors reviewed the results and approved the final version of the manuscript.

Data availability

Data will be made available on request.

Acknowledgement

This research is partially funded by Science and Engineering Research Board, India under project titled '*Modeling and Analysis of crash Risk & Performance of Motorbike Riders under Influence of Human Behavioral Factors*' (funding reference number: ECR/2018/000898). The contents of this publication are the sole responsibility of the authors of this paper and can in no way be taken to reflect the views of the funding agency.

References

Abdul Manan, M.M., Syed Tajul Arif, S.T.M., Sim, H.J., Khaidir, N.M., Jamil, H.M., Abd Ghani, M.R., 2019. Red light running motorcyclists at signalized intersection in Malaysia: an empirical study. IOP Conf. Ser. Mater. Sci. Eng. 512 (1) https://doi.org/10.1088/1757-899X/512/1/012019.

Alver, Y., Demirel, M.C., Mutlu, M.M., 2014. Interaction between socio-demographic characteristics: traffic rule violations and traffic crash history for young drivers. Accid. Anal. Prev. 72, 95–104. https://doi.org/10.1016/J.AAP.2014.06.015.

Aupetit, S., Espié, S., Bouaziz, S., 2015. Naturalistic study of riders' behaviour in lane-splitting situations. Cognit. Technol. Work 17 (2), 301–313. https://doi.org/10.1007/s10111-014-0293-z.

Automotive Industry, Marklines, 2019. Indian Two-Wheeler Production and Plant Capacity Analysis - MarkLines Automotive Industry Portal. https://www.marklines.com/en/report_all/rep1872_201906.

Ayuso, M., Guillén, M., Alcañiz, M., 2010. The impact of traffic violations on the estimated cost of traffic accidents with victims. Accid. Anal. Prev. 42 (2), 709–717. https://doi.org/10.1016/J.AAP.2009.10.020.

Brühlmann, F., Petralito, S., Aeschbach, L.F., Opwis, K., 2020. The quality of data collected online: an investigation of careless responding in a crowdsourced sample. Method Psychol. 2, 100022 https://doi.org/10.1016/J.METIP.2020.100022.

C. and Mallia, L. L. F. G. L. C. A. A. F. C. M. V, 2019. Personality traits and attitudes toward traffic safety predict risky behavior across young, adults. Front. Psychol. 10, 536. https://doi.org/10.3389/fpsyg.2019.00536.

Castillo Sierra, R., Oviedo-Trespalacios, O., Candelo, J.E., Soto, J.D., 2015. Assessment of the risk of failure of high voltage substations due to environmental conditions and pollution on insulators. Environ. Sci. Pollut. Control Ser. 22 (13), 9749–9758. https://doi.org/10.1007/S11356-015-4153-Z/TABLES/2.

Castillo-Manzano, J.I., Castro-Nuño, M., Fageda, X., 2015. Are traffic violators criminals? Searching for answers in the experiences of European countries. Transport Pol. 38, 86–94. https://doi.org/10.1016/J.TRANPOL.2014.12.003.

Castillo-Manzano, J.I., Castro-Nuño, M., López-Valpuesta, L., Pedregal, D.J., 2019. From legislation to compliance: the power of traffic law enforcement for the case study of Spain. Transport Pol. 75, 1–9. https://doi.org/10.1016/J.TRANPOL.2018.12.009.

Cestac, J., Paran, F., Delhomme, P., 2011a. Young drivers' sensation seeking, subjective norms, and perceived behavioral control and their roles in predicting speeding intention: how risk-taking motivations evolve with gender and driving experience. Saf. Sci. 49 (3), 424–432. https://doi.org/10.1016/j.ssci.2010.10.007.

Cestac, J., Paran, F., Delhomme, P., 2011b. Young drivers' sensation seeking, subjective norms, and perceived behavioral control and their roles in predicting speeding intention: how risk-taking motivations evolve with gender and driving experience. Saf. Sci. 49 (3), 424–432. https://doi.org/10.1016/j.ssci.2010.10.007.

Chan, D.C.N., Wu, A.M.S., Hung, E.P.W., 2010. Invulnerability and the intention to drink and drive: an application of the theory of planned behavior. Accid. Anal. Prev. 42 (6), 1549–1555. https://doi.org/10.1016/j.aap.2010.03.011.

Chorlton, K., Conner, M., Jamson, S., 2012. Identifying the psychological determinants of risky riding: an application of an extended Theory of Planned Behaviour. Accid. Anal. Prev. 49, 142–153. https://doi.org/10.1016/j.aap.2011.07.003.

Choudhary, P., Velaga, N.R., 2019a. Driver behaviour at the onset of yellow signal: a comparative study of distraction caused by use of a phone and a music player. Transport. Res. F Traffic Psychol. Behav. 62, 135–148. https://doi.org/10.1016/j.trf.2018.12.022.

Choudhary, P., Velaga, N.R., 2019b. Effects of phone use on driving performance: a comparative analysis of young and professional drivers. Saf. Sci. 111 (October 2017), 179–187. https://doi.org/10.1016/j.ssci.2018.07.009.

Clabaux, N., Fournier, J.Y., Michel, J.E., 2017. Powered two-wheeler riders' risk of crashes associated with filtering on urban roads. Traffic Inj. Prev. 18 (2), 182–187. https://doi.org/10.1080/15389588.2016.1225298.

Classen, S., Shechtman, O., Awadzi, K.D., Joo, Y., Lanford, D.N., 2010. Traffic violations versus driving errors of older adults: informing clinical practice. Am. J. Occup. Ther. 64 (2), 233–241. https://doi.org/10.5014/ajot.64.2.233.

Dong, H., Zhong, S., Xu, S., Tian, J., Feng, Z., 2021. The relationships between traffic enforcement, personal norms and aggressive driving behaviors among normal e-bike riders and food delivery e-bike riders. Transport Pol. 114, 138–146. https://doi.org/10.1016/J.TRANPOL.2021.09.014.

Elliott, M.A., Thomson, J.A., 2010. The social cognitive determinants of offending drivers' speeding behaviour. Accid. Anal. Prev. 42 (6), 1595–1605. https://doi.org/10.1016/j.aap.2010.03.018.

Elmitiny, N., Yan, X., Radwan, E., Russo, C., Nashar, D., 2010a. Classification analysis of driver's stop/go decision and red-light running violation. Accid. Anal. Prev. 42 (1), 101–111. https://doi.org/10.1016/J.AAP.2009.07.007.

Elmitiny, N., Yan, X., Radwan, E., Russo, C., Nashar, D., 2010b. Classification analysis of driver's stop/go decision and red-light running violation. Accid. Anal. Prev. 42 (1), 101–111. https://doi.org/10.1016/j.aap.2009.07.007.

Fitzpatrick, C.D., Samuel, S., Knodler, M.A., 2017. The use of a driving simulator to determine how time pressures impact driver aggressiveness. Accid. Anal. Prev. 108, 131–138. https://doi.org/10.1016/J.AAP.2017.08.017.

Forward, S.E., 2009. The theory of planned behaviour: the role of descriptive norms and past behaviour in the prediction of drivers' intentions to violate. Transport. Res. F Traffic Psychol. Behav. 12 (3), 198–207. https://doi.org/10.1016/j.trf.2008.12.002.

Gupta, M., Pawar, N.M., Velaga, N.R., 2021. Impact of lockdown and change in mobility patterns on road fatalities during COVID-19 pandemic. Transpor. Lett. 13, 447–460. https://doi.org/10.1080/19427867.2021.1892937.

Gupta, M., Pawar, N.M., Velaga, N.R., Mishra, S., 2022. Modeling distraction tendency of motorized two-wheeler drivers in time pressure situations. Saf. Sci. 154, 105820 https://doi.org/10.1016/J.SSCI.2022.105820.

Haghani, M., Behnood, A., Dixit, V., Oviedo-Trespalacios, O., 2022. Road safety research in the context of low-and middle-income countries: Macro-scale literature analyses, trends, knowledge gaps and challenges. Safety science 146, 105513. https://doi.org/10.1016/j.ssci.2021.105513.

Hair, J., 2009. Multivariate Data Analysis. Faculty Publications. https://digitalcommons.kennesaw.edu/facpubs/2925.

Hair, J.J., Celsi, Wolfinbarger, M., H Money, A., Samouel, P., J Page, M., 2015. Business Research Methods. Armonk, New York, pp. 1–494.

Haque, M.M., Ohlhauser, A.D., Washington, S., Boyle, L.N., 2016. Decisions and actions of distracted drivers at the onset of yellow lights. Accid. Anal. Prev. 96, 290–299. https://doi.org/10.1016/J.AAP.2015.03.042.

James, Reason, Antony, Manstead, Stephen, Stradling, James, Baxter, Campbell, Karen, 2011. Errors and Violations on the Roads: a Real Distinction. ERGONOMICS.

Kass, G.V., 1980. An Exploratory Technique for Investigating Large Quantities of Categorical Data Author (S): G . V . Kass Published by. Wiley for the Royal Statistical Society. Stable URL : http://www.jstor.org/stable/2986296. An Exploratory Technique for Investigating L. Journal of the Roral Statistical Society, 29(2), 119–127.

Limanond, T., Prabjabok, P., Tippayawong, K., 2010. Exploring impacts of countdown timers on traffic operations and driver behavior at a signalized intersection in Bangkok. Transport Pol. 17 (6), 420–427. https://doi.org/10.1016/J.TRANPOL.2010.04.009.

Lin, M.R., Kraus, J.F., 2009. A review of risk factors and patterns of motorcycle injuries. Accid. Anal. Prev. 41 (4), 710–722. https://doi.org/10.1016/j.aap.2009.03.010.

M, W., Nc, S., M, C., M, F., DE, M.-H., 2006. The role of effort in moderating the anxiety-performance relationship: testing the prediction of processing efficiency theory in simulated rally driving. J. Sports Sci. 24 (11), 1223–1233. https://doi.org/10.1080/02640410500497667.

Mackett, R.L., 2021. Policy interventions to facilitate travel by people with mental health conditions. Transport Pol. 110, 306–313. https://doi.org/10.1016/J.TRANPOL.2021.06.014.

McBride, M., Carter, L., Phillips, B., 2020. Integrating the theory of planned behavior and behavioral attitudes to explore texting among young drivers in the US. Int. J. Inf. Manag. 50 (September 2019), 365–374. https://doi.org/10.1016/j.ijinfomgt.2019.09.003.

Micucci, A., Mantecchini, L., Sangermano, M., 2019. Analysis of the relationship between turning signal detection and motorcycle driver's characteristics on urban roads; a case study. Sensors 19 (8). https://doi.org/10.3390/s19081802.

Ministry of Road Transport & Highways, 2020. Ministry of road Transport and Highways (MORTH)(2018)-Road accidents in India 2018. In: Ministry of Road Transport and Highways ,Transport Research Wing. Government of India. www.morth.nic.

Ministry of Road Transport and Highways, 2016. Road Transport Year Book (2016-17). http://www.morth.nic.in.

Moan, I.S., Rise, J., 2011. Predicting intentions not to "drink and drive" using an extended version of the theory of planned behaviour. Accid. Anal. Prev. 43 (4), 1378–1384. https://doi.org/10.1016/j.aap.2011.02.012.

Nguyen-Phuoc D, Q., de Gruyter, C., Oviedo-Trespalacios, O., Diep Ngoc, S., Tran, A.T.P., 2020. Turn signal use among motorcyclists and car drivers: the role of environmental characteristics, perceived risk, beliefs and lifestyle behaviours. Accid. Anal. Prev. 144 https://doi.org/10.1016/j.aap.2020.105611.

Nguyen-Phuoc, D.Q., de Gruyter, C., Nguyen, H.A., Nguyen, T., Ngoc Su, D., 2020. Risky behaviours associated with traffic crashes among app-based motorcycle taxi drivers in Vietnam. Transport. Res. F Traffic Psychol. Behav. 70, 249–259. https://doi.org/10.1016/j.trf.2020.03.010.

Nguyen-Phuoc, D.Q., Ngoc Thi Nguyen, L., Ngoc Su, D., Nguyen, M.H., Oviedo-Trespalacios, O., 2023. Deadly meals: the influence of personal and job factors on burnout and risky riding behaviours of food delivery motorcyclists. Saf. Sci. 159, 106007 https://doi.org/10.1016/J.SSCI.2022.106007.

Nguyen-Phuoc, D.Q., Oviedo-Trespalacios, O., Nguyen, T., Su, D.N., 2020. The effects of unhealthy lifestyle behaviours on risky riding behaviours–A study on app-based motorcycle taxi riders in Vietnam. J. Trans. Health 16, 100666. https://doi.org/10.1016/j.jth.2019.100666.

NHTSA, 2021. Motorcycle Safety | NHTSA. https://www.nhtsa.gov/road-safety/motorcycles.

Okamura, K., Fujita, G., Kihira, M., Kosuge, R., Mitsui, T., 2012. Predicting motivational determinants of seatbelt non-use in the front seat: a field study. Transport. Res. F Traffic Psychol. Behav. 15 (5), 502–513. https://doi.org/10.1016/j.trf.2012.05.001.

Oviedo-Trespalacios, O., Haque, M.M., King, M., Washington, S., 2019. "Mate! I'm running 10 min late": an investigation into the self-regulation of mobile phone tasks while driving. Accid. Anal. Prev. 122, 134–142. https://doi.org/10.1016/J.AAP.2018.09.020.

Paul, M., Ghosh, I., 2020. Influence of green signal countdown timer on severe crash types at signalized intersections due to red light violations. Transportation Letters 12 (8), 528–539. https://doi.org/10.1080/19427867.2019.1651571.

Pawar, N.M., Velaga, N.R., 2020. Modelling the influence of time pressure on reaction time of drivers. Transport. Res. F Traffic Psychol. Behav. 72, 1–22. https://doi.org/10.1016/j.trf.2020.04.017.

Pawar, N.M., Velaga, N.R., 2021. Effect of time pressure on steering control of the drivers in a car-following situation. Transport. Res. F Traffic Psychol. Behav. 80, 218–236. https://doi.org/10.1016/j.trf.2021.04.007.

Prat, F., Gras, M.E., Planes, M., Font-Mayolas, S., Sullman, M.J.M., 2017. Driving distractions: an insight gained from roadside interviews on their prevalence and factors associated with driver distraction. Transport. Res. F Traffic Psychol. Behav. 45, 194–207. https://doi.org/10.1016/j.trf.2016.12.001.

Rendon-Velez, E., van Leeuwen, P.M., Happee, R., Horváth, I., van der Vegte, W.F., de Winter, J.C.F., 2016. The effects of time pressure on driver performance and physiological activity: a driving simulator study. Transport. Res. F Traffic Psychol. Behav. 41, 150–169. https://doi.org/10.1016/j.trf.2016.06.013.

Rusli, R., Oviedo-Trespalacios, O., Abd Salam, S.A., 2020. Risky riding behaviours among motorcyclists in Malaysia: a roadside survey. Transport. Res. F Traffic Psychol. Behav. 74, 446–457. https://doi.org/10.1016/j.trf.2020.08.031.

Sanchez-Diaz, I., Altuntas Vural, C., Halldórsson, Á., 2021. Assessing the inequalities in access to online delivery services and the way COVID-19 pandemic affects marginalization. Transport Pol. 109, 24–36. https://doi.org/10.1016/J.TRANPOL.2021.05.007.

Satiennam, W., Satiennam, T., Triyabutra, T., Rujopakarn, W., 2018. Red light running by young motorcyclists: factors and beliefs influencing intentions and behavior. Transport. Res. F Traffic Psychol. Behav. 55, 234–245. https://doi.org/10.1016/j.trf.2018.03.007.

Scott-Parker, B., Oviedo-Trespalacios, O., 2017. Young driver risky behaviour and predictors of crash risk in Australia, New Zealand and Colombia: same but different? Accid. Anal. Prev. 99, 30–38. https://doi.org/10.1016/j.aap.2016.11.001.

Shahar, A., 2009. Self-reported driving behaviors as a function of trait anxiety. Accid. Anal. Prev. 41 (2), 241–245. https://doi.org/10.1016/j.aap.2008.11.004.

Şimşekoğlu, Ö., Lajunen, T., 2008. Social psychology of seat belt use: a comparison of theory of planned behavior and health belief model. Transport. Res. F Traffic Psychol. Behav. 11 (3), 181–191. https://doi.org/10.1016/j.trf.2007.10.001.

Sperley, Myra, Joy Pietz, Amanda, 2010. Motorcycle Lane-Sharing : Literature Review. Oregon Department of Transportation Research Section. https://rosap.ntl.bts.gov/view/dot/18016.

Staubach, M., 2009. Factors correlated with traffic accidents as a basis for evaluating Advanced Driver Assistance Systems. Accid. Anal. Prev. 41 (5), 1025–1033. https://doi.org/10.1016/J.AAP.2009.06.014.

Stephens, A.N., Brown, J., de Rome, L., Baldock, M.R.J., Fernandes, R., Fitzharris, M., 2017. The relationship between Motorcycle Rider Behaviour Questionnaire scores and crashes for riders in Australia. Accid. Anal. Prev. 102, 202–212. https://doi.org/10.1016/J.AAP.2017.03.007.

Strayer, D.L., Drews, F.A., 2004. Profiles in driver distraction: effects of cell phone conversations on younger and older drivers. Hum. Factors 46 (4), 640–649. https://doi.org/10.1518/hfes.46.4.640.56806.

Sunitha, Anup, 2021. Market analysis of the new two-wheeler fleet in India for fiscal year 2020–21. https://www.siam.in/statistics.

Vanessa, Beanland, Kristen, Pammer, Monika, Śledziowska, Stone, Alexander, 2015. Drivers' Attitudes and Knowledge Regarding Motorcycle Lane Filtering Practices. - University of the Sunshine Coast, Queensland. https://research.usc.edu.au/esploro/outputs/conferencePaper/Drivers-attitudes-and-knowledge-regarding-motorcycle/99449886502621#file-0.

Verheyen, W., Kołacz, M.K., 2022. Enhancing safety in B2C delivery chains. Transport Pol. 117, 12–22. https://doi.org/10.1016/J.TRANPOL.2021.12.020.
Walsh, S.P., White, K.M., Hyde, M.K., Watson, B., 2008. Dialling and driving: factors influencing intentions to use a mobile phone while driving. Accid. Anal. Prev. 40 (6), 1893–1900. https://doi.org/10.1016/j.aap.2008.07.005.
Wang, X., 2022. Impact of health on driving for America's older adults: a nationwide, longitudinal study. Transport Pol. 120, 69–79. https://doi.org/10.1016/J.TRANPOL.2022.02.005.
Washington, S., 2000. Iteratively specified tree-based regression: theory and trip generation example. J. Transport. Eng. 126 (6), 482–491. https://doi.org/10.1061/(ASCE)0733-947X(2000)126:6(482).
Wei, L., Zhao, P., Li, Y., Chen, Y., Liao, M., 2021. Behaviour analysis of left-turning mopeds at signal controlled intersections – a case study in yancheng city. Promet - Traffic - Traffico 33 (4), 609–620. https://doi.org/10.7307/ptt.v33i4.3740.
White, K.M., Hyde, M.K., Walsh, S.P., Watson, B., 2010. Mobile phone use while driving: an investigation of the beliefs influencing drivers' hands-free and hand-held mobile phone use. Transport. Res. F Traffic Psychol. Behav. 13 (1), 9–20. https://doi.org/10.1016/j.trf.2009.09.004.
Wong, S.C., Wong, C.W., Sze, N.N., 2008. Attitudes of public light bus drivers to penalties to combat red light violations in Hong Kong. Transport Pol. 15 (1), 43–54. https://doi.org/10.1016/J.TRANPOL.2007.10.009.
World Health Organization, 2020. Timeline: WHO's COVID-19 Response.
Yadav, A.K., Velaga, N.R., 2019. Laboratory analysis of driving behavior and self-perceived physiological impairment at 0.03%, 0.05% and 0.08% blood alcohol concentrations. Drug Alcohol Depend. 205 (April), 107630 https://doi.org/10.1016/j.drugalcdep.2019.107630.
Yan, F., Li, B., Zhang, W., Hu, G., 2016. Red-light running rates at five intersections by road user in Changsha, China: an observational study. Accid. Anal. Prev. 95, 381–386. https://doi.org/10.1016/j.aap.2015.06.006.
Yang, H., Liu, X., Su, F., Cherry, C., Liu, Y., Li, Y., 2018. Predicting e-bike users' intention to run the red light: an application and extension of the theory of planned behavior. Transport. Res. F Traffic Psychol. Behav. 58, 282–291. https://doi.org/10.1016/j.trf.2018.05.027.
Zhang, G., Yau, K.K.W., Chen, G., 2013. Risk factors associated with traffic violations and accident severity in China. Accid. Anal. Prev. 59, 18–25. https://doi.org/10.1016/J.AAP.2013.05.004.
Zhang, Y., Huang, Y., Wang, Y., Casey, T.W., 2020. Who uses a mobile phone while driving for food delivery? The role of personality, risk perception, and driving self-efficacy. J. Saf. Res. 73, 69–80. https://doi.org/10.1016/j.jsr.2020.02.014.