Zhang *et al. BMC Psychology (2025) 13:216*
https://doi.org/10.1186/s40359-025-02555-w

BMC Psychology

RESEARCH Open Access

ERP insights into speed control: role of risk types and levels

Xiaoying Zhang[1], Ruosong Chang[2] and Xue Sui[2,3*]

Abstract

This study investigates the neural mechanisms underlying the inhibitory control of speed when drivers encounter varying levels of risk posed by pedestrians and motor vehicles. Two variables (risk level and risk type) were controlled in this study. The experimental materials included traffic images depicting pedestrians or motor vehicles, each associated with different risk levels. Drivers were presented with these images and tasked with adjusting their vehicle speed according to the traffic scenario. Specifically, they were instructed to either maintain their current speed or decelerate as needed. Electroencephalograms (EEGs) responses were simultaneously recorded. Results showed that in low-risk scenarios, the deceleration score was significantly higher for pedestrian risks than for motor vehicle risks. Under conditions of elevated risk, various risk types did not result in significant variations in deceleration scores. EEG data revealed that high-risk scenarios elicited a larger amplitude in the P3 component compared to low-risk scenarios. Additionally, the average amplitude of the N2 component was greater for pedestrian risks than for motor vehicle risks. These findings suggest that risk level and type do not act as independent factors influencing speed control. Specifically, when the risk originates from pedestrians, drivers tend to reduce their speed even when the risk level is low, in order to mitigate potential hazards and prioritize safety. Furthermore, high-risk situations elicit a more pronounced brain response and demand greater attentional resources compared to low-risk situations. This study provides valuable insights for establishing speed limits based on different sources of risk in driving scenarios.

Keywords behavioral inhibition, Speed control, Risk type, risk level, driving speed

Introduction

Traffic accidents result in a significant number of fatalities annually and are projected to become the fifth leading cause of death globally by 2030 [1]. Research has demonstrated a strong link between poor driving behavior and involvement in fatal crashes [2]. Driving behavior is goal-oriented and relies on cognitive processes such as risk perception, reaction time, and inhibitory control [3, 4]. Among these, inhibitory control enables drivers to reduce impulsive behavior, suppress inappropriate responses, and significantly impacts traffic safety [5]. Studies have shown that drivers' poor behavioral inhibition can predict traffic violations and driving errors, particularly deficiencies in speed control [4, 6].

Drivers' speed control is influenced by factors including driver characteristics, vehicle performance, and road conditions [7–9]. Notably, road conditions contribute to approximately 7.7% of the variability in drivers' likelihood of speeding, significantly impacting speed control [10]. The level of risk in road conditions affects drivers' behavioral inhibition. For instance, in urban areas, high traffic volume and variable road conditions require drivers to inhibit excessive speeds to avoid conflicts with other vehicles or pedestrians. However, at the same time, complex road environments may increase drivers' cognitive load and impair their

*Correspondence:
Xue Sui
suixue88@163.com
[1] Department of Psychology, Guangzhou University, Guangzhou, China
[2] The School of Psychology, Liaoning Normal University, Dalian, China
[3] Huanghe Road No. 850, Shahekou District, Dalian 116029, China

inhibitory control, thus posing challenges to safe driving [10, 11]. Conversely, rural roads, with lighter traffic and better visibility, impose fewer demands on speed control, allowing drivers to travel at faster speeds. Additionally, compared to daytime, there are fewer vehicles on the road at night, with reduced noise and disturbances. This may lower drivers' speed control requirements, increasing the likelihood of speeding [10, 12].

Furthermore, the type of road risk also affects drivers' speed control [13]. Road risks are mainly posed by pedestrians, motor vehicles, and nonmotor vehicles such as electric vehicles and bicycles [14]. Surveys from emergency departments indicate that traffic accidents primarily involve vehicle-to-vehicle and vehicle-to-pedestrian collisions [1], with motor vehicle accidents being the most common cause of injury [15]. Therefore, understanding the impact of pedestrian and motor vehicle risks on driving speed control is crucial for improving traffic safety. Pedestrians, often emerging from the sides of the road, present a challenge due to their smaller size, which may not immediately capture the driver's attention. Studies have shown that drivers miss pedestrian risks up to 65% of the time [16], which can negatively impact their speed control and lead to speeding or failure to decelerate in time. In contrast, motor vehicles, typically positioned in the center of the roadway, are more conspicuous due to their size [17], making it easier for drivers to adjust their speed. However, previous studies have not examined pedestrian and motor vehicle risks at different risk levels. For instance, when pedestrians are in the middle of the road and motor vehicles are on the roadside, the speed control characteristics of drivers require further exploration.

Physiological indicators collected by event-related potentials (ERPs) contribute to understanding the neural mechanisms underlying cognitive processing in drivers. Studies have indicated that the P3 amplitude decreases significantly when drivers are distracted and need to respond to visual stimuli while driving [18]. The P3 amplitude is positively correlated with the allocation of attentional resources [19, 20], a reduction in P3 amplitude signifies a decrease in the driver's focus on the driving task. Previous studies have found that traffic images with different risk levels induce variations in the P300 amplitude in both pedestrians and drivers [21, 22]. The P300 amplitude was significantly larger in drivers exposed to overt hazard images compared to those exposed to covert hazard or no-hazard images [23]. Moreover, images of natural scenes, with or without pedestrians, induced different P300 latency periods in college students [24]. In summary, the P300 amplitude is a sensitive indicator of road risk, reflecting the driver's allocation of attentional resources [25].

In addition, previous studies have shown that various types of traffic risks can elicit different N2 amplitudes in drivers. For instance, warning signs trigger larger N2 amplitudes compared to prohibition and mandatory signs [26]. When exposed to blurred traffic signals (yellow lights), the N2 amplitude in college students increases [27]. The N2 component reflects the level of cognitive resources engaged in conflict resolution and is associated with heightened alertness [28, 29]. In situations where traffic signals are unclear, the driving scenario at the intersection becomes more complex, prompting the driver to increase alertness and focus on adapting to the evolving traffic conditions. Based on the findings of these studies, this research selects the N2 and P300 components as indices.

In this study, we selected young drivers who are prone to speeding behaviors as participants to explore the neural mechanisms underlying the impact of risk level and risk type on driving speed control [30]. Building on previous research paradigms [31], this study utilized authentic traffic images depicting varying risk levels (high and low) and risk types (pedestrian and motor vehicle) to assess driver responses. Participants were tasked with deciding whether to decelerate or maintain speed while their Event-Related Potential (ERP) was monitored for fluctuations. Pedestrians, as indicated by previous studies [32], are considered vulnerable road users, and walking paths are characterized by their flexibility and increased risk [33]. Therefore, the study's initial hypothesis posited that, in comparison to motor vehicle risk scenarios, drivers are more likely to adjust their speed when confronted with pedestrian risk scenarios. It is expected that this difference in cognitive response will be reflected in the N2 component, which is linked to attention processing. The second hypothesis suggests that, when exposed to high-risk situations, drivers are more likely to control their speed compared to low-risk situations. High-risk conditions require a greater allocation of cognitive resources than low-risk ones, and it is anticipated that this difference in neural activity will be observed in the P3 component. The findings of this study may offer valuable insights into the formulation of speed limits for various types of roads, thereby contributing to traffic safety.

Methods

Participants

G-power 3.1.9.7 software was used to determine the sample size, setting a significance level of $\alpha = 0.05$ and power of $1 - \beta = 0.80$. The effect size was set at $f = 0.80$, resulting in a minimum calculated sample size of $N = 32$ [34]. Participants were required to meet the criteria of being of legal age and possessing a valid driver's license. A total of 35 participants, including 14 males, were enrolled. The age range was 18-30 years, with an average age of 21.49 years (SD = 2.59 years). 31.4% of participants owned a car. The average driving experience was 18.06 months, with an average mileage of 3462.86 kilometers. Over the past year, 19 participants drove on average once a month, 13 once a week, and 3 once a day. All participants were right-handed, with normal or corrected vision and no color blindness. Color blindness test materials are shown in Figure 1 (Yu Ziping's color blindness test chart, 6th edition). All participants provided informed consent. This research was approved by the Ethics Committee of the College of Psychology at Liaoning Normal University, ensuring the protection of participants' rights, health, and dignity in accordance with the Declaration of Helsinki (1964).

Stimuli

A high-definition vehicle recorder was installed in a vehicle operating in urban areas under favorable weather conditions to capture video footage from the driver's perspective. An experienced driver reviewed the footage and selected images depicting potential traffic hazards. The selection criteria were based on road risks commonly reported in Chinese accident reports, alongside recommendations from three experts in traffic psychology. These experts, professors and associate professors with extensive experience in traffic safety research, also serve as safety consultants for the local traffic police department [23]. The hazards involved either pedestrians or motor vehicles. Fifteen graduate psychology students, all with valid driver's licenses, evaluated the perceived risk level of the images on a scale from 1 to 7. 1 represented minimal risk, 4 represented moderate risk, and 7 represented substantial risk. Image assessment was conducted using E-Prime 2.0, with the mean score given by the 15 students serving as the final image rating.

Images were categorized based on risk score, resulting in 20 high-risk pedestrian images, 20 high-risk vehicle images, 20 low-risk pedestrian images, and 20 low-risk vehicle images. To prevent participant fatigue, an additional set of 20 non-challenging images depicting clear road conditions was included as experimental fillers. A total of 100 images were selected. No-risk images depicted clear roads without obstacles. High-risk images (Figure 2) featured obvious obstacles, such as motor vehicles or pedestrians, which required drivers to adjust their speed to avoid potential traffic risks [35, 36]. Low-risk images showed hidden obstacles, such as early-stage traffic risks from pedestrians or motor vehicles. Whether to control speed to avoid traffic risks depends on the driver's choice [37, 38].

The mean score of high-risk pedestrian images (M = 5.73, SD = 0.87) was significantly higher than for low-risk pedestrian images (M = 2.76, SD = 0.73), t (38) = -11.73, p < 0.001. Similarly, the mean score for high-risk vehicle images (M = 5.45, SD = 0.85) was significantly greater than for low-risk vehicle images (M = 2.38, SD = 0.90), t (38) = -11.10, p < 0.001. There was no significant difference in the image scores between high-risk vehicles (M = 5.45, SD = 0.85) and high-risk pedestrians (M = 5.73, SD = 0.87), t (38) = -1.05, p = 0.303. Similarly, no significant difference was found between low-risk vehicles (M = 2.38, SD = 0.90) and low-risk pedestrians (M = 2.76, SD = 0.73), t (38) = -1.47, p = 0.151. Table 1 provides details on the types of risks in the images, their locations, and corresponding actions.

Design and procedure

The experiment used a within-participants design, incorporating a 2 (risk type: pedestrian and vehicle) × 2 (traffic risk level: high-risk and low-risk) factorial design. The dependent variables included the deceleration score and the average amplitude of the ERP component.

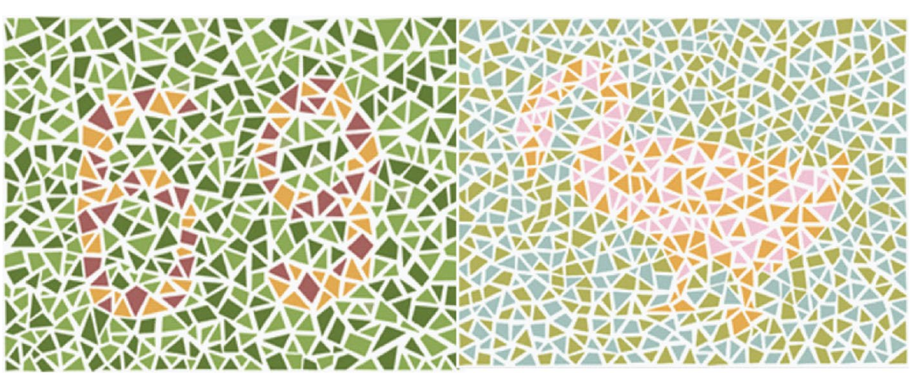

Fig. 1 Colour blindness test material.

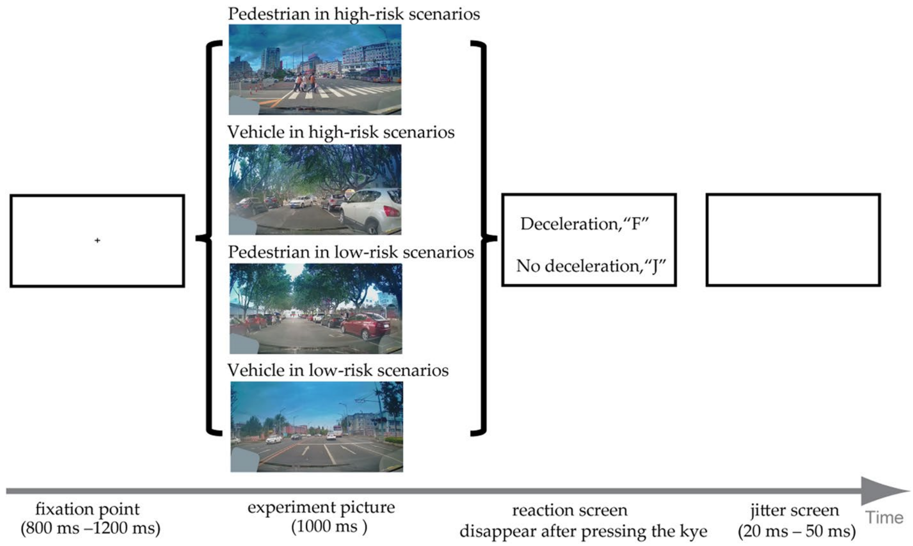

Fig. 2 The experimental procedure flowchart.

Table 1. Risk description of experimental materials

Risk level	Risk type	Risk description	Number
Low -risk	vehicle	Vehicles ahead turn or brake	13
		Vehicles on the left or right side turn or merge	7
	pedestrian	Pedestrians ahead	11
		Pedestrians on the left or right side	9
High-risk	vehicle	Vehicles ahead turn or brake	11
		Vehicles on the left or right side turn or merge	9
	pedestrian	Pedestrians ahead	14
		Pedestrians on the left or right side	6

This study employed ERPs to capture participants' decision-making processes while driving. The procedure involved presenting a random fixation point "+" for 800 to 1200 ms at the center of the screen, followed by a 1000 ms image (high-risk with pedestrians, high-risk with vehicles, low-risk with pedestrians, low-risk with vehicles, or no-risk), shown in a random order. Participants were instructed to mentally simulate driving on a road and decide whether to reduce speed based on the depicted road conditions. After 1000 ms, the image disappeared. Participants were instructed to press the "F" key if they decided to decelerate, and the "J" key if they did not. A decision was required promptly. Then, a blank screen appeared for 20 to 50 ms. The experiment included a practice phase with 10 trials, followed by a formal phase with three blocks. Each block contained 100 trials, totaling 300 trials. A short break separated the three phases. The experimental procedure is shown in Figure 2. In the high-risk pedestrian images, the pedestrian is relatively close to the moving vehicle that is capturing the road situation; in the high-risk vehicle images, the vehicle on the left is about to overtake the moving vehicle; in the low-risk pedestrian images, the pedestrian is far ahead of the moving vehicle; in the low-risk vehicle images, the vehicle is far ahead of the moving vehicle.

Electroencephalogram (EEG) recordings and analysis

EEG data were recorded using the Brain Products workstation (Germany) with a 64-electrode cap, following the International 10-20 system. EEG signals were recorded using Brain Vision Recorder 2.0 software, and data processing was performed with Analyzer 2.0 software. The binaural mastoid process served as the reference electrode. Electrode impedances were maintained below 5 kΩ, and data were recorded at a sampling rate of 500 Hz. ERP analysis covered a duration from 200 ms before stimulus presentation to 1000 ms after stimulus presentation. After removing ocular artifacts, the signals were band-pass filtered between 0.1 Hz and 30 Hz. The data were then segmented, with baseline correction applied using a 200 ms window before stimulus onset. Any artifacts exceeding ±80 μV in amplitude were removed. The averages for different conditions were superimposed.

The selection of electrode sites for N2 and P3 analysis was based on ERP waveform. Frontal electrodes (F3, Fz, F4), frontal-central electrodes (FC3, FCz, FC4), central electrodes (C3, Cz, C4), central-parietal electrodes (CP3, CPz, CP4), and parietal electrodes (P3, Pz, P4) were chosen for N2 analysis. Based on previous studies [29, 39] and the waveform diagram of this study, a 280-330 ms window was selected for the N2 component. Additionally, parietal electrodes (P3, Pz, P4) were selected for P3 analysis. According to previous studies [19, 25, 40] and the waveform diagram from this study, a 300-500ms window was chosen for the P3 component.

Data statistics

Behavioral and EEG data were processed using SPSS 22.0. To address the random effects structure and improve model fitting and parameter estimation, we employed Generalized Linear Mixed Models (GLMM) for statistical analysis. Given the linking functions and distributional assumptions of the data, we used the Linear Mixed Models (LMM) framework within the GLMM. The fixed factors included risk level (high-risk and low-risk), risk type (pedestrian and vehicle), and their interaction. The random factor was the subject.

Results

Behavioral results

The deceleration score was calculated as the proportion of decelerations across all trials within the same condition, assigning a score of 1 for selecting "F" and 0 for selecting "J". For example, under the high-risk pedestrian condition, there were 60 trials. The participant received 1 point for decelerating and 0 points for not decelerating. The score was then divided by 60 to obtain the participant's deceleration score for that condition.

A GLMM was used to analyze the effect of risk level (high-risk and low-risk) and risk type (pedestrian and vehicle) on the deceleration score. The deceleration score followed a normal distribution. The results showed: Fixed effects, there were significant differences in the impact of high and low risks on deceleration scores, F (1, 136) = 342.021, $p < 0.001$, risk level (high-low), B = 0.428, SE = 0.023, $t = 18.494$, $p < 0.001$. There were significant differences in the impact of vehicle risk and pedestrian risk on deceleration scores, F (1, 136) = 72.093, $p < 0.001$, risk type (vehicle-pedestrian), B = -0.170, SE = 0.020, $t = -8.491$, $p < 0.001$. The interaction between risk level and risk type was significant, F (1, 136) = 51.855, $p < 0.001$. At the high-risk level, there was no significant difference in the predictive power of vehicle risk and pedestrian risk on deceleration scores, risk type (vehicle-pedestrian), B = -0.016, SE = 0.029, $t = -0.537$, $p = 0.592$. At the low-risk level, pedestrian risk was a stronger predictor of deceleration scores than vehicle risk, risk type (vehicle-pedestrian), B = -0.323, SE = 0.029, $t = -11.059$, $p < 0.001$. Random effects, $Z = 2.241$, $p = 0.025$, which was statistically significant.

ERP results

According to the ERP waveform (Figure 3), GLMM was used to analyze the predictive effect of risk level (high-risk and low-risk) and risk type (pedestrian and vehicle) on the average amplitude of N2 (280-330 ms) in 5 brain regions (frontal, frontal-central, central, central-parietal, and parietal). Additionally, GLMM was used to analyze the predictive effect of risk level (high-risk and low-risk) and risk type (pedestrian and vehicle) on the average amplitude of P3 (300-500 ms) in the parietal region.

N2 component (280-330 ms)

Using the average amplitude of the N2 component as the dependent variable, GLMM analysis was performed to examine the predictive effects of risk level and risk type on the amplitude across different brain regions. The average amplitude of the N2 component in 5 brain regions followed a normal distribution. The results (Table 2) revealed: At the low-risk level, in the central and central-parietal regions, the N2 amplitude evoked by pedestrian risk was significantly larger than that evoked by vehicle risk. For random effects in the central and central-parietal regions, $Z = 4.014$, $p < 0.001$; $Z = 3.953$, $p < 0.001$, both of which were statistically significant. In the frontal, frontal-central, and parietal regions, the N2 amplitude evoked by pedestrian risk was marginally larger than that evoked by vehicle risk. At the high-risk level, in the frontal-central region, the N2 amplitude evoked by pedestrian risk was marginally significantly larger than that evoked by vehicle risk. Random effects in the frontal, frontal-central, and parietal regions, $Z = 4.006$, $p < 0.001$; $Z = 3.996$, $p < 0.001$; $Z = 3.970$, $p < 0.001$, all of which were statistically significant.

P3 component (300-500 ms)

Using the average amplitude of the P3 component as the dependent variable, GLMM analysis was conducted to examine the predictive effects of risk level and risk type on the amplitude in the parietal region. The average amplitude of the P3 component in the parietal region followed a normal distribution. The results indicated: Fixed effects, there were significant differences in the impact of high-risk and low-risk on the P3 amplitude, F (1, 136) =

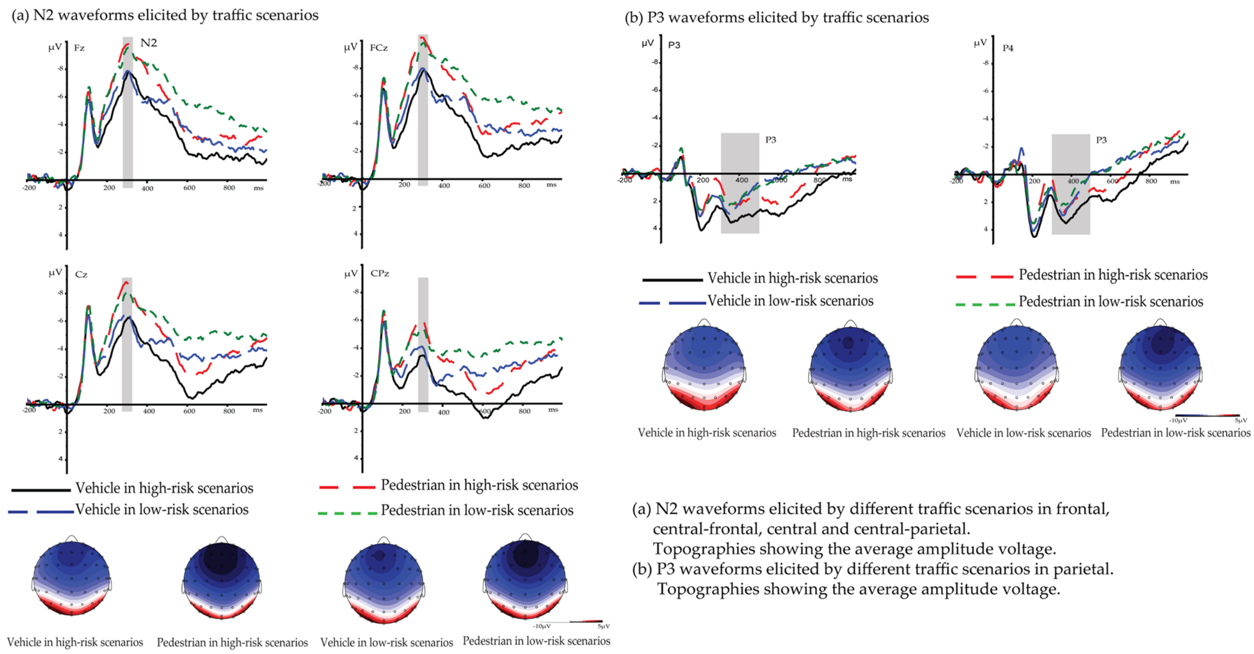

Fig. 3 Grand-average ERP waveforms elicited by different traffic scenarios.

Table 2. The predictive effect of risk level and risk type on N2 in 5 brain regions

Variable			Statistical indicators			
Brain region	**Risk level**	**Risk type**	***B***	***t***	***p***	***M***
Frontal	high	vehicle–pedestrian	0.161	0.512	0.609	−6.673, −8.922
	low	vehicle–pedestrian	−0.578	−1.884	0.067	−6.834, −8.344
Frontal-central	high	vehicle–pedestrian	−0.610	−1.926	0.056	−6.052, −7.486
	low	vehicle–pedestrian	−0.600	−1.894	0.060	−5.442, −6.886
Central	high	vehicle–pedestrian	0.209	0.747	0.456	−4.707, −6.956
	low	vehicle–pedestrian	−0.599	−2.137	0.034	−4.916, −6.357
Central-parietal	high	vehicle–pedestrian	0.372	1.309	0.193	−2.055, −4.115
	low	vehicle–pedestrian	−0.699	−2.457	0.015	−2.428, −3.415
Parietal	high	vehicle–pedestrian	0.529	1.643	0.103	1.298, −0.283
	low	vehicle–pedestrian	−0.620	−1.924	0.056	0.769, −0.337

10.665, $p = 0.001$, with the P3 amplitude evoked by high-risk (1.553) significantly larger than that evoked by low-risk (0.793), risk level (high-low), B = 0.760, $t = 3.266$, $p = 0.001$. There were significant differences in the impact of vehicle risk and pedestrian risk on the P3 amplitude, F (1, 136) = 13.927, $p < 0.001$, with the P3 amplitude evoked by vehicle risk (1.594) significantly larger than that evoked by pedestrian risk (0.751), risk type (vehicle-pedestrian), B = 0.843, $t = 3.732$, $p < 0.001$. The interaction between risk level and risk type was not significant, F (1, 136) = 2.189, $p = 0.141$. Random effects: $Z = 3.912$, $p < 0.001$, which was statistically significant.

Discussion

This study employed ERP technology to investigate the neural mechanisms involved in speed control for pedestrians and motor vehicles under varying risk levels. Drivers decided whether to adjust their speed based on the perceived risk level in the traffic scenario, while their ERPs were concurrently recorded. The results indicate that, at the low-risk level, drivers tended to prioritize slowing down in response to pedestrian risk rather than motor vehicle risk. Compared to the risk posed by motor vehicles, pedestrian risk evoked a larger N2 amplitude in the driver's frontal, central-frontal, central, and central-parietal areas. The high-risk scenario evoked a larger P3 amplitude in the driver's parietal region compared to the low-risk scenario.

The effect of risk type on drivers' speed control is modulated by the risk level. In high-risk scenarios, the reduction in both pedestrian and motor vehicle risk through deceleration is substantial, with no significant difference. In these scenarios, the proximity of the risk increases, urgency rises, and the potential for traffic accidents is heightened. Drivers tend to reduce their speed when encountering risks involving pedestrians and motor vehicles. In low-risk scenarios, drivers show a significantly stronger tendency to decelerate when confronted with pedestrian hazards compared to motor vehicle hazards. Pedestrian risks are more unpredictable and variable on the road. Research indicates that the sudden appearance of pedestrians often triggers fear in drivers, leading to more frequent speed adjustments [41, 42]. In contrast, motor vehicle risks are relatively stable, especially when the speeds of vehicles traveling in the same direction are similar, allowing drivers to maintain their initial speed. This suggests that different speed limits should be set based on specific road risk factors to prevent frequent deceleration from causing traffic disruptions.

The risk of pedestrians induces a greater N2 amplitude in drivers. N2 is a negative wave, characterized by its highest amplitude at the central electrode of the frontal lobe, occurring between 200 ms and 400 ms following the onset of stimulation. A heightened N2 amplitude indicates increased alertness in individuals [29]. Pedestrians, as vulnerable road users [32], elevate drivers' alertness. Research has shown that novel stimuli elicit a more pronounced N2 component compared to standard stimuli [42]. In the motor vehicle lane, pedestrians are less common than motor vehicles on the road. Therefore, pedestrians serve as prominent stimuli that capture the driver's attention and enhance vigilance.

The high-risk scenario elicited a larger P3 amplitude. The P3 is a positive wave that peaks between 300 ms and 600 ms following the onset of stimulation, with its highest amplitude typically observed in the parietal lobe. The P3 amplitude correlates positively with the allocation of attention during cognitive processing [19]. A greater P3 amplitude indicates that high-risk situations require more attention from the driver. Over the course of evolution, humans have developed a heightened response to dangerous situations. When individuals encounter a threat to their safety, they allocate attentional resources to the perceived danger and react quickly to ensure survival [43]. Unlike low-risk scenarios, high-risk traffic situations pose a greater threat to drivers, necessitating increased attentional resources to control speed and prevent accidents. Furthermore, the results show that the P3 amplitude was larger in response to motor vehicle risk than to pedestrian risk within the same parietal region. This suggests that motor vehicles, being larger and more centrally located in the driver's field of vision, receive more attention than pedestrians.

Limitations and future research

Firstly, it is important to note that young drivers are more likely to exceed speed limits and are at higher risk of traffic accidents [44]. Therefore, young drivers were selected as participants in this study. However, this limits the generalizability of the findings. Future research should expand the age range and driving experience of participants to broaden the results. Second, this study used images captured from real traffic videos as experimental stimuli. While this method has been proven feasible in previous research [21, 22, 26, 45], images cannot fully convey dynamic road information, such as risk precursors. Therefore, the findings are based on inferences about traffic scenarios, and whether they are directly applicable to traffic conditions needs to be tested in practice. Future research could employ virtual reality technology to recreate real driving conditions, thereby improving the study's validity. Lastly, since traffic accidents mainly involve vehicle-to-vehicle and vehicle-to-pedestrian collisions [1], this study focused on pedestrians and motor vehicles as road risk types. Future research could explore the effects of other road risk types on driver speed control to expand the field of driver inhibitory control.

Conclusion

This study used real traffic video intercept images as experimental stimuli to explore the neural mechanisms underlying the effects of risk level and risk type on speed control. At low risk levels, drivers are more likely to adjust their speed in response to pedestrian risk than to motor vehicle risk. Compared to motor vehicle risk, pedestrian risk elicited a larger N2 amplitude, enhancing drivers' alertness. In contrast to low-risk scenarios, high-risk situations resulted in a larger P3 amplitude and required greater allocation of attentional resources. This study contributes to the existing knowledge on speed control and offers insights for establishing speed limit regulations tailored to various road conditions. However, the applicability of laboratory findings to real-world settings needs to be tested in practice. Future research could employ virtual reality technology to recreate realistic driving environments, thus enhancing the validity of the findings.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40359-025-02555-w.

Supplementary Material 1.

Authors' contributions

Conceptualization, X.-Y.Z. and R.-S.C.; methodology, X.S. and X.-Y.Z.; software, X.-Y.Z. and X.S.; validation, X.-Y.Z.; formal analysis, X.-Y.Z. and X.S.; investigation, X.-Y.Z.; resources, X.S. and X.-Y.Z.; data curation, X.-Y.Z.; writing—original draft preparation, X.-Y.Z. and R.-S.C.; writing—review and editing, X.S. and X.-Y.Z.; visualization, X.-Y.Z.; supervision, X.S.; project administration, X.S. and X.-Y.Z. All authors have read and agreed to the published version of the manuscript.

Funding

There were no funding support.

Data availability

The datasets produced and analyzed during this study are available upon reasonable request. Interested researchers may contact the corresponding author for access to the data.

Declarations

Ethics approval and consent to participate

This research has been approved by the Ethics Committee of the College of Psychology at Liaoning Normal University. All participants have provided their informed consent by signing the document.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Received: 25 March 2024 Accepted: 27 February 2025
Published online: 08 March 2025

References

1. Akman C, Kuru T. Analysis of emergency department presentations due to injuries from motor vehicle crashes and pedestrian strikes. Cureus. 2022;12(7):e9468. https://doi.org/10.7759/cureus.9468.
2. Joshi E, Gautam P, Khadka A, Pilkington P, Parkin J, Joshi SK, Mytton J. Experience of living near a highway in Nepal: Community perceptions of road dangers in Makwanpur district. Journal of Transport & Health. 2022;24(3):101337. https://doi.org/10.1016/j.jth.2022.101337.
3. Scarpelli S, Alfonsi V, Gorgoni M, Camaioni M, Giannini AM, De Gennaro L. Age-related effect of sleepiness on driving performance: a systematic-review. Brain Sciences. 2021;11(8):1090. https://doi.org/10.3390/brainsci11081090.
4. Tabibi Z, Borzabadi HH, Stavrinos D, Mashhadi A. Predicting aberrant driving behaviour: The role of executive function. Transportation Research Part F: Traffic Psychology and Behaviour. 2015;34(10):18–28. https://doi.org/10.1016/j.trf.2015.07.015.
5. Watanabe, T., Kubo, N., Chen, X., Yunoki, K., Matsumoto, T., Kuwabara, T., ... Kirimoto, H. Null effect of transcranial static magnetic field stimulation over the dorsolateral prefrontal cortex on behavioral performance in a go/nogo task. Brain Sciences. 2021; 11(4): 483. https://doi.org/10.3390/brainsci11040483
6. Wang X, Zhou Q, Quddus M, Fan T. Speed, speed variation and crash relationships for urban arterials. Accident Analysis & Prevention. 2018;113(3):236–43. https://doi.org/10.1016/j.aap.2018.01.032.
7. Hassan HM, Shawky M, Kishta M, Garib AM, Al-Harthei HA. Investigation of drivers' behavior towards speeds using crash data and self-reported questionnaire. Accident Analysis & Prevention. 2017;98:348–58. https://doi.org/10.1016/j.aap.2016.10.027.
8. Chen FX, Fu R, Xu QJ, Yuan W. Mobile phone use in a car-following situation: impact on time headway and effectiveness of driver's rear-end risk compensation behavior via a driving simulator study. Int J Environ Res Public Health. 2020;17(4):1328. https://doi.org/10.3390/ijerph17041328.
9. Su BF, Hu JB, Zeng JC, Wang RH. Traffic safety improvement via optimizing light environment in highway tunnels. Int J Environ Res Public Health. 2022;19(14):8517. https://doi.org/10.3390/ijerph19148517.
10. Liang Z, Xiao Y. Analysis of factors influencing expressway speeding behavior in China. Plos One. 2020;15(9):e0238359. https://doi.org/10.1371/journal.pone.0238359.
11. Roca J, Lupiáñez J, López-Ramón MF, Castro C. Are drivers' attentional lapses associated with the functioning of the neurocognitive attentional networks and with cognitive failure in everyday life? Transportation Research Part F: Traffic Psychology and Behaviour. 2013;17(2):98–113. https://doi.org/10.1016/j.trf.2012.10.005.
12. Kim J, Hwang L, Kwon S, Lee S. Change in blink rate in the metaverse VR HMD and AR glasses environment. International Journal of Environmental Research and Public Health. 2020;19(14):8551. https://doi.org/10.3390/ijerph19148551.
13. Baldo N, Marini A, Miani M. Drivers' braking behavior affected by cognitive distractions: An experimental investigation with a virtual car simulator. Behavioral Sciences. 2020;10(10):150. https://doi.org/10.3390/bs10100150.
14. Qiu CQ, Zhang S, Ji J, Zhong Y, Zhang H, Zhao SQ, Meng MY. Study on a risk model for prediction and avoidance of unmanned environmental hazard. Scientific Reports. 2022;12(1):10199. https://doi.org/10.1038/s41598-022-14021-3.
15. Zhang XY, Ma LL, Chen N, Wu DD, Yan YX. Trend analysis and prediction of injury death in Xi'an city, China, 2005–2020. Archives of Public Health. 2022;80(1):238. https://doi.org/10.1186/s13690-022-00988-y.
16. Sanocki T, Islam M, Doyon JK, Lee C. Rapid scene perception with tragic consequences: observers miss perceiving vulnerable road users, especially in crowded traffic scenes. Attention, Perception, & Psychophysics. 2015;77:1252–62. https://doi.org/10.3758/s13414-015-0850-4.
17. Sánchez-Mateo S, Pérez-Moreno E, Jiménez F. Driver monitoring for a driver-centered design and assessment of a merging assistance system based on V2V communications. Sensors. 2020;20(19):5582. https://doi.org/10.3390/s20195582.
18. Karthaus M, Wascher E, Getzmann S. Distraction in the driving simulator: an event-related potential (ERP) study with young, middle-aged, and older drivers. Safety. 2021;7(2):36. https://doi.org/10.3390/safety7020036.
19. Donchin E, Coles MGH. Is the P3 component a manifestation of context updating? Behavioral & Brain Sciences. 1988;11(3):357–74. https://doi.org/10.1017/S0140525X00058027.
20. Qin T, Fias W, Weghe NVD, Huang HS. Differentiating everyday map tasks: unique attention-related eye movements and electrophysiological signatures of map use. Annals of the American Association of Geographers. 2024;114:1604–24. https://doi.org/10.1080/24694452.2024.2353845.
21. Zhu, P., Chang, R.S. , Sun, L. The effect of situational hazard level on pedestrian hazard perception: evidence from event-related potentials. Neuroscience Letters. 2019; 714. https://doi.org/10.1016/j.neulet.2019.134546
22. Li HZ, Chang RS, Sui X. The effect of the degree and location of danger in traffic hazard perception: An ERP study. Neuroreport. 2022;33(5):215–20. https://doi.org/10.1097/WNR.0000000000001770.
23. Sun L, Yu SL, Wang YX, Liang S, Cheng L. Effects of hazard type on the hazard perceptions of violation-involved and violation-free drivers: An ERP study. Transportation Research Part F: Traffic Psychology and Behaviour. 2024;11:29–38. https://doi.org/10.1016/j.trf.2024.08.025.
24. Zhang, C., Qiu, S., Wang, S., He, H. Target detection using ternary classification during a rapid serial visual presentation task using magnetoencephalography data. Frontiers in Computational Neuroscience. 2012; 15. https://doi.org/10.3389/fncom.2021.619508
25. Johnson R Jr, Barnhardt J, Zhu J. The contribution of executive processes to deceptive responding. Neuropsychologia. 2004;42(7):878–901. https://doi.org/10.1016/j.neuropsychologia.2003.12.005.
26. Bian J, Fu H, Jin J. Are we sensitive to different types of safety signs? Evidence from ERPs. Psychology Research and Behavior Management. 2020;13:495–505. https://doi.org/10.2147/prbm.s248947.

27. Kostermans, E., Spijkerman, R., Engels, R. C., Bekkering, H., de Bruijn, E. R. To cross or not to cross: Monitoring decisions based on everyday life experience in a simulated traffic task. Journal of Psychophysiology. 2013; 27(3): 113. https://doi.org/10.1027/0269-8803/a000096
28. Buss KA, Dennis TA, Brooker RJ, Sippel LM. An ERP study of conflict monitoring in 4–8year old children: Associations with temperament. Developmental Cognitive Neuroscience. 2011;1(2):131–40. https://doi.org/10.1016/j.dcn.2010.12.003.
29. Chu CH, Chen SR, Wu CH, Cheng YC, Cho YM, Chang YK. The effects of negative air ions on cognitive function: an event-related potential (ERP) study. International Journal of Biometeorology. 2019;63:1309–17. https://doi.org/10.1007/s00484-019-01745-7.
30. Fanai S, Mohammadnezhad M. The perception of public transport drivers (PTDs) on preventing road traffic injury (RTIs) in Vanuatu: a qualitative study. International Journal of Qualitative Studies on Health and Well-being. 2022;17(1):2047253. https://doi.org/10.1080/17482631.2022.2047253.
31. Pammer K, Sabadas S, Lentern S. Allocating attention to detect motorcycles: the role of inattentional blindness. Human factors: The journal of the Human Factors Society. 2018;60(1):5–19. https://doi.org/10.1177/0018720817733901.
32. Krishna KV, Kapruwan R, Choudhary P. Understanding distracted pedestrians' risky behaviour: The role of walking and visual characteristics through a field study. Transportation Research Part F: Traffic Psychology and Behavior. 2024;101:111–29. https://doi.org/10.1016/j.trf.2024.01.003.
33. Zhang, W., Guo, H., Wang, C., Wang, K., Huang, W., Xu, Q., ... Yan, R. Analysis of pedestrian illegal crossing at unmarked segments: environmental factors, pedestrian characteristics and crossing behaviors. Transportation Research Part F: Traffic Psychology and Behavior. 2023; 99: 339–355. https://doi.org/10.1016/j.trf.2023.10.022
34. Faul F, Erdfelder E, Buchner A, Lang AG. Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. Behavior Research Methods. 2009;41(4):1149–60.
35. Crundall D, Chapman P, Trawley S, Collins L, Van Loon E, Andrews B, et al. Some hazards are more attractive than others: Drivers of varying experience respond differently to different types of hazard. Accident Analysis and Prevention. 2012;45:600–9. https://doi.org/10.1016/j.aap.2011.09.049.
36. Vlakveld WP. A comparative study of two desktop hazard perception tasks suitable for mass testing in which scores are not based on response latencies. Transportation Research Part F: Traffic Psychology and Behaviour. 2014;2014(22):218–31. https://doi.org/10.1016/j.trf.2013.12.013.
37. Underwood G, Ngai A, Underwood J. Driving experience and situation awareness in hazard detection. Safety Science. 2013;2013(56):29–35. https://doi.org/10.1016/j.ssci.2012.05.025.
38. Jackson, L., Chapman, P., & Crundall, D. (2009). What happens next? Predicting other road users' behaviour as a function of driving experience and processing time. Ergonomics. 2009; 52(2), 154–164. https://doi.org/10.1080/00140130802030714
39. Ligeza TS, Maciejczyk M, Kałamała P, Szygula Z, Wyczesany M. Moderate-intensity exercise boosts the N2 neural inhibition marker: A randomized and counterbalanced ERP study with precisely controlled exercise intensity. Biological Psychology. 2018;135:170–9. https://doi.org/10.1016/j.biopsycho.2018.04.003.
40. Duncan, C. C., Barry, R. J., Connolly, J. F., Fischer, C., Michie, P. T., Näätänen, R., ... Van Petten, C. Event-related potentials in clinical research: guidelines for eliciting, recording, and quantifying mismatch negativity, P3, and N400. Clinical Neurophysiology. 2009; 120(11): 1883–1908. https://doi.org/10.1016/j.clinph.2009.07.045
41. Horberry T, Anderson J, Regan MA, Triggs TJ, Brown J. Driver distraction: The effects of concurrent in-vehicle tasks, road environment complexity and age on driving performance. Accident Analysis & Prevention. 2006;38(1):185–91. https://doi.org/10.1016/j.aap.2005.09.007.
42. Rosenbloom T, Wultz B. Thirty-day self-reported risky driving behaviors of ADHD and non-ADHD drivers. Accident Analysis & Prevention. 2011;43(1):128–33. https://doi.org/10.1016/j.aap.2010.08.002.
43. Strien JV, Isbell LA. Snake scales, partial exposure, and the snake detection theory: a human event-related potentials study. Scientific Reports. 2017;7:46331. https://doi.org/10.1038/srep46331.
44. Green C, Krehic L. An extra hour wasted? Bar closing hours and traffic accidents in Norway. Health Economics. 2022;31(8):1752–69. https://doi.org/10.1002/hec.4550.
45. Liang B, Lin Y. Using physiological and behavioral measurements in a picture-based road hazard perception experiment to classify risky and safe drivers. Transportation Research Part F: Traffic Psychology and Behaviour. 2018;58:93–105. https://doi.org/10.1016/j.trf.2018.05.024.

Publisher's Note