

Research Paper

Investigating the Relationship Between Subjective and Interpretive drowsiness With Lane Departure in Simulator Driving



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ABSTRACT

Background: Driver drowsiness is a significant factor contributing to road accidents and the overall increase in road mortality rates. This study investigates the relationship between number of lane crossing (LC), the amount of lateral position deviations and driver drowsiness. The proposed method, due to precision and convenience, has great potential for developing driver-assistant systems.

Materials and Methods: In this experimental research, 34 sub-urban bus drivers participated in a 2-h driving session in a simulator designed based on visual reality. Sensors attached to the steering recorded right and left deviations and relevant information was matched with the recorded videos and the amount of the standard deviation of lane position (SDLP). The number of LC was determined with the designed indicator on the road software. Then, the association between SDLP and the number of LC was compared with the results of the Karolinska sleepiness scale (KSS) and observer rating of drowsiness (ORD), which determined the level of drowsiness, by facial features.

Results: The results of multivariate analysis of variance indicated that the time variable has a significant effect on both ORD and SDLP ($P < 0.05$). These two variables provided over 99% of the variance. The same results were obtained for KSS and SDLP ($P < 0.05$). Meanwhile, the linear combination of these two dependent variables over 12 periods of the research has significant variations. In addition, the results show the progression of KSS and ORD ($P < 0.05$) and an increase in SDLP and LC ($P < 0.05$). In the same manner, LC has a tight association with the level of drowsiness and other factors ($P < 0.05$).

Conclusion: Drowsiness increases the variation in line tracking. However, it is not an appropriate signal for drowsiness detection. The SDLP and the number of line crossings is an

Keywords:

Lane crossing (LC), Karolinska sleepiness scale (KSS), observer rating of drowsiness (ORD), Standard deviation of lane position (SDLP), Drowsiness, Driving crashes, Transportation safety

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Introduction

Drowsiness, fatigue, distracted driving, and an inability to properly control the vehicle on a safe path are important factors that can significantly contribute to road accidents [1]. In recent years, driver drowsiness has been a common reason for road accidents, leading to physical harm, death, and considerable economic losses [2]. The American National Highway Traffic Safety Administration (NHTSA) estimates that in 2017, a total of 91000 police-reported crashes involved drowsy drivers, resulting in an estimated 50000 injuries and nearly 800 deaths [3]. According to the US National Safety Council (NHTSA), drowsy driving is responsible for approximately 100000 incidents on the roads each year. These accidents result in about 71000 injuries and 1550 deaths [4]. Meanwhile, driver drowsiness is a factor in 10% to 20% of motor vehicle accidents [5]. The German Road Safety Organization (DGUV) states that about 25% of human-caused road accidents are a direct result of driver drowsiness on highways [6]. The negative effects of drowsiness on driving are apparent and it is important to study and understand drivers' behaviors during drowsiness [7]. The American Academy of Sleep Medicine (AASM) encourages more research to better define indicators of drowsy driving and identify the threshold at which sleepiness while driving becomes dangerous [8]. Continuous and long hours of driving in monotonous circumstances at night and early in the morning are reasons for driver drowsiness and a decrease in driver's performance [9]. The effects of drowsiness on driving can vary from person to person, and there is no set period for when drowsiness can begin to affect driving. However, according to research by American Centers for Disease Control and Prevention, drowsiness can impair a driver's ability to pay attention to the road, slow their reaction time, and affect their decision-making abilities [10]. Based on the study by Mabry et al. [11], drowsiness and fatigue can affect a person's coordination, reaction time, focus, judgment, and memory, which are all necessary for safe driving. Mascord [12] confirms that at different levels of drowsiness, physiological provocation decreases and slow intuitive performances and subsequently defective processing of information will decrease the driver's responses to stimuli from the environment, unusual circumstances and emergencies. Sleepiness, drowsiness and fatigue are used interchangeably in scientific literature to describe the impaired state caused by the lack of sleep. However, fatigue can have multiple causes, like physical exertion or mental workload. On the other hand, sleepiness and drowsiness refer

to the condition induced by sleep loss only [5]. Based on the study by Poursadeghiyan et al. [13], driving between lines and preventing line crossing are principal efforts that are affected by driver's drowsiness. Therefore, the standard deviation of lane position (SDLP) is a sign of drowsiness [14]. Driving for a long time on monotonous roads can cause fatigue in drivers [13]. As a result, a fatigued driver crosses lines frequently [13, 15]. However, based on a conducted study by Higgins et al. [16], drowsy driving accidents can be prevented by using various methods, such as public awareness campaigns, developing drowsiness detection technologies, implementing hours of service regulations and fatigue risk management for commercial drivers, and introducing laws to prosecute and deter dangerous driving due to fatigue. However, the success of some of these interventions has been variable [5]. Additionally, since scientists do not agree on whether drivers are accurately aware of their drowsiness when driving has significant implications for legal proceedings related to crashes caused by drivers falling asleep behind the wheel [5, 17]. Hence, factors such as the importance of road crashes, the significant role of drowsy driving, the varied success of prevention measures, and the high cost of technology in cars used, especially in poor and developing countries, along with the lack of access to higher safety vehicles should be considered. Therefore, the current study is conducted in the Khajeh-Nasir Tosi University Applied Design Laboratory to explore the relationship between subjective and interpretive drowsiness and going off-road in a driving simulator.

Materials and Methods

This experimental study was carried out in Khajeh-Nasir Tosi University Applied Design Laboratory in 2022. A total of 34 men aged 18 to 50 years were randomly selected from the suburbs. They had healthy eyes (no glasses) and normal physical appearance (no long beards or mustaches). The criterion for entering the study included having healthy drivers who are not addicted and do not consume caffeine. In addition, those who did not become severely drowsy during 2 h of continuous driving to the point of deviating from the road were excluded from the study.

Description of the experiments condition

To determine the level of drowsiness and record the driver's images, a virtual-reality driving simulator was utilized in a fixed temperature and acoustic-controlled and calm room [18]. The participants began driving to detect drowsiness by analyzing facial features. They



Figure 1. Scania BI 301 simulator

were noticed to neglect the unrealities of the test and driving the simulator according to traffic regulations. The drivers also drove the simulator tentatively before the test. In this research to provide real conditions of driving a Scania BI 301 simulator (Figure 1) was designed. The driving simulator used in this study can automatically simulate park, reverse and forward gears, as well as display all the gauges on the dashboard virtually. Three 3D projectors and a 180-degree half-cylindrical screen in front of the windshield and two 18' Liquid-crystal-display televisions (LCD TVs) operate as side mirrors and a 17' LCD TV operates as the back mirror

The virtual road simulated in the research was a loop with the least side components and the minimum curvatures to induce fatigue. Finally, by matching and synchronizing this data and the data available in libraries and previous studies, the initial model of dynamic facial changes was developed.

Vehicle performance data recording

The device records the data of every frame when it renders the frame; therefore, the rate of sampling is not constant and ranges between 90 Hz to 350 Hz. To suppress these changes, by utilizing linear correlation, the rate of 100 Hz is determined as the rate of sampling. Then, by using the data on the location of the vehicle and information on the side-road lines, the distance between the center of the vehicle and the side-road line is calculated and saved in the output of the device.

Driver selection

In the study, 25 drivers were selected. The criteria were that they should be physically normal with no long

beards or moustaches and should have no drug addiction or brain damage. Also, they should not have consumed caffeine-containing drugs foods, or cigarettes for 12 h before the study. In addition, their sleep patterns for a week were assessed using checklists. Both criteria were closely monitored.

Experiment protocol

As the test begins, the driver starts driving on a monotonous road at the speed of 110 km/h for 2 h. A camera takes the driver's face images by the Karolinska sleepiness scale (KSS) [19] simulated on the road, and appeared once every 10 min. Also, according to the observer rating of drowsiness (ORD) [19], the level of drowsiness was determined by the observer every 10 min. Whole devices, such as the camera and simulator were checked to prevent unexpected ceases in this step of the test. The observer finished the test when the vehicle left the road completely.

Record of ORD, KSS, SDLP and lane crossing (LC) in driving test

In this research, the average ORD, as an objective determination of drowsiness and facial changes is determined according to the review of the video while driving every 10 min, by the observer, KSS criteria as a subjective estimation of sleepiness, displayed 12 times during 120 min on the road monitor screen and the driver must answer it [18]. SDLP approach calculates the deviation of the vehicle's position from the lane's center [20]. The LC or lane change criterion reports the number of crossings on the side of the road by the observer in a 10 min period and by observing the road video while driving [21]. Finally, to check the correlation between

ORD and KSS during driving by employing the number of line crossings on both sides of the road and changes in the lateral position of the vehicle, repeated measure multivariate analysis of variance was employed. Then, a significant correlation between ORD and KSS, or the number of line crossings and the level of lateral position changes was observed. For every dependent variable variance analysis test with repeated measures and to obtain an appropriate model by considering events in time, the interaction test was conducted for every factor.

Results

Statistical survey on the correlation between ORD and KSS

The results of the multiple variable tests showed that the time variable significantly affects ORD and KSS. Specifically, the combined linear regression of the two dependent variables throughout the 12-period research exhibited a significant difference ($F=180.85$, $P=0.001$).

Given that the assumption of independence for the two variables was not maintained after being evaluated using the Mauchly test ($P<0.05$). Meanwhile, the Greenhouse-Gayser test showed that the variable of KSS exhibited significant changes across the twelve research periods ($F=178.3$, $P=0.001$).

The Greenhouse-Gayser test also reported a significant difference at the 5% error level for the ORD variable within the study period. Specifically, the results of the test were $F=151.73$ and $P=0.001$ (Figure 2 and Table 1).

Statistical survey on the correlation between ORD and LC

The results of the multiple variable tests showed that the time variable significantly affects ORD and LC. Specifically, the combined linear regression of the two dependent variables throughout the 12-period research exhibited a significant difference ($F=170.71$, $P=0.001$).

Given that the assumption of independence for the two variables was not maintained after being evaluated using the Mauchly test ($P<0.05$), the Greenhouse-Gayser test showed that the variable of LC exhibited significant changes across the twelve research periods ($F=4.05$, $P=0.02$).

The Greenhouse-Gayser test also reported a significant difference at the 5% error level for the ORD variable within the study period. Specifically, the results of the test were $F=151.73$, $P=0.001$ (Figure 3 and Table 1).

Statistical survey on the correlation between ORD and SDLP

The results of the multiple variable tests showed that the time variable significantly affects ORD and SDLP. Specifically, the combined linear regression of the two dependent variables throughout the 12-period research exhibited a significant difference ($F=148.89$, $P=0.001$).

Given that the assumption of independence for the two variables was not maintained after being evaluated using the Mauchly test ($P<0.05$). The Greenhouse-Gayser test showed that the variable of ORD exhibited significant changes across the twelve research periods ($F=140.31$, $P=0.001$).

The Greenhouse-Gayser test also failed to show a significant difference at the 5% error level for the SDLP variable within the study period. Specifically, the results of the test were $F=3.17$ and $P=0.052$ (Figure 4 and Table 1).

Statistical survey on the correlation between LC and KSS

The results of multiple variable tests showed that the time variable significantly affects KSS and LC. Specifically, the combined linear regression of the two dependent variables throughout the 12-period research exhibited a significant difference ($F=167.19$, $P=0.001$).

Given that the assumption of independence for the two variables was not maintained after being evaluated using the Mauchly test ($P<0.05$). The Greenhouse-Gayser test showed that the variable of LC exhibited significant changes across the twelve research periods ($F=4.05$, $P=0.001$).

The Greenhouse-Gayser test also reported a significant difference at the 5% error level for the ORD variable within the study period. Specifically, the results of the test were $F=178.3$ and $P=0.001$ (Figure 5 and Table 1).

Statistical survey on the correlation between SDLP and KSS

The results of multiple variable tests showed that the time variable significantly affects KSS and SDLP. Specifically, the combined linear regression of the two dependent variables throughout the 12-period research exhibited a significant difference ($F=643.35$, $P=0.002$).

Table 1. Relationship between variables

Statistical Experiments	Wilks Lambda		Greenhouse-Gayser	
	F	P	F	P
ORD-KSS	180.85	0.001	151.73	0.001
ORD-LC	170.71	0.001	151.73	<0.001
ORD-SDLP	148.89	0.01	140.31	<0.001
LC-KSS	167.19	0.001	178.03	<0.001
SDLP-KSS	643.35	0.0001	165.21	<0.001

Abbreviations: ORD: Observer rating of drowsiness; KSS: Karolinska sleepiness scale; SDLP: Standard deviation of lane position; LC: Lane crossing.

Given that the assumption of independence for the two variables was not maintained after being evaluated using the Mauchly test ($P < 0.05$), the Greenhouse-Gayser test showed that the variable of KSS exhibited significant changes across the twelve research periods ($F = 165.21$, $P = 0.002$).

The Greenhouse-Gayser test also failed to show a significant difference at the 5% error level for the SDLP variable within the study period. Specifically, the results of the test were $F = 3.17$ and $P = 0.047$ (Figure 6 and Table 1).

Discussion

According to Figure 2, the ORD and KSS indices have an almost similar upward trend during the 120 min of monitoring. The upward trend of these scales occurred at a faster rate between 60 and almost 70 min. The study by Uchiyama et al. [22] found that there are significant positive correlations between the levels of ORD and all

other forms of drowsiness, such as subjective self-rating (KSS scores). This indicates an association between objective drowsiness (determined by ORD measurements) and perceived sleepiness (from the KSS scores). The study results by Poursadeghiyan et al. [19] found a significant correlation between the measurement trends of drowsiness levels using KSS and ORD scales, suggesting a connection between both scales. Moreover, the study found that there is a link between the dynamics of mouth movements during the test and drowsiness levels (as measured by KSS and ORD). While this research did not provide specific details on the strength or consistency of the correlation between ORD and KSS, it indicates that there is a significant relationship between the two measures of drowsiness. Figure 3 shows that the mean of changes in drowsiness according to the number of line crossings increases as time progresses and in minutes 50 and 80, two fluctuations were observed but changes had an upward trend. These fluctuations are related to the differences in driving among different drivers [23].

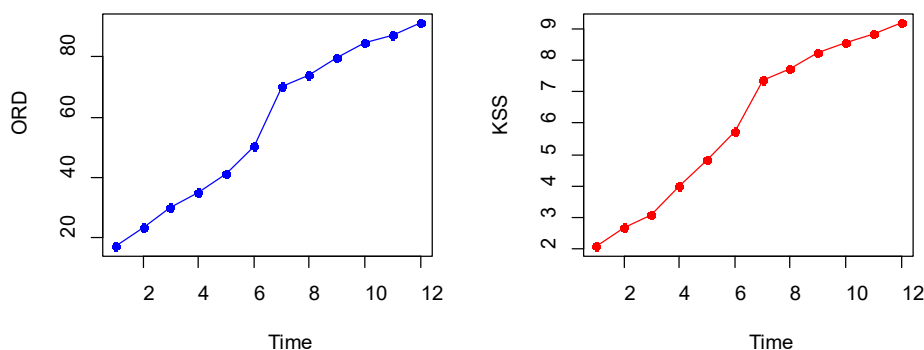


Figure 2. Trend of change in average drowsiness levels based on ORD and KSS (120 minutes)

ORD: Observer rating of drowsiness; KSS: Karolinska sleepiness scale.

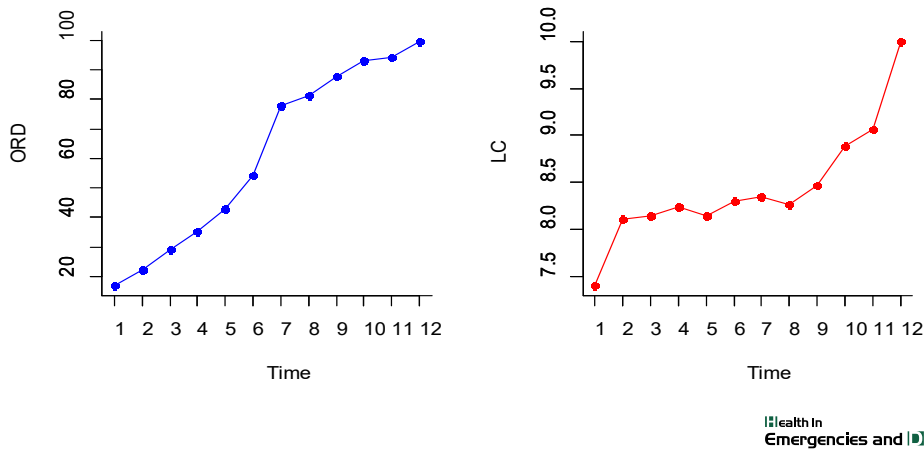


Figure 3. Trend of change in average drowsiness levels based on LC and ORD Score (120 minutes)

ORD: Observer rating of drowsiness; LC: Lane crossing.

The general upward trend is because of an increase in the level of drowsiness and number of line crossings [24]. The trend of changes in drowsiness shows that in the first thirty minutes of driving, KSS has a gradual upward trend. There is a moderate increase in this trend from minute 30 to minute 80. Then, it slowly increases from minute 80 to minute 120. These different trends can be interpreted as follows. In the first 30 min of driving, drivers confess to the impression of drowsiness on the driving errors, because at the beginning of driving, they do not feel drowsiness or are not drowsy. Then, by minute 80, drivers admit to the drowsiness by answering to KSS questionnaire. Drowsiness exists after minute 80. However, the rate of drowsiness in this period has a slow increase. This may be due to omitting some drivers from the test by lane deviation or line crossing. Nevertheless, this upward trend continues as time progresses [25]. Poursadeghiyan et al. [19], using artificial neural network models, found that the number of line crossings

was one of the factors used to detect and predict driver drowsiness. In addition, the study by Jacobé de Naurois et al. [15] found that ORD relies on a persistent scale from “alert” to “extremely drowsy” with a list of criteria that can be observable in the driver, including the number of line crossings. Another study by Akerstedt et al. [23] and Sandberg et al. [26] also confirmed that KSS scores were significantly correlated with the number of line crossings.

Figure 4 shows that the ORD scale has an upward trend during the 120 min of monitoring, while in SDLP, three different slopes are observed. From the beginning of the test to minute 50, there is a slow increase whereas from minute 50 to minute 80 there is a sharp increase. Then, there is a sharp decrease to the end of the test. Garaguzlou and et al. [27] mentioned two reasons for these changes. First, the majority of drivers have not been driving the whole of the time. Second, these changes

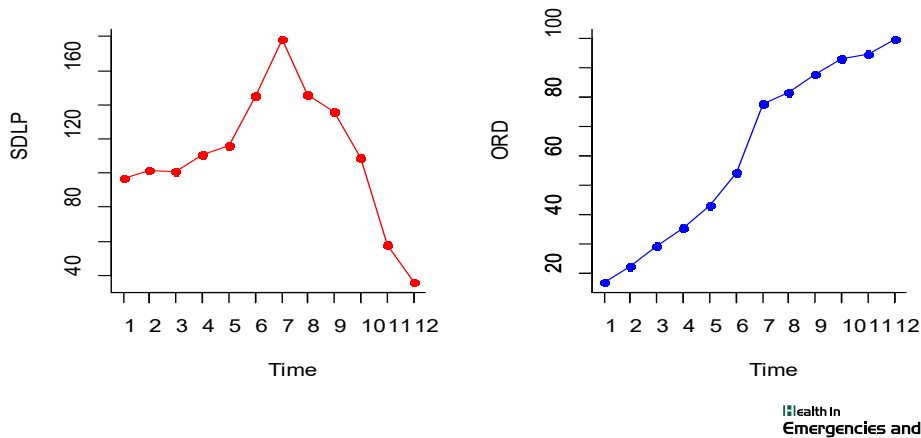


Figure 4. Trend of change in average drowsiness levels based on ORD and SDLP (120 minutes)

SDLP: Standard deviation of lane position; ORD: Observer rating of drowsiness.

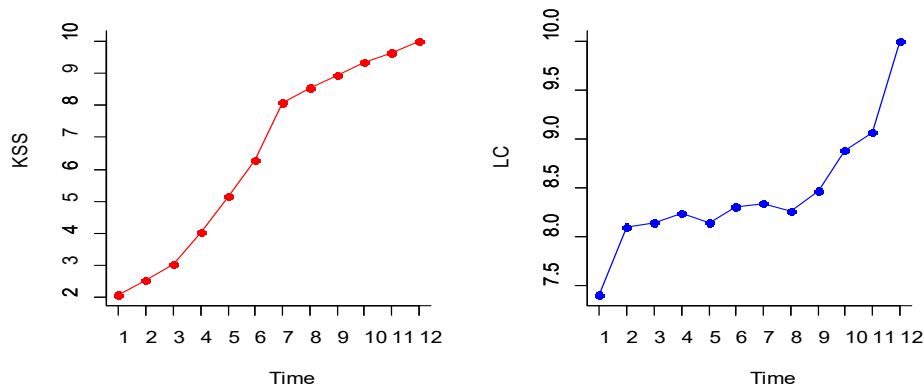


Figure 5. Trend of change in average drowsiness levels based on LC and KSS (120 minutes)

KSS: Karolinska sleepiness scale; LC: Lane crossing.

would be related to the personal performance of every driver. While a linear relationship between the increase in SDLP and with increase in the level of drowsiness has been confirmed [28]. SDLP is a measure of the variability of a vehicle’s lateral position within a lane. It is used as an objective measure of drowsiness and driver performance [22]. Different studies reported significant positive correlations between the ORD levels and all other drowsiness measures, including SDLP [19, 22]. Figure 5 shows that the KSS index has an upward trend with a steep slope until minute 70, but after this time, although the slope has softened, it is still upward. On the other hand, although LC has fluctuation, it has continued its upward trend throughout monitoring duration.

Based on Table 1, in the present study, although a linear combination of SDLP and ORD during 120 min was significant, the Greenhouse-Gayser test showed that ORD over 12 periods of the test had significant changes. This

test did not show a significant difference at the level of 5% error of lane deviation during the test. In a study conducted by Kircher et al. [30], it was argued that SDLP is dependent on external contributors such as road marks, weather, and illumination. Another weakness of SDLP is related to microsleep because a device functioning based on lateral position does not detect microsleep. The linear combination of KSS and SDLP is significant. However, Greenhouse-Gayser is only significant for KSS. Our findings are in line with related studies [19, 26, 31, 32]. Based on our investigation of the contributions of drowsiness to driving errors, the correlation between factors of sleepiness, such factors KSS, ORD and LC with neglectable changes yields reasonable results. This can ensure the effectiveness of these variables in determining the level of drowsiness since as time progresses, these variables increase. In addition, by considering the limitations of SDLP it would not be an indicator of drowsiness whereas drowsiness increases the level of SDLP;

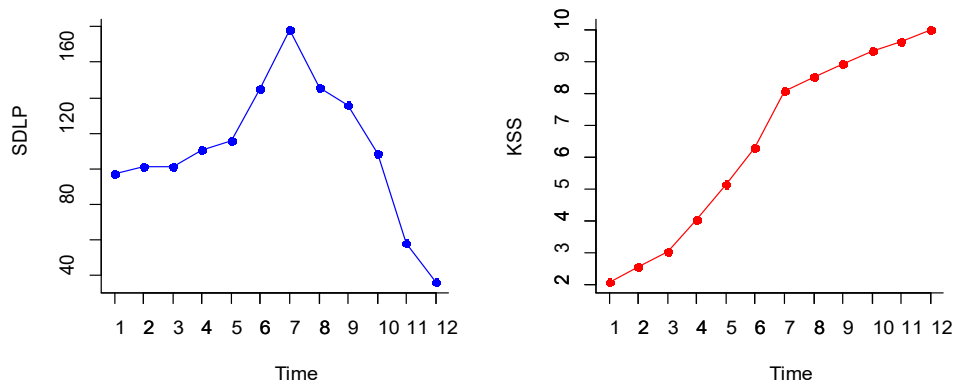


Figure 6. Trend of change in average drowsiness levels based on SDLP and KSS (120 minutes)

SDLP: Standard deviation of lane position; KSS: Karolinska sleepiness scale.

accordingly, drowsiness leads to lane deviation but lane deviation does not indicate that the driver is drowsy. Therefore, researchers of this study do not account for SDLP as a signal of drowsiness. Thus, an appropriate sign of drowsiness is images of facial features in which as drowsiness is detected, the level of lane deviation is recorded.

Conclusion

Overall, the available results suggest that there is a significant relationship between the level of drowsiness according to KSS and ORD, as well as between the level of drowsiness according to SDLP and ORD. The number of line crossings is a factor used to detect and predict driver drowsiness. In addition, using a combination of sleepiness information and deviation from the lanes, we can detect dangerous levels of drowsiness. It is important to note that drowsiness-related car accidents are a serious problem that can lead to injuries and fatalities, and drivers should take steps to prevent drowsy driving, such as getting enough sleep and taking breaks during long drives.

Study limitations

The study limitation is results of the tests while driving on the road and in a controlled environment will be different. Therefore, the most important limitation of the study was the impossibility of testing in real conditions.

Ethical Considerations

Compliance with ethical guidelines

The current study was registered with the Ethics Committee of [Ardabil University of Medical Sciences](#) (Code: IR.ARUMS.REC.1401.151).

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Authors' contributions

All authors equally contributed to preparing this article.

Conflict of interest

The authors declared no conflict of interest.

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