The 9th European Congress on Computational Methods in Applied Sciences and Engineering
ECCOMAS Congress 2024
3 – 7 June 2024, Lisbon, Portugal

ASSESSING INATTENTIVENESS AND HUMAN ELEMENTS IN CRITICAL DRIVING SAFETY EVENTS

Jamal Raiyn[1] and Galia Weidl[1]
[1] Connected Urban Mobility, University of Applied Sciences Aschaffenburg, Germany
Jamal.Raiyn@th-ab.de; Galia.Weidl@th-ab.de

Key Words: *Autonomous vehicle, Deep learning, Bayesian Network, Driving behavior*

Summary. Road accidents, with their potential for severe consequences, pose an ongoing global challenge. Within the multitude of factors contributing to these incidents, inattentiveness and the intricate human elements inherent in driving behaviors stand out as pivotal. As indicated by reports and studies on traffic safety, a significant share of accidents can be attributed to driver inattentiveness, encompassing activities such as texting, talking on the phone, or simply being distracted by the surrounding environment. Beyond these observable behaviors lie complex human elements, influenced by factors ranging from cognitive processes to emotional states, which significantly contribute to the occurrence and severity of critical safety events.
Inattentiveness is defined as a state in which a driver's eye gaze behavior deviates from attentive driving patterns. It can be influenced by human factors and adverse weather conditions, serving as an indicator of an increased risk of inattentiveness and the potential to contribute to safety-critical events on the road. Recognition of inattentiveness occurs when the average gaze duration on the road or critical areas falls below a specified threshold. The driver's response time is crucial to the braking process of the vehicle and, therefore, has a significant impact on safety in critical situations. This paper aims to explore the various dimensions of inattentive driving and propose effective solutions to mitigate its risks.

1. INTRODUCTION

Inattentive driving, often termed distracted driving, is defined as any activity that diverts attention from driving. This includes visual, manual, and cognitive distractions, all of which compromise road safety. The visual distractions occur when drivers take their eyes off the road, such as when reading a text message. Manual distractions involve taking hands off the wheel, such as eating or adjusting the car's controls. Cognitive distractions happen when a driver's mind is not focused on driving, such as daydreaming or being preoccupied with personal problems. The consequences of inattentive driving are severe, with thousands of accidents and fatalities reported annually. The economic impact includes not only the cost of accidents but also lost productivity and increased insurance premiums. The social cost, in terms of lives lost and families affected, is immeasurable. Various strategies have been proposed for preventing inattentive driving. Technological solutions, like lane departure warnings and automatic braking systems, can help mitigate the risks.

This research aims to pinpoint and analyze the human factors contributing to critical driving safety incidents and to measure the extent of inattentiveness among drivers during such events. The exploration encompasses the various forms inattentiveness may take and its correlation with accident severity. The motivation behind this research lies in comprehending the relationship between eye gaze patterns, and various external factors, specifically human influences and adverse weather conditions, which can significantly impact driver reaction times. In understanding and evaluating inattentiveness and human factors in critical driving safety events, the proposed combination of deep learning and a Bayesian network hold promise. Deep learning models showcase the capability to predict inattentiveness and human elements in real-time by estimating gaze angle directly from eye images and eye landmark coordinates. These models leverage advanced neural network architectures to analyze complex driving behavior patterns and are envisioned to serve as an effective early warning system, offering timely alerts when drivers exhibit signs of inattentiveness or heightened risk due to specific human factors. This paper is organized as follows: Section 2 gives an overview of research related to driving analysis. Section 3 describes the methodology of the ML schemes. Section 4 discusses the results. Section 5 concludes the discussion and points out directions for future research.

2. RELATED RESEARCH

Road accidents, with their potential for severe consequences, pose an ongoing global challenge. Within the multitude of factors contributing to these incidents, inattentiveness, and the intricate human elements inherent in driving behaviors stand out as pivotal [1]. As indicated by reports and studies on traffic safety, a significant share of accidents can be attributed to driver inattentiveness, encompassing activities such as texting, talking on the phone, or simply being distracted by the surrounding environment [2]. Beyond these observable behaviors lie complex human elements, influenced by factors ranging from cognitive processes to emotional states, which significantly contribute to the occurrence and severity of critical safety events. Inattentiveness is defined as a state in which a driver's eye gaze behavior deviates from attentive driving patterns [3-6]. It can be influenced by human factors and adverse weather conditions, serving as an indicator of an increased risk of inattentiveness and the potential to contribute to safety-critical events on the road. Recognition of inattentiveness occurs when the average gaze duration on the road or critical areas falls below a specified threshold. The driver's response time is crucial to the braking process of the vehicle and, therefore, has a significant impact on safety in critical situations [9]. This study aims to pinpoint and analyze the human factors contributing to critical driving safety incidents and to measure the extent of inattentiveness among drivers during such events. The exploration encompasses the various forms inattentiveness may take and its correlation with accident severity. The motivation behind this research lies in comprehending the relationship between eye gaze patterns and various external factors, specifically human influences, and adverse weather conditions, which can significantly impact driver reaction times. In understanding and evaluating inattentiveness and human factors in critical driving safety events, the proposed combination of deep learning and a bias network holds promise. Deep learning models showcase the capability to predict inattentiveness and human elements in real-time by estimating gaze angle directly from eye images and eye landmark coordinates [10-11]. These models leverage advanced neural network architectures to analyze complex driving behavior patterns and are envisioned to serve as an effective early warning system, offering timely alerts when drivers exhibit signs of inattentiveness or heightened risk due to specific human factors [7][12]. By utilizing deep learning techniques to analyze eye gaze metrics, a significant correlation was uncovered between these metrics and the impact of human factors and adverse weather conditions on driver reaction times [8]. Furthermore, by establishing thresholds for each eye gaze metric, the estimation and prediction of their impact on reaction times have been achieved. This capability enables the detection of potential data anomalies, such as those resulting from cyber-attacks on the vehicle's data. Examining the relationship between inattentiveness, eye gaze patterns, and safety-critical events is essential for understanding driver behavior and enhancing road safety. To enhance the practical application of our approach, thresholds have been set for each eye gaze metric. These serve as reference points to estimate and predict the potential influence of these metrics on driver reaction times. This predictive capability enables the detection of deviations from expected behavior, making it possible to identify instances of data anomalies. Our contribution is focused on recognition of inattentiveness in order to perform a seamless handover between human intelligence and artificial intelligence.

3. METHODOLOGY

The data will be collected by driving simulator at technical University of Munich (TUM). The TUM test track is located in the south of the Munich metropolitan region near Taufkirchen. It comprises a total size of approximately 85×85 meters. It combines novel technology testing, like an inductive charging lane and an innovative parking garage, with conventional test bed equipment such as variable test bed designs using infrastructure and traffic control components (Figure 1). Highly valuable for data collection are the external sensor systems with LiDAR and cameras, covering the whole test bed from different angles to avoid occlusion effects. Also special is the nearby simulator center, which enables to connect simulator and test bed in real time. The data types recorded during the experiments are listed as high-level description in Table 1.

Table 1: Data types recorded during the experiments

Data type	Description	Linkage to Evaluation Criteria
Ego Vehicle Data	Data about the ego vehicle’s position, rotation, and speed measured via external sensors (LiDAR and Camera)	Speed Change, Basic Measurements
Eye-Tracking Data	Data recorded from Pupil Core eye tracking system (Varjo XR-3 HMD in case of AR-TTE). Raw data will be aggregated to gaze distributions and patterns. Also, Pupil and Iris Diameter are recorded	Gaze Behavior
Physiological Data	Heartrate Measurement	Physiological Response

Environmental Conditions	Data on lighting and weather conditions to ensure result comparability.	Basic Measurements

3.1 Features Extraction

One approach uses a deep learning model to extract features from the data. Feature extraction is based on naturalistic driving data and is important for the analysis of driving behavior related to safety-critical events. Human driving behavior can be identified however, it is difficult to control because, although human drivers are affected by external factors that can be estimated and predicted, there are internal factors affecting human cognition which cannot be distinguished or controlled. However, for CCAMs, both internal and external factors are predictable. The relevant features that may influence eye gaze coordinates are described in Table 1. These features could include temporal information, spatial context, or any other factors that might contribute to eye gaze behavior.

Table 2: Eye gaze metrics

TIM REL	relative time stamp
GT Xmm, GT Ymm	Ground truth x, y positions
Xmm, Ymm	Gaze x, y positions in mm
YAW GT	Ground truth and estimated yaw angles
PITCH GT	Ground truth and estimated yaw angles
GAZE GT	GAZE ANG
DIFF GZ"	Gaze angular accuracy
AOI_IND,AOI_X,AOI_Y	Area of Interest Index, X, Y

3.2 Concept

By utilizing deep learning techniques to analyze eye gaze metrics, a significant correlation was uncovered between these metrics and the impact of human factors and adverse weather conditions on driver reaction times. Furthermore, by establishing thresholds for each eye gaze metric, the estimation and prediction of their impact on reaction times have been achieved. This capability enables the detection of potential data anomalies, such as those resulting from cyber-attacks on the vehicle's data. Examining the relationship between inattentiveness, eye gaze patterns, and safety-critical events is essential for understanding driver behavior and enhancing road safety. To enhance the practical application of our approach, thresholds have been set for each eye gaze metric. These serve as reference points to estimate and predict the potential influence of these metrics on driver reaction times. This predictive capability enables the detection of deviations from expected behavior, making it possible to identify instances of data anomalies. Multinomial logit (MNL) model is justified for estimation, given that the model provides a framework for calculating relevant probabilities using a simple mathematical form. The framework can be further expanded to include relevant variables that are associated with reward probabilities. The logit model, particularly the Multinomial Logit (MNL) model, is commonly used in transportation research to model choice behavior. In this case, it is employed to understand and predict the likelihood of drivers choosing different driving actions (acceleration, deceleration, or maintaining constant speed) based on the given driving conditions. Situational awareness encompasses various dimensions of perception, including distraction and gaze time that refers to the duration a driver spends fixating on specific areas within the driving environment. The distribution of gaze time across different areas, such as the rear-view mirror, side mirrors, dashboard, and the road ahead, provides insights into the driver's attentional focus and task demands. Higher task demands typically lead to increased gaze time as drivers allocate more attention to critical areas to gather information and make decisions. To understand these factors is essential for designing interventions and strategies to manage task demand effectively and enhance road safety, we consider that each scenario includes actions ($a \in A$) , states ($s \in S$), and a transition function $T(s, a, s')$. Actions refer to driver actions that exhibit variability due to various factors such as their level of aggressiveness, willingness to accept gaps, and personal preferences. In this scenario, a set of preferred actions within the Markov Decision Process (MDP) includes accelerating, braking, changing lanes to the left, changing lanes to the right, and maintaining a constant speed. The states of instantaneous driving decisions. The transition probabilities, denoted as T (s, a, s'), quantify the likelihood of transitioning from an initial state, s, to a landed state, s', given that the agent took action, a. Mathematically, this is represented as P(s' | s, a). Task demand perception is $TD_{Right}(t)$, $TD_{Left}(t)$, $TD_{Front}(t)$, $TD_{Behind}(t)$.

$$TD_R(t) = \beta_{0R} + \beta_{1R} X_1 +,....,+ \beta_{nR} X_n$$
$$TD_L(t) = \beta_{0L} + \beta_{1L} X_1 +,....,+ \beta_{nL} X_n$$
$$TD_F(t) = \beta_{0F} + \beta_{1F} X_1 +,....,+ \beta_{nF} X_n$$
$$TD_B(t) = \beta_{0B} + \beta_{1B} X_1 +,....,+ \beta_{nB} X_n$$

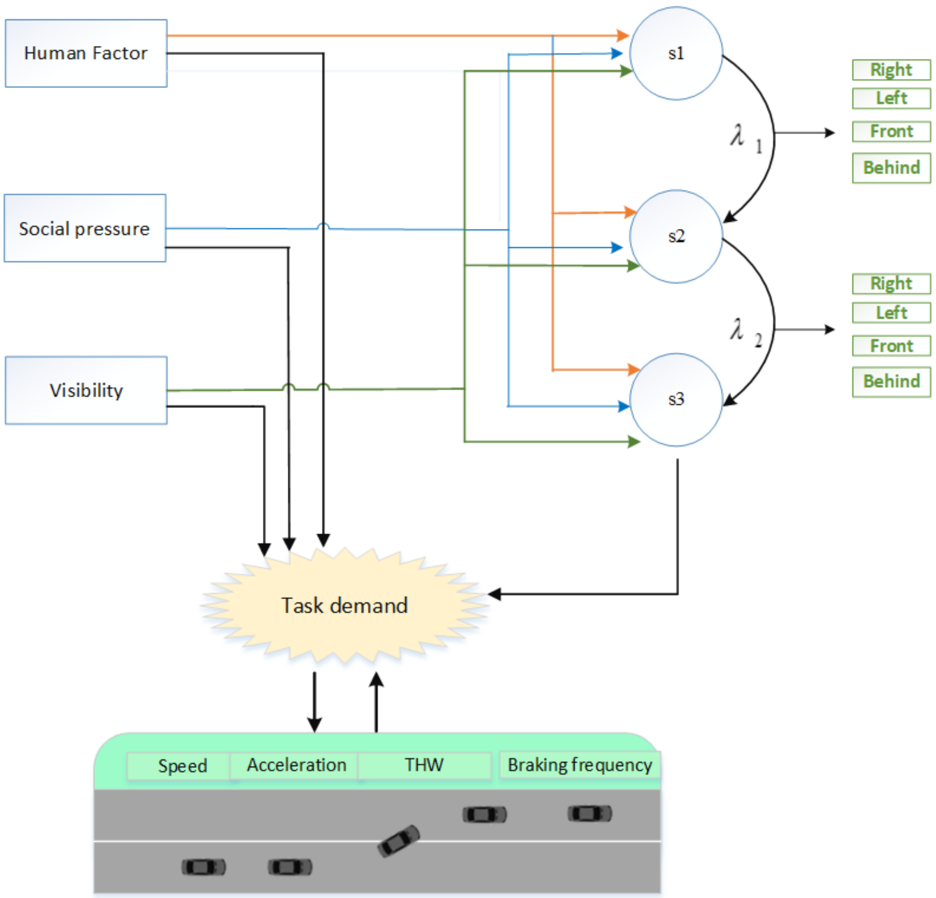

Figure 1: Task demand

3.3 Inattentiveness Detection

Driver behavior is affected by various internal and external factors that influenced the perceptions and reactions to environmental changes. Under such complex conditions, drivers' decision-making processes can hardly be tracked. In this scenario, an HMM model is applied to describe driving behaviors of drivers when they approach intersections, which is entitled a Hidden Markov Driving Model (HMDM) [13][14]. This model assumes that drivers' perception under certain traffic conditions are fairly consistent, and their resulting behaviors can be observed and derived from their previous actions. Based on the assumption, it's possible to predict driver behaviors based on vehicles' dynamic data and drivers' previous performance using HMDM. A hidden Markov chain with the HMDM is used to represent stochastic states of driver behaviors and the transition from states in one step to the states in the following step. And the probability of a state at a certain moment depends only on its accurate previous state.

3.4 Rules extraction based on driving behavior analysis

A rule, *R* covers a set of data points at time, *t* if the characteristics of the data points satisfy the condition of the rule, *R*. Let, *R* = *R*0, *R*0, ..., *Rn* is applied to the data points of time series *T Sax*, *T Say* and *T Swz* related to a particular maneuver. Time series contains certain attributes and depending on attributes, rules are learned. A set of attributes, *A* =*A*1, *A*2, ..., *Aj where j* is the number of attributes or aspects of the time series data. Each time series data point represents an individual maneuver class.

The maneuver classes are defined as, *C* = {*Cnon*, *Cacl* , *Cbrk*, *Clt* , *Crt*, *Cllc*, *Crlc*} where *Cnon*, *Cacl* , *Cbrk*, *Clt* , *Crt* , *Cllc* and *Crlc* are non-aggressive, aggressive acceleration, aggressive braking, aggressive LT, aggressive RT, aggressive LLC and aggressive RLC, respectively.

The performance of each learned rule on the training dataset using a function evaluation before including it in the ruleset *R*. Based on the performance of the rules, the highest promising rule is used to positively classify the class. In the next iteration, another adjunct simple rule is added with logical propositional relation and the performance of the newly formed rule is measured. The gain of two simple rules is calculated by the algorithm. If the gain is significant (*i.e.*, above the threshold) means that the combination of both rules improves performance. Otherwise, the added rule is discarded.

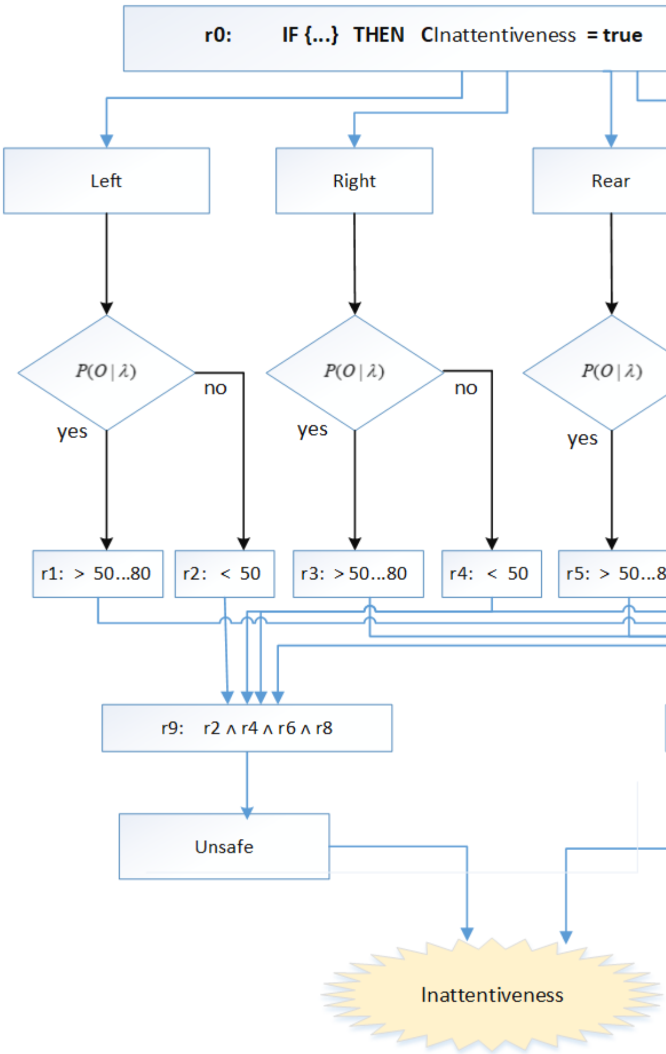

Figure 2: Rules Extraction

4. RESULTS ANALYSIS

We will use statistical methods (e.g., Pearson correlation, regression analysis) to explore the relationship between gaze behavior and other variables, such as speed, acceleration, steering wheel angle, and head rotation, provide insights into how gaze direction in the x-axis is influenced by driving dynamics and the driver's actions. The correlation analysis was performed on partial of the vehicle kinematic data, with results shown in Table 3. The collection between head rotation_y and leteral_acceleration is 0.7276, which is highly positively correlated. Furthermore, the head rotation_y and steering_wheel angle is 0.6673, which is highly positively correlated.

Table 3: Feature selection

	speed	longitudinal_acceleration	lateral_acceleration	steering_wheel_angle	headway_EGO	head_rotation_x	head_rotation_y	head_rotation_z	gaze_direction_filtered_x	gaze_direction_filtered_y	gaze_direction_filtered_z
Speed		-0.0539	0.089	0.6461	-0.4494	0.4339	0.3004	-0.1197	0.2801	-0.01095	0.1487
longitudinal_acceleration	-0.05386		0.16215	0.11456	-0.20946	0.27491	0.41267	-0.42751	0.23822	-0.00405	0.08889
lateral_acceleration	0.089	0.1622		0.6673	0.2822	0.1385	0.7276	-0.07006	0.4711	0.119	0.4043
steering_wheel_angle	0.6461	0.1146	0.6673		-0.072	0.3621	0.682	-0.5944	0.4955	0.0426	0.3729
Headway	-0.4494	-0.2095	0.2822	-0.072		-0.1985	0.0622	0.0131	-0.0748	0.1084	0.0486
head_rotation_x	0.434	0.275	0.138	0.362	-0.199		0.438	-0.249	0.467	-0.272	0.299
head_rotation_y	0.30047	0.41267	0.72764	0.68196	0.06216	0.43773		-0.79491	0.63071	0.00117	0.5254
head_rotation_z	-0.1197	-0.4275	-0.7006	-0.5944	0.0131	-0.2486	-0.7949		-0.464	-0.0433	-0.3323
gaze_direction_filtered_x	0.2801	0.2382	0.4711	0.4955	-0.0748	0.4672	0.6307	-0.464		-0.4137	0.7815
gaze_direction_filtered_y	-0.10947	-0.00405	0.119	0.04257	0.10844	-0.19087	0.00117	-0.04329	-0.27207		-0.4137
gaze_direction_filtered_z	0.1487	0.0889	0.4043	0.3729	0.0486	0.2985	0.5254	-0.3323	0.7815	-0.1909	

We can use statistical methods, such as regression analysis. Regression analysis allows us to model the relationship between a dependent variable (e.g., Inattentiveness) and one or more independent variables in a quantitative manner. Mathematically, the multiple linear regression model can be written as:

$$Inattentiveness = \beta_0 + \beta_1 \times Head\_rotation + \beta_2 \times Gaze\_beh + \beta_3 \times Vehicle\_beh + \varepsilon \qquad (1)$$

Where, β_0,β_1,β_2, and β_3 are the coefficients of the model. ϵ is the error term. Based on a dataset with observations for different drivers, and the dependent variable representing safe driving behavior.

Figure 3 illustrates the relationship between lateral acceleration (EGO), head rotation, and gaze direction. The correlations highlighted in this figure suggest that when a driver is preparing to execute a cut-in maneuver, there are observable patterns in their lateral acceleration, head movements, and where they are looking. Specifically, it indicates that the driver is aware of their surroundings and is actively monitoring them, as evidenced by the synchronized changes in head rotation and gaze direction with the vehicle's lateral acceleration. This awareness is crucial for safely executing the cut-in maneuver, as it involves both physical movements and visual attention to ensure a safe transition. Figure 4 depicts how various vehicle kinematics parameters are related to glance time, which is the duration for which a driver takes their eyes off the road to look at something else (like a dashboard or a side mirror). This relationship is important for understanding driver behavior and safety, as longer glance times can indicate potential distractions that might affect driving performance. The figure helps to identify which kinematic factors are most associated with changes in glance time, potentially guiding improvements in vehicle design or driver assistance systems.

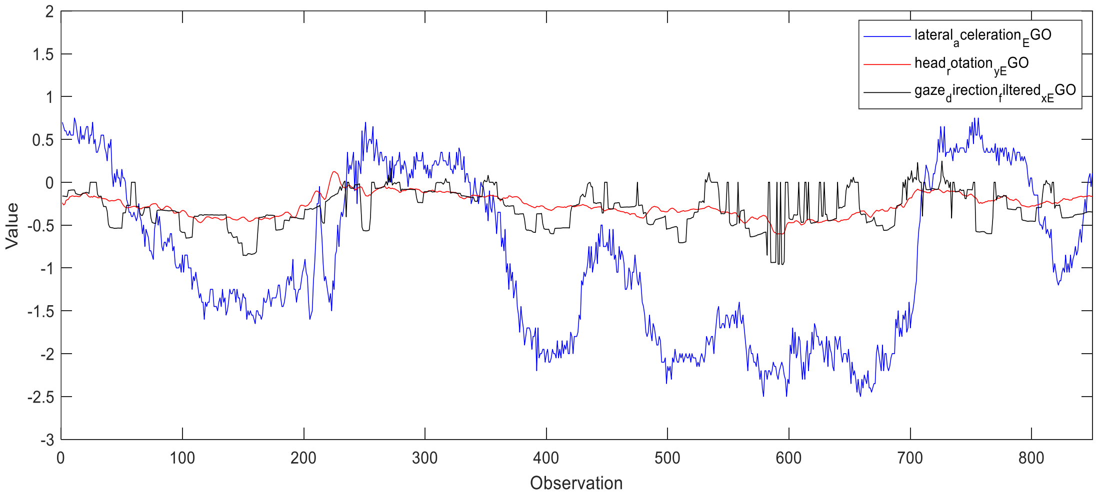

Figure 3: Correlation between glance time parameters

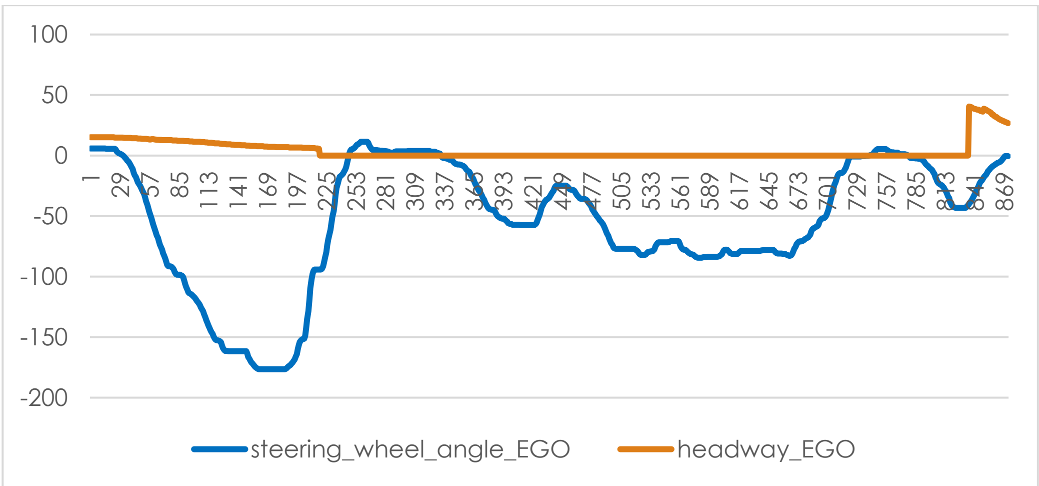

Figure 4: Relation between glance time and vehicle kinematics parameters

5. CONCLUSION

Inattentive driving is a major threat to road safety that requires concerted efforts to address. A multifaceted approach, combining strict legislation, innovative technology, and continuous public education, is essential to mitigate the risks. Future research should focus on evaluating the long-term effectiveness of various prevention strategies and exploring new technologies to assist drivers in maintaining focus on the road.

ACKNOWLEDGEMENT

This study was supported by Project 101076165 —i4Driving within Horizon Europe under the call HORIZON-CL5-2022-D6-18 01-03, which is programmed by the European Partnership on 'Connected, Cooperative and Automated Mobility' (CCAM).

REFERENCES

[1] Kotseruba, I. and Tsotsos, J-K. 2022. "Attention for Vision-Based Assistive and Automated Driving: A Review of Algorithms and Datasets," *IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS*, VOL. 23, NO. 11, NOVEMBER 2022. 19907-19928.

[2] Doshi, A. and Trived, M. 2008. "A Comparative Exploration of Eye Gaze and Head Motion Cues for Lane Change Intent Prediction," *IEEE Intelligent Vehicles Symposium*, Eindhoven University of Technology Eindhoven, The Netherlands, June 4-6, 2008.

[3] Lee,S-J. Jo, J. and Jung, H-G. 2011. "Real-Time Gaze Estimator Based on Driver's Head Orientation for Forward Collision Warning System," IEEE *Transactions on Intelligent Transportation Systems,* April. OI: 10.1109/TITS.2010.2091503.

[4] Ali, S.F. Aslam, A.S. Awan, M.J. Yasin, A. and Damaševiˇcius R. 2021. "Pose Estimation of Driver's Head Panning Based on Interpolation and Motion Vectors under a Boosting Framework." *Appl. Sci.*, 11, 11600. https://doi.org/10.3390/app 112411600.

[5] Shah, S.M. Sun, Z. Zaman, K. Hussain, A. Shoaib, M. and Pei, L. 2022. "A Driver Gaze Estimation Method Based on Deep Learning," *Sensors*, 22, 3959. https:// doi.org/10.3390/s22103959

[6] Yoo, S. Jeong, S. and Jang, Y. 2021. "Gaze Behavior Effect on Gaze Data Visualization at Different Levels of Abstraction," *Sensors,* 21, 4686. https://doi.org/10.3390/s21144686.

[7] Nakayama, M., Sun, Q. and Xia, J. 2022. Estimation of Older Driver's Cognitive Performance
and Workload using Features of Eye movement and Pupil Response on Test Routes, 26th International Conference Information Visualization (IV), IEEE. DOI 10.1109/IV56949.2022.00033

[8] Wang, Z. Yao, K. and Guo, F. 2023. „Driver Attention Detection Based on Improved YOLOv5," *Appl. Sci.* ,13, 6645. https://doi.org/10.3390/ .

[9] Engström, Johan, E., Liu,S-Y., Dinparastdjadid, A. and Simoiu, C. 2023. "Modeling Road User Response Timing in Naturalistic Traffic Conflicts: A surprise-based framework, "arXiv:2208.08651v2, 14 Jul 2023.

[10] Nan-ning ZHENG, Zi-yi LIU, Peng-ju REN, Yong-qiang MA, Shi-tao CHEN, Si-yu YU, Jian-ru XUE, Ba-dong CHEN, and Fei-yue WANG. 2017. "Hybrid-augmented intelligence: collaboration and cognition," *Front Inform Technol Electron Eng*, 18(2):153-179.

[11] Chaabene, S., Bouaziz, Band Boudaya, A., Hökelmann, A., Ammar, A. and Chaari, L. 2021. "Convolutional Neural Network for Drowsiness Detection Using EEG Signals," *Sensors*, 21, 1734. https://doi.org/10.3390/ s21051734

[12] Arakawa, T. 2021. "Trends and Future Prospects of Drowsiness Detection and Estimation Technology," *Sensors*, 21, 7921. https://doi.org/10.3390/s21237921

[13] Juan Li, J., He, Q., Zhou, H., Guan, Y. and Dai, W. 2016. "Modeling Driver Behavior near Intersections in Hidden Markov Model," *Int. J. Environ. Res. Public Health* 13, 1265; doi:10.3390/ijerph13121265.

[14] Mahdi, R.A. Nazaruddin, Y.Y. and Mandasari, M.I. 2023. "Driver Behavior Prediction Based on Environmental Observation Using Fuzzy Hidden Markov Model," International Journal of Sustainable Transportation Technology, Vol. 6, No. 1, April, 22-27.

[15] J.Raiyn and G.Weidl. 2023. "Naturalistic Driving Studies Data Analysis Based on a Convolutional Neural Network," 9th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2023), Prague, Czech Republic, 26-28 April 2023. 248-256.

[16] A. Fries, L. Lemberg, F. Fahrenkrog, M. Mai and A. Das. 2023. „Modeling driver behavior in critical traffic scenarios for the safety assessment of automated driving," *Traffic Injury Prevention*, 24. 105-110, DOI: 10.1080/15389588.2023.2211187.