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Driving risk assessment using driving behavior data under continuous tunnel environment

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ABSTRACT

Objective: Driving behavior is the key feature for determining the nature of traffic stream qualities and reflecting the risk of operating environments. However, evaluating the driving risk accurately and practically in continuous tunnels (tunnels with a space more than 250 m and less than 1000 m) still faces severe challenges due to the complex driving conditions. The objective of this study is to predict the driving risk indicators and determine different risk levels.
Methods: The naturalistic driving system equipped with a road environment and driving behavior data acquisition system combined with the fixed-point test method was used for data collection in 130 tunnels on four highways. A traditional AASHTO braking model and convex hull algorithm were adopted to predict the critical safety speed and the critical time headway of each risk feature point in tunnels. According to the risk constraints under free-flow, car-following and lane-changing conditions, the average traffic flow risk index (TFRI) representing six risk levels and the safety threshold of the corresponding risk indicators were determined.
Results: The findings of this study revealed that the critical safety speed at nighttime is slower than in other daytime conditions in continuous tunnels. The time headway slightly changes under 90 km/h. As the speed continues to increase, speed has a significant influence on the critical time headway. The only reliable interaction involved the different adverse weather conditions on the mean critical safety speed in the continuous tunnels (short plus long) ($F = 9.730$, $p < 0.05$) and single long tunnels ($F = 12.365$, $p < 0.05$).
Conclusions: It can be concluded that driving behaviors significantly vary in different tunnel risk feature points and the combined effect of high speed and luminance variation may result in high driving risk. The performance validation indicted that the risk assessment level determined by the proposed approach is consistent with the real safety situations. The study provides an effective and generally acceptable method for identifying driving risk criteria that can also be applied for traffic management and safety countermeasures with a view to possible implementation in continuous tunnels.

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KEYWORDS
Driving behavior; risk assessment; continuous tunnels; critical safety speed; time headway

Introduction

By the end of 2016, there were 15,181 highway tunnels with a length of 14,039.7 km in China (Ministry of Transport of the People's Republic of China 2018). Among them, the proportion of tunnel groups accounts for 68.86% of the total mileage of highway tunnels. Tunnels are forming a critical and complex section with a special operating environment in the road system. Currently, no distinct standard is applied for the definitions of adjacent tunnels, continuous tunnels or tunnel groups. Specifications for Design of Highway Tunnels (JTG D70/2-2014) only classify a single tunnel according to its actual length.

In view of the number of tunnels and the distance between tunnels, definitions are proposed from the perspectives of ventilation, lighting, visual adaptation, fire safety and other factors (Yan et al. 2017). The so-called tunnel groups refer to two or more tunnels within a certain space on the highway, including the continuous tunnels and adjacent tunnels. Continuous tunnels are defined as tunnels with a space more than 250 m and less than 1000 m. When drivers travel through continuous tunnels, they will experience a continuous alternating change in the light environment and a sudden transformation of visual adaptation, thus seriously affecting the rapid response to environmental information and correct

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operation of vehicles. Such driving behaviors are more prone to high driving risk. In contrast, the driving behavior in adjacent tunnels (space less than 250 m) is relatively simple and seems similar to a single tunnel.

Statistical surveys from the Special Investigation on National Road and Waterway Transport for 2017 revealed that 38% of tunnel accidents are closely related to bad driving behavior. There are likely some potential risks related to considerable tunnel accidents in the tunnel operating environment. However, there has been an argument regarding how the potential risks affect driving behavior.

Tunnel risk researches involve drivers, vehicles and the driving environment. Calvi and D'Amico (2013) analyzed the relationship between driving behavior, dynamic characteristics of vehicles and accident rates by utilizing the driving simulation on eight tunnel scenes. Worm (2006) in Netherlands investigated how the driving behaviors in tunnels influence tunnel safety. Driving through a tunnel is stressful even fearful, for a considerable number of drivers (Ricard 2005). Additional psychological reactions that may lead drivers to completely unsuitable behavior in tunnels have also been observed (PIARC 2008). As proven in practice (Transportation Research Board, National Cooperative Highway Research Program 2011), in addition to the physical characteristics of the tunnels themselves and the traffic conditions, driving behavior is a key factor that cannot be ignored.

In view of the increasing number and severity of tunnel accidents, the European Commission launched Directive (EU Directive document 2004/54/EC 2004) on minimum safety requirements for tunnels in the Trans-European Road Network, which suggests the implementation of a risk assessment in several tunnel cases apart from technical measures imposed on the basis of tunnel length and traffic volume.

Significant development has occurred in the area of risk assessment. Beard (2010) provided a brief introduction of prescriptive requirements for risk assessment and criteria for acceptability of risk. Schlosser et al. (2014) introduced the assessment procedure of the safety of road tunnels and calculated the specific level of risk that can be used in classifying individual tunnels into hazard classes in Slovak Republic. Overall, many risk assessment methods have been proposed worldwide, most of them based on qualitative risk assessment (e.g. what-if method, Delphi method and expert judgement), quantitative risk assessment, or a mixture of these methods (i.e. deterministic risk models, computational fluid dynamics models, zone models, fault tree and stochastic models) (Tang et al. 2019; additional references in online Appendix, Supplementary material).

The qualitative methods are simple and flexible. However, their main pitfall is their subjective character and the fact that they do not consider the interaction and correlation among different elements of the tunnel system (Kazaras and Kirytopoulos 2014). For this reason, recently, there has been an increase in the use of quantitative risk assessment techniques that can assist decision making by providing objective estimates of risks. Nevertheless, these methods are also subject to many limitations, as mentioned in (Apostolakis 2004; Kirytopoulos et al. 2014; additional references in online Appendix, Supplementary material). One of the most striking limitations is the fact that the variability in behavior of the drivers, although it plays an extremely important role in the development of driving risk, is not taken into consideration by the analyst. Simultaneously, the aforementioned studies are mainly based on static data (i.e. tunnel infrastructure indicators and road alignment indicators) or long-term accident and traffic investigation data. These methods cannot be directly applied to real-time or dynamic risk assessment in tunnels. Thus, many scholars have proposed micro-risk analysis approaches based on real-time driving behavior dynamic data.

According to the relative movements between the vehicle and the surrounding vehicles or obstacles, these driving risk assessments mainly use traffic conflict technology to explore dangerous spots (Mahmoud et al. 2018; additional references in online Appendix, Supplementary material). The performance indicators (Hayward 1972; Hauer 1982; additional references in online Appendix) for this method include time headway (THW) and time to collision (TTC), maximum deceleration rate of collision presented by the deceleration rate to avoid crash (DRAC) and minimum equivalent safety distance presented by the minimum safety distance equation (MSDE). Overall, multiple fatalities in tunnels result from speeding-related and unsafe distance incidents. In addition, it can be concluded that the micro risk assessment for normal sections of expressways as well as tunnels easily to provides accurate and acceptable risk levels.

Another important issue to emphasize in driving risk assessment in tunnels is data collection methods. Guo and Fang (2013) stated that driving behavior plays a central role in driving risk but it is difficult to measure in real-world driving situations. Current studies have been conducted on the application of different data, such as the Stated preference (SP) survey data (Machado-León et al. 2016; de Oña et al. 2014; Cardamone et al. 2014), simulation data (Calvi and D'Amico 2013), GPS data and naturalistic driving data (Eboli et al. 2017; additional references in online Appendix, Supplementary material). Recent developments in vehicle instrumentation techniques, such as naturalistic driving have made it both technologically possible and economically feasible to monitor behaviors and kinematic signatures on a large scale. The naturalistic driving method has advantages in presenting the instantaneous kinematic track of the vehicle (i.e. acceleration and speed) through real tests on the road and in providing an opportunity to link the driver behavior with risk (Dingus et al. 2006).

Despite the encouraging findings on driving behaviors and risk assessment in tunnels, limited studies have been conducted on continuous tunnel environments. The research problem raised here is to explore a novel micro risk assessment method by using objective indicators that can characterize the driver's behavior and then identify the risk level in the real field test of continuous tunnels. The remainder of this paper is organized as follows: The methodology is presented in Section 2. Section three describes the data collection. Section four discusses the results and puts forward the risk assessment standards. Concluding remarks are given in Section 5.

Data collection

The field tests were carried out in the daytime on selected sections of Xihan Highway (four-lanes in two directions, design speed of 60-100 km/h according to the topographic conditions) and the Baomao Highway (four-lanes in two directions, design speed of 100 km/h) in Shannxi Province, the Jinliwen Highway (four-lanes in two directions, design speed of 100 km/h) in Zhejiang Province and Kunmo Highway (six-lanes, design speed of 100 km/h) in Yunnan Province. The proportion of tunnels on these four highways is extremely high. The experiments in this study involved 130 tunnels with a total length of 118 km comprising 75 continuous tunnels, 25 short tunnels and 30 long tunnels. A portion of the test tunnels is shown in Table A1 (see Appendix E, Supplementary material).

The sample is composed of 40 test participants between 25 and 59 years old mainly through recruiting or random hires with certain cash reword. The selected drivers must hold legal licenses for the corresponding vehicle types. Although the selection of the test subjects considered other factors including age, gender, and driving experience that may be associated with different driving risks, the differences in individuals were still treated as random effects, and were not analyzed in this study.

To record the kinematic parameters along the trajectory of the vehicle followed by the driver, Road Environment and Driving behavior Data Acquisition systems were instrumented with six high-definition cameras, GPS, microwave radar, speedometer, three-dimension accelerometer etc. This system was equipped in a car (two axles, four wheels, $H \leq 1.3$m) during the naturalistic driving. Each driver was notified to drive the car through all the selected tunnels on one highway and choose how to travel according to his or her own driving habit and willingness.

In addition, we also applied the fixed-point test method to supplement the naturalistic driving data and weather data. Furthermore, the traffic and weather sensors had to be closely located because rainfall intensity or other weather indices might vary from place to place and bias the study. The time span of the data was 1 yr, running from January 2017 to December 2017. The weather report was available at aggregation time intervals of every 10 min and averages of 1 h.

All vehicle movement data obtained by various sensors were collected synchronously through Datastream and synchronized processing on the D-Lab driver factor software platform. Some invalid data were reduced manually based on the kinematic and video records. The fuzzy C-means method was adopted to eliminate the abnormal value. In addition, a Kalman filter was used to smooth the data to remove the impact of statistical errors in testing.

Methodology

Indicators as a risk metric

The driving risk usually occurs in a conflict situation that requires a rapid, severe evasive operation to avoid a crash. These risky operations involve conducting maneuvers that include steering, braking, accelerating, or any combination of control inputs that approaches the limits of the vehicle capabilities (Dingus et al. 2006).

Maintaining a safe speed and headway distance are essential for safe driving. Previous studies have shown a significant relationship between driving risk, car speed, and headway distance (Dingus et al. 2006; additional references in online Appendix, Supplementary material). Therefore, these two factors are used to characterize the driving risk under the continuous tunnel environment.

Risk feature points on continuous tunnels

Operating environment analysis

The emergency events (i.e. obstacles, sudden deceleration or incident) together with such sharp luminance change in tunnels are apt to cause psychological panic and inappropriate judgment by drivers.

Segmentation method

The risk feature points of driving behavior are the variation points that significantly influence the vehicle performance or the physiology and psychology of drivers. These points may result in driving risk due to the sharp change in the operating environment. According to the investigation of 75 continuous tunnels, a *K*-means cluster method was adopted to classify primary risk feature points into six kinds on the basis of the influence pattern of physical features of the continuous tunnels on driving behavior. The six risk feature points are described in Appendix A (Supplementary material).

Driving risk assessment

The study was designed to evaluate two objectives: predict driving risk indicators and determine different risk levels.

Classical braking model for predicting critical safety speed

The classical AASHTO braking model is widely used for traffic risk modeling (Ricardo and José 2007). The following step establishes the driving braking model of the risk feature points on the continuous tunnel sections on the basis of the AASHTO model and then predicts the critical safety speed (calculation details are provided in Appendix B, Supplementary material).

Due to the transition of the environment at the entrances and exits of tunnels, the friction coefficient inside and outside the tunnels is different, which is the cause of different braking distances among the entrance, the exit and a single environment. The critical safety speed on two types of the friction coefficient of the pavement can be calculated as (Appendix C, Supplementary material).

Convex hull algorithm for identifying critical time headway

Previous studies (Habtemichael et al. 2012) suggested that the time headway obeyed a negative exponential distribution or k-order Erlang distribution with varied traffic volumes. However, an in-depth analysis of the time headway distribution in continuous tunnels has not been addressed in the literature.

Test data for the time headway of the different risk feature points are numerous planar scattered points. To identify the relationships among the time headway, critical safety speed and driving risk, the convex hull algorithm is used to identify the critical time headway.

Defining risk level based on risk value calculation of three driving states

The risk value of free driving is calculated in terms of the collision acceleration after 3 s of braking in an emergency condition. Then, the free driving risk can be established under different speed sections in combination with the risk level. The car-following and lane-changing risk can be regarded as the difference between the critical and actual time headways, respectively (details in Appendix D, Supplementary material).

The final step is to calculate the traffic flow risk value. The risk value is determined based on the operating speed in the free flow condition, whereas the risk value is calculated based on the time headway in the car-following or lane-changing condition.

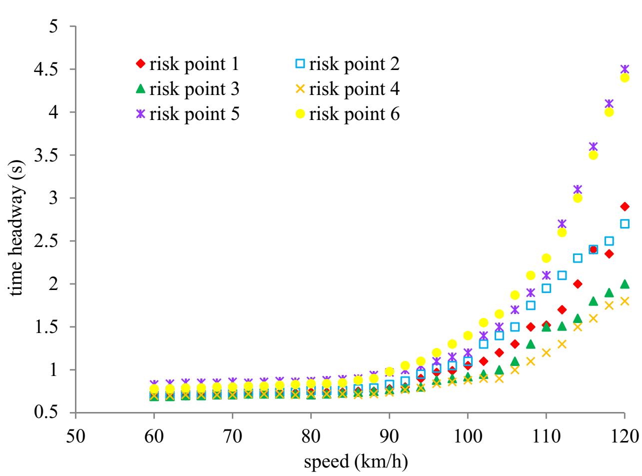


Figure 1. Speed and time headway of risk feature points in continuous tunnels.

In this paper, the average traffic flow risk index (TFRI) which represents different risk levels that drivers decide to take during driving and the interaction of each vehicle is proposed as the following function:

$$TFRI = \frac{\sum_{i=1}^{n} r_i}{N} \tag{1}$$

where r_i denotes the individual risk of vehicle i; and N is the total number of vehicles.

Considering the ultimate acceleration that each part of the human body can bear and the deceleration of the vehicle in the process of collision, the risk level is divided into six levels. The first risk level with a TRFI value from 0.8 to 1.0 corresponds to a lower risk and the second with a TRFI value from 0.6 to 0.8 is a higher level of risk. The TRFI intervals of the third and fourth levels are (0.4 to 0.6) and (0.2 to 0.4) respectively. Furthermore, the sixth level with a TRFI value from 0 to 0.2 represents the highest risk level.

Results

Data analysis

The relationships between the speed and the critical time headway of each risk feature point are analyzed by extracting the average time headway data of less than 10 s in all 75 continuous tunnels and employing the convex hull algorithm.

The lower edge of the convex hull algorithm model, which denotes the critical time headway at certain speed, is extracted to establish the critical time headway model. The analysis results are described in Figure 1. The critical time headway calculation results are listed in (Table A2, see Appendix E, Supplementary material).

On average, speed has a significant influence on critical time headway because the mean critical time headway of the total risk feature points is 0.715 s at 60 km/h, while it is 3.5 s at 120 km/h.

For risk feature point 1(the entrance of the first tunnel), the average critical time headway is 1.297 s longer than at point 3 (the exit of the second tunnel) with a value of 0.997 s. Furthermore, as the speed increases, this difference in the critical time headway gradually increases accordingly. Referring to the gap between the continuous tunnels, the critical time headway of the risk feature point 5 (exit section of the first tunnel) and point 6 (entrance section of the second tunnel) are 1.726 s and 1.793 s respectively. Both are larger than at the other four risk feature points.

In addition, the time headway remains stable under 90 km/h even if the speed increases. Then, the time headway on the second tunnel entrance exceeds that on the first tunnel exit section. This notion is supported by the fact that

Table 1. Driving behavior risk assessment criteria in continuous tunnels.

Risk level	First	Second	Third	Fourth	Fifth	Sixth
Risk value TFRI	0.8∼1.0	0.6∼0.8	0.4∼0.6	0.3∼0.4	0.2∼0.3	0.1∼0.2
Free driving risk			$\Delta V = v_i - V_l^{n,m}$ (km/h)			
	$\Delta V > 20$	$15 < \Delta V \leq 20$	$10 < \Delta V \leq 15$	$5 < \Delta V \leq 10$	$0 < \Delta V \leq 5$	$\Delta V \leq 0$
Car-following risk			$h_i - H_l^{n,v}$ (s)			
	$\leq 0.1H_l^{n,v}$	$\leq 0.2H_l^{n,v}$	$\leq 0.4H_l^{n,v}$	$\leq 0.6H_l^{n,v}$	$\leq 0.8H_l^{n,v}$	$\leq 1H_l^{n,v}$
Lane changing risk	≤1 s	1∼2 s	2∼3 s	3∼4 s	4∼5 s	—

driving behavior is an outcome of the interacting variables arising from the nature of traffic stream qualities and acceptance level of risk.

The driving risk assessment criteria in continuous tunnels are obtained on the correction of the standard on highway as well as by applying the results of the critical safety speed and the critical time headway of each risk feature point (Table 1) where, $V_l^{n,m}$ is the critical safety speed of risk feature point n under the condition m, $n = 1, 2, 3, 4, 5, 6$. The condition m consists of typical working conditions, such as sunny, cloudy, night, and disaster weather including fog, rain, snow, ice, and wind. h_i is the time headway between the vehicle and the leading vehicle. $H_l^{n,v}$ is the critical safety time headway for feature section n at v km/h, as shown in Table 1.

Validation of effectiveness

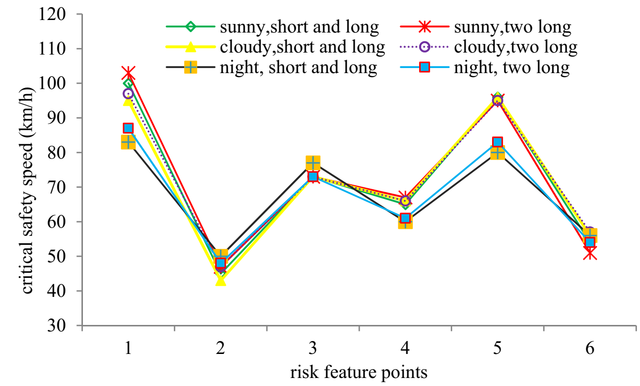
The field driving data of 16 other risk feature points (section) of two continuous tunnels and five sections of 30 km common road with a total of 300 vehicles on Xihan Highway for an extended period of time were collected. The results of the proposed risk assessment approach in the risk feature points are compared with those of the common road section in Table A3 (see Appendix E, Supplementary material). The statistics of historical traffic accident data provide the opportunity to evaluate crash risk.

In common road sections, the percentage of the fourth risk level is 35.01. In contrast, the percentage of the first risk level is 6.79. This finding indicates that the common road sections have a relatively low risk. In the continuous tunnels, the first level risk accounts for the largest ratio up to mean value of 42.8.

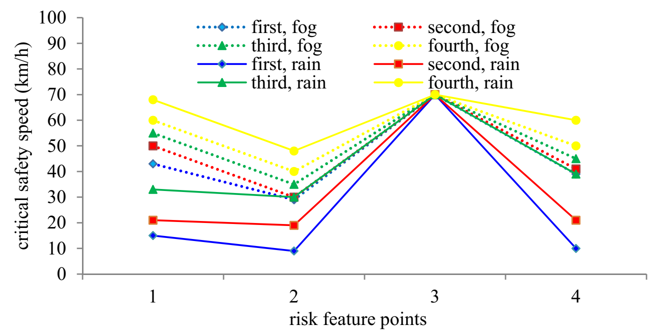
The results from Table A3 (see Appendix E, Supplementary material) also show that there is a positive correlation between the first, second and third levels of driving risk and crashes. The first level of risk has the highest correlation with the crash correlation coefficient of 0.95. However, there is a negative correlation between the driving risk and the crash at four, five and six levels, which indicates that the traffic flow is in a safe operation state under the three levels of risk. Among them, the negative correlation coefficient between the six levels and the crash is the largest, which is approximately 0.66, that is, the sixth level is the lowest risk of traffic flow state. It is conforms to the actual traffic flow operating condition.

Discussions

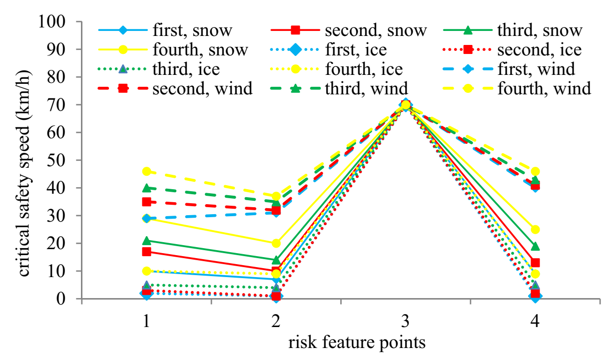
Considering the significant influence of driver's reaction time and the friction coefficient of the pavement on the critical safety speed, this study selects three lighting conditions (i.e. sunny day I, cloudy day II and nighttime III), two continuous tunnel types (i.e. a short tunnel plus a long tunnel, and two continuous long tunnels), two pavement conditions (i.e. asphalt and concrete), five adverse weathers (i.e. fog, rain, snow, ice and wind) comprising 12 kinds of typical operating conditions to make comparisons. On the basis of the limited collected adverse weather data, we revise the reaction time under different adverse weather (Table A4, see



(a) Continuous tunnels



(b) Long tunnels in fog and rain



(c) Long tunnels in ice, snow and wind

Figure 2. Critical safety speed of risk feature points under various weathers.

Appendix E, Supplementary material) in the related study (Guo et al. 2010). The average critical safety speed of each risk feature point in 75 continuous tunnels and 30 long tunnels are calculated as shown in Figure 2.

The variability of the critical safety speed is found to be more or less consistent in the six risk feature points of continuous tunnels during sunny and cloudy days (Figure 2 (a)). In contrast, the critical safety speed at night time is lower than that in the other daytime conditions. This result can be interpreted as an indication for what may happen if the driver actually travels in a low luminance environment. However, the influence of space length, which determines whether the driver can complete the visual adaptation on the speed, is not clear. No significant difference was found between the combination of two long tunnels and one short plus one long tunnel.

Figure 2 (b) and (c) show that the driver behaviors are dramatically affected by the medium or heavy rain condition in the long tunnels. Critical speed variation remains at a lower level in the foggy situation. In contrast, drivers should pay more attention to the emergency incidents to maintain safe speed at a low range in snowy and icy conditions. Meanwhile, changes in four risk points of long tunnels in adverse weather conditions indicate a similar variation, except for speed values. In addition, the critical safety speed at risk point three remains stable because of the adaption after long driving and the consistency of the environment inside the tunnel. The analysis results regarding the influence of adverse weather and tunnel types on critical safety speed are summarized in (Table A5, see Appendix E, Supplementary material).

The same luminance of environment (i.e. sunny, cloudy or night) has few effects on mean value of the critical safety speed in continuous tunnels. However, in one type continuous tunnels (i.e. short plus long or long plus long), the critical safety speed is much lower during night time than during daytime. The only reliable interaction involved the different adverse weather conditions on the mean critical safety speed in the continuous tunnels (short plus long) ($F = 9.730$, $p < 0.05$) and single long tunnels ($F = 12.365$, $p < 0.05$). This phenomenon illustrated that these two tunnel types have significant environmental differences with common roads, especially in entrances and exits, which may lead to higher driving risk.

In this paper, the study only focuses on continuous tunnels that mainly contain two tunnels. Variations remain unclear in terms of driving behavior in adjacent tunnels (space of two tunnels less than 250 m) or tunnel groups. The influences of spacing length between continuous tunnels are also not discussed. Adverse weather is considered in long tunnels to facilitate comparison. Due to limited data, the effects of adverse weather on critical safety speed in continuous tunnels are not analyzed deeply. Another limitation of this study is the sample selection. The characteristics of drivers such as gender, age, driving experience and workload can contribute to main differences in driving behavior. Unfortunately, this study does not examine these factors and the results cannot be generalized. It is suggested that more comprehensive evaluation may be concluded from the human perspective. In summary, a multitude of factors may play a role in risky driving behavior and different combinations can yield different results. Future work in this area can be expected on the factors mentioned above.

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