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Enhancing road safety: In-vehicle sensor analysis of cognitive impairment in older drivers

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Abstract
With the ongoing expansion of the aging population, it is increasingly critical to prioritize the safety of older drivers. The objective of this study is to utilize sensor data in order to detect early indications of impairment, thereby facilitating proactive interventions and enhancing road safety for the elderly. This article provides an overview of the research approach, presents significant results, and analyzes the consequences of utilizing in-vehicle sensors i.e. vision and telematics, to mitigate cognitive decline among elderly drivers; in doing so, it promotes progress in the domains of public health and transportation safety by standardizing the use of such devices to automatically assess the drivers' cognitive functions.

Keywords Alzheimers · Mild cognitive impairment · In-vehicle sensors · Driver behaviors · Driver monitoring system

1 Introduction

The current global demographic landscape is experiencing a substantial shift, marked by a notable rise in the proportion of elderly individuals. As individuals progress in age, the maintenance of cognitive abilities becomes a matter of utmost importance, particularly in relation to tasks that need prolonged focus and the ability to make informed choices, such as driving. The confluence of an increasingly elderly population and vehicle mobility gives rise to urgent inquiries regarding road safety and the potential hazards linked to cognitive deterioration in older drivers. Mild Cognitive Impairment (MCI) is a significant transitional phase that lies between the typical aging process and more pronounced cognitive deficits, such as those observed in dementia. Elderly adults who are experiencing MCI may display inconspicuous cognitive impairments that have an effect on their day-to-day functioning [44], such as their capacity to operate a vehicle safely. The increasing number of elderly drivers on the road due to the aging population has made it crucial to prioritize the detection and treatment of cognitive impairment in this group to maintain public safety.

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This study aims to investigate the utilization of in-vehicle sensor technology for the analysis of MCI in elderly drivers. The conventional approaches employed for evaluating cognitive function within a clinical context frequently exhibit limitations in effectively capturing dynamic, real-world situations, such as driving. The utilization of in-vehicle sensors is a potentially fruitful approach for the ongoing observation of driving behavior, hence furnishing unbiased data that can be associated with cognitive function [22].

The primary objective of this study is to assess the viability of employing in-vehicle sensors as a means of promptly identifying cognitive deterioration in elderly drivers and providing important insights into the possible impact of technology on improving road safety for the elderly population by examining the association between sensor data and cognitive tests. The paper examines the research methodologies, findings, and implications with the main goal of offering insights for future policies and practices that try to tackle the unique challenges that arise from the combination of aging, cognition, and mobility.

This study covers the literature review in Section 2, the methodology in Section 3, the data dnalysis of supporting results in Section 4, results and future directions in Section 5, and the conclusion in Section 6.

1.1 Background

The unprecedented growth of the aging population worldwide presents a multifaceted challenge, particularly concerning road safety. As individuals live longer, the proportion of older drivers on the road continues to rise, necessitating a comprehensive understanding of the implications of aging on driving capabilities. Older drivers may experience age-related changes in vision, reaction time, and cognitive function, contributing to an increased vulnerability to accidents. Recognizing the unique challenges posed by this demographic shift is imperative for developing targeted interventions and technologies that promote both the mobility and safety of older individuals on the road.

The prevalence of MCI among older drivers is a significant concern in the context of road safety. Studies indicate that a notable proportion of older individuals experience MCI, a condition characterized by subtle cognitive deficits [1]. As cognitive functions play a crucial role in driving, understanding the prevalence of MCI among older drivers is essential for addressing the potential risks associated with this demographic in transportation scenarios.

This study holds paramount significance as it addresses the critical intersection of an aging population and road safety. Investigating the correlation between MCI and driving performance in older individuals contributes valuable insights that can inform targeted interventions. The findings have the potential to enhance public safety by identifying early markers of cognitive decline, allowing for proactive measures to be implemented in support of older drivers. Moreover, the study's implications extend beyond individual well-being, influencing policy development and technological innovations to foster a safer and more inclusive transportation environment for an aging demographic.

2 Literature review

2.1 Cognitive impairment and driving performance

Several research publications have evidenced that cognitive impairment significantly impacts driving performance among older individuals. A study by Ott et al. [2] found that cognitive deficits, particularly in attention and executive functions, were associated with a higher risk of traffic accidents among older drivers. Similarly, a meta-analysis by Roe et al. [3] demonstrated a consistent relationship between cognitive decline and decreased driving abilities in older adults. These studies underscore the importance of understanding the nuanced connections between cognitive impairment and its impact on the complex task of driving among the aging population. The relationship between cognitive decline and driving abilities has been extensively explored in the literature, highlighting the intricate interplay between cognitive functions and safe driving. Studies such as the work by Anstey et al. demonstrated a clear association between declines in processing speed, visual attention, and working memory with diminished driving performance in older adults [4]. Additionally, a longitudinal investigation by Ball et al. found that declines in executive function were predictive of subsequent driving cessation among older individuals [5]. These findings underscore the critical need to understand how cognitive decline influences the complex task of driving and support the exploration of innovative approaches, such as in-vehicle sensors, to objectively assess and mitigate these challenges.

2.2 Existing research on the impact of MCI on driving

Various methods have been employed to assess cognitive impairment in older drivers, reflecting the complexity of the task. Standardized cognitive tests, such as the Mini-Mental State Examination (MMSE) and the Montreal Cognitive Assessment (MoCA), are commonly utilized in clinical settings to screen for cognitive deficits [6, 7]. However, these assessments may not fully capture the dynamic cognitive demands of driving. Research by Dawson et al. emphasizes the limitations of traditional neuropsychological tests in predicting real-world driving performance, suggesting the need for more ecologically valid [8]. To address these challenges, emerging technologies, including virtual reality-based assessments, are being explored. For example, a study by Classen et al. investigated the utility of a virtual reality driving simulator in identifying cognitive deficits that may impact driving ability [9]. As research progresses, these novel approaches hold promise in providing a more comprehensive understanding of cognitive impairment in the context of driving.

Research on driving fitness has predominantly focused on individuals with Alzheimer's disease (AD), particularly in complex traffic situations where those with AD exhibit heightened self-restriction owing to impaired attention and executive functioning [23]. Studies indicate that AD patients commit significantly more driving errors than their healthy counterparts, facing challenges in route and traffic rule recollection, as well as identifying landmarks and traffic signs [24–27]. Their misjudgments encompass distances to other vehicles, errors at intersections, and delayed actions or reactions [24]. In a driving simulator study by Rizzo and colleagues, 29% of AD patients were involved in crashes, contrasting with the absence of incidents in the healthy control group. Notably, near accidents occurred more than twice as often in AD patients (74% vs. 35%), with impairments in visual-spatial attention and spatial thinking emerging as key predictors of accident risk [28]. Surveys of AD patients' relatives indicated changes in driving behavior in 58% of patients, with orientation deficits being a prominent dysfunction and nearly 20% being responsible for at least one accident post-diagnosis [29]. The overall accident risk in Alzheimer patients surpasses that of healthy older individuals by more than four times [2], and it increases with the time of driving since disease onset [30].

It's crucial to note that these findings might not uniformly apply to early-stage, very mild, or mild stages of the disease. The early-stage, defined as amnestic mild cognitive impairment (aMCI), characterized by isolated episodic memory dysfunction, suggests that drivers with aMCI exhibit suboptimal rather than definitively impaired driving fitness [24, 31].

In the case of very mild AD, meta-analytical evidence points to on-road fail rates of approximately 13%, in contrast to 1.6% in healthy controls [24]. This discrepancy may be attributed in part to inappropriate behavior at intersections, such as excessive stopping [24]. For mild AD, a striking 33% of patients fail an on-road test, with individual studies reporting even higher fail rates of 50.6% and 58% for patients with very mild and mild ADD, respectively, compared to 4.4% and 11% in healthy controls [25, 32]. On-road performances of drivers with very mild and mild AD are compromised on operational, tactical, and visual levels, involving more turning errors, loss of orientation, and maneuvers jeopardizing road safety [26]. Carr and colleagues reported that drivers with very mild and mild AD tend to be involved in more at-fault crashes than healthy drivers, including accidents resulting in personal injuries [33].

2.3 In-vehicle sensor technologies

In-vehicle sensor technologies offer a promising avenue for objectively assessing driving performance in real time. These sensors, capable of capturing various aspects of driver behavior and vehicle dynamics, have been applied in research to understand and monitor driver performance. For instance, studies by Horrey et al. [10] and Dingus et al. [11] utilized in-vehicle sensors, including accelerometers and gyroscopes, to analyze driving behavior and assess factors contributing to safety. Moreover, advancements in sensor technology, such as eye-tracking systems and lane departure warning systems, have been instrumental in quantifying visual attention and detecting deviations in driving behavior. Research by Mehler et al. demonstrated the effectiveness of eye-tracking technology in assessing cognitive load and attention allocation during driving tasks [12]. Additionally, studies by Bosurgi et al. and Eskandarian (2012) have explored the application of sensors in assessing driver behavior and performance in the context of driver assistance systems and advanced driver assistance technologies (ADAS) [13, 14]. Apart, from this, In [34], a real-time intelligent system is proposed, utilizing traffic cameras and the You Only Look Once (YOLO) algorithm for object detection. The Kalman filter tracks vehicle location, and anomaly detection, based on speed, is performed with an impressive real-time capability. Article [35] introduces a framework based on the Strategic Highway Research Program 2 (SHRP 2) and Naturalistic Driving Study (NDS) datasets. Using a Random Forest (RF) algorithm, the study calculates a driver's risk profile, achieving an accuracy rate of 90%. In [36], the Serial-Feature Network (SF-Net) algorithm is proposed for recognizing normal and abnormal driver behavior using smartphone inertial sensors like GPS and gyroscope. The approach achieves remarkable accuracy (97.10%) and recall rate (98.4%). Paper [37] classifies driver behaviors and road anomalies using smartphone sensor data. The k-Nearest Neighbor (KNN) and Dynamic Time Warping (DTW) algorithms exhibit significant accuracy rates, reaching 78.06% and 96.75%, respectively. In [38], the "Project Drive" mobile application is introduced, employing the k-means algorithm on GPS data to detect negative driver behavior and encourage safer practices. Papers [39] and [40]] classify driver behavior as positive and negative. Babić et al. [39] explores the impact of road signs on young drivers' behavior in nighttime conditions, while [40] investigates the effects of optical circles and chevron patterns on driver behavior using simulator data and the MANOVA statistical technique. Papers [41], [42], and [43] focus on distinguishing between safe and unsafe driver behavior. Eren [41] classifies driver behavior through smartphone sensors using an optimal path detection algorithm and Bayesian classification, achieving a correct classification rate of 93.3%. Wadley et al. [31] proposes a system based on Local and LARA traffic datasets to provide driving advice, achieving a precision rate of 95.52%. In [32], a smartphone-based system utilizes Long Short-term Memory (LSTM) and Convolutional Neural Network (CNN) models, reaching a mean percentage error (MPE) of 0.36 for analyzing driver behavior at intersections.

3 Methodology

3.1 Participants Characteristics

The study sample comprises 225 participants with a mean age of 78.00 years (SD = 6.05), ranging from 65 to 91 years. The majority of participants identified as White (n = 172), followed by Black (n = 36), Asian (n = 3), Multiracial (n = 4), and Other (n = 2), with 18 respondents choosing not to disclose their race. Education levels ranged from 0 to 26

Table 1 Descriptive Statistics of the Sample

Variable	Mean (SD)	Min	Max	Count
Age	78 (6.05)	65	91	225
Undisclosed	–	–	–	8
65-69	–	–	–	46
70-74	–	–	–	47
75-79	–	–	–	68
80-84	–	–	–	34
85-89	–	–	–	21
90-94	–	–	–	1
Race				
White	–	–	–	172
Black	–	–	–	36
Asian	–	–	–	3
Multiracial	–	–	–	4
Other	–	–	–	2
No Answer	–	–	–	8
Years of Education	15.99 (4.33)	0	26	225
Undisclosed	–	–	–	6
– 12	–	–	–	21
12 – 14	–	–	–	41
15 – 16	–	–	–	69
16+	–	–	–	88
Gender				
Male	–	–	–	86
Female	–	–	–	135
Undisclosed	–	–	–	4

years, with an average of 15.99 years (SD = 4.33) with a majority of them having a graduate degree (16 yrs). In terms of gender distribution, 86 participants identified as male and 135 as female, as shown in Table 1 These demographic details provide a comprehensive overview of the diverse characteristics within the study population, essential for understanding potential associations in subsequent analyses (Fig. 1).

3.2 In-vehicle sensor setup

The architectural design, as shown in Fig. 2, of the proposed in-vehicle sensors consists of two distributed sensing units:

- An in-vehicle vision sensing unit is utilized to capture visual data within a vehicle.
- An in-vehicle telemetry unit is employed to collect and transmit data related to the vehicle's performance and operation.

3.2.1 In-vehicle vision sensors

The placement and calibration of camera-based sensors integrated with a Mobile Digital Video Recorder (MDVR) play a crucial role in optimizing their effectiveness for monitoring and assessing driving behavior. Interior cameras can monitor driver behavior, eye movements [15], and alertness, while exterior cameras contribute to recording traffic conditions and potential hazards. The calibration of these cameras is of utmost importance in order to

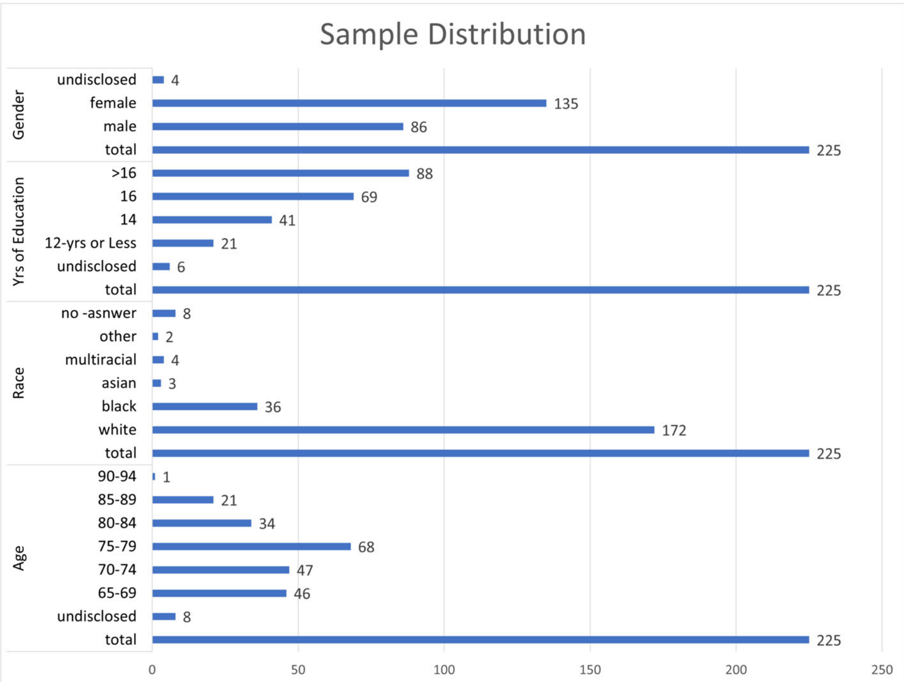


Fig. 1 Overall distribution of all demographics groupings

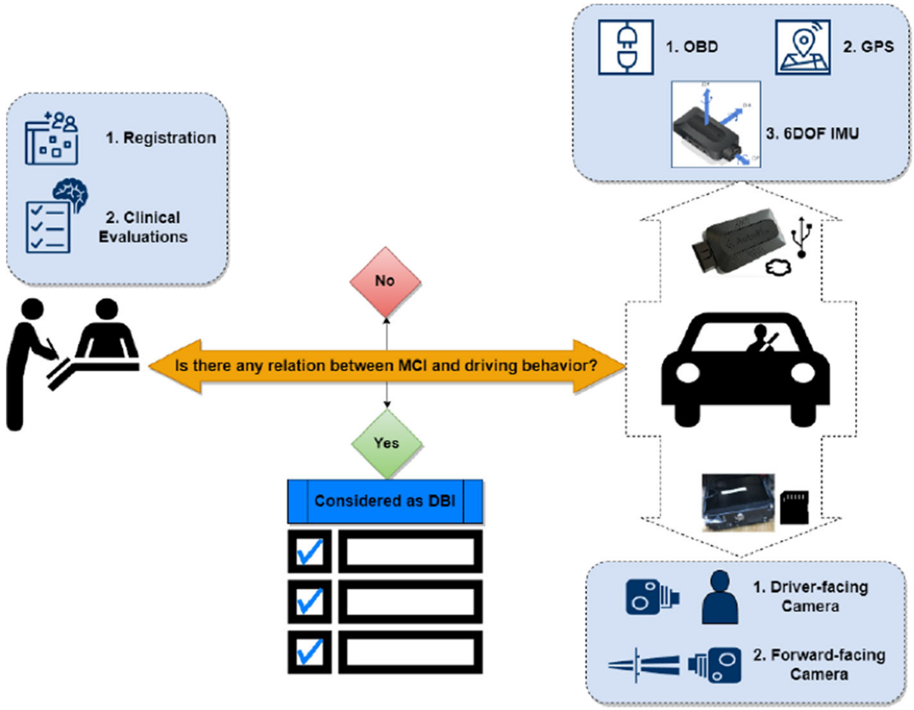


Fig. 2 In-Vehicle Sensors

guarantee the precision and dependability of data collecting. The accurate alignment and setup of cameras ensure the precise tracking of events and activities, hence aiding further analysis. The MDVR, functioning as a centralized storage device, assumes a crucial role in securely preserving the recorded data for subsequent retrieval and analysis. Table 2 shows the features that are collected through the vision sensors (Fig. 3).

Table 2 Feature used for Driver's behaviors

Camera type	Features
Driver's Camera	Face Detection
	Eyes Detection
	Yawning
	Distraction
	Phone Usage
Front Camera	Traffic Sign Detection
	Object Detection
	Lane Departure
	Near Collision
	Pedestrian

Fig. 3 In-Vehicle Vision Sensors, 2 Cameras + MDVR

3.2.2 In-vehicle telematic sensors

This study uses Auto Pi's Telematics Unit (TMU), built on Raspberry Pi 4 Model B, as an open-source platform for vehicle data collection. Figure 4 shows an overview of the Telematic Unit. This programmable unit supports hardware and software expandability, allowing for customized sensing parameters. Each TMU consists of a GPS (Geographic Positioning Systems) sensor, an Inertial Measurement Unit (IMU), an On-Board Diagnostics (OBD) connector, a 4G/LTE cellular modem, an SD card, and a USB flash drive. Tri-axial gyroscopes are added to capture angular velocity. The TMU also has a smart power system that monitors voltage levels and sleeps or hibernates when necessary. In-vehicle data can be collected from the Controller Area Network (CAN bus) and augmented sensor hardware. Table 3 shown different types of data and their statistical analysis that are being performed (Fig. 5)

3.3 Data collection and extraction

The data extraction and analysis workflow [Fig. 6], has been carefully designed to ensure efficient management and utilization. Vision and telematic sensors are systematically installed

Fig. 4 In-Vehicle Telematic Sensors Workflow [20]

Table 3 In-Vehicle Telematic Sensors Indices

Groups	DBIs	Analytics
From OBD	Number of Trips, Duration, Distance, Speed, RPM, Engine Load, Fuel Level, Ambient Air Temperature, Throttle Positioning	Statistical Analysis, Artificial Intelligence (AI) and Machine Learning (ML)
From IMU	Harsh-acceleration (count, value), Hard-braking (count, value), Hard-turn (count, value)	
From GPS	SOG (Speed Over Ground), Longitude, Latitude, COG (Course over Ground), Altitude	

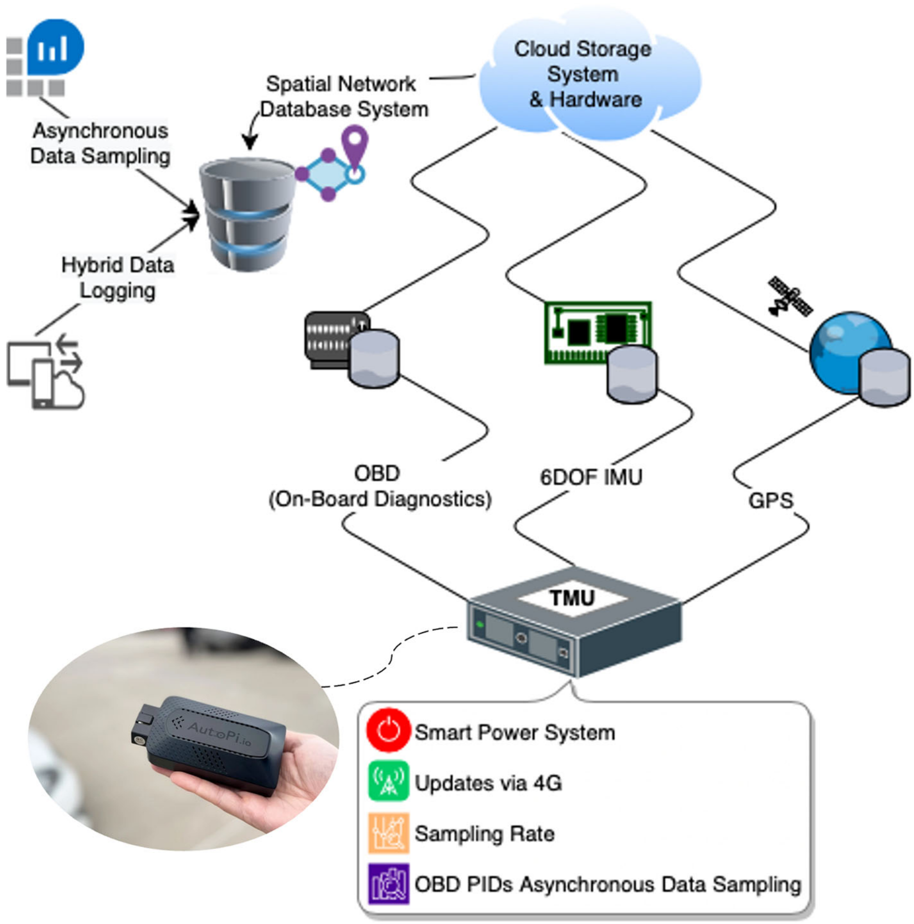


Fig. 5 In-Vehicle Telematic Sensor

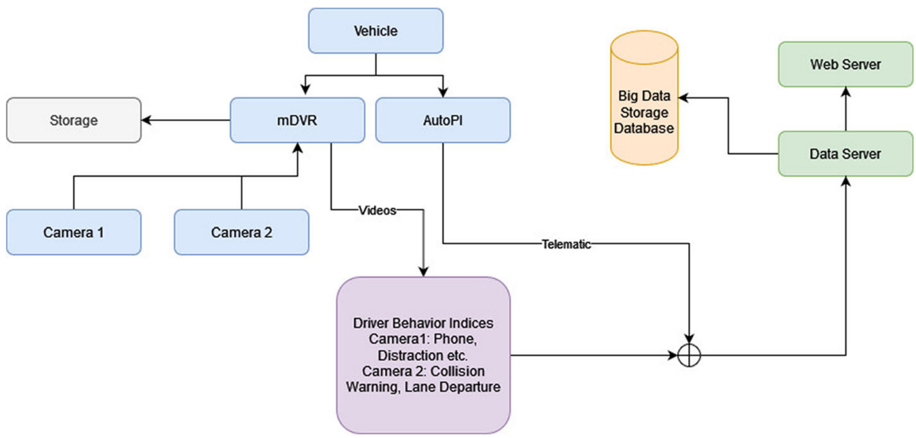


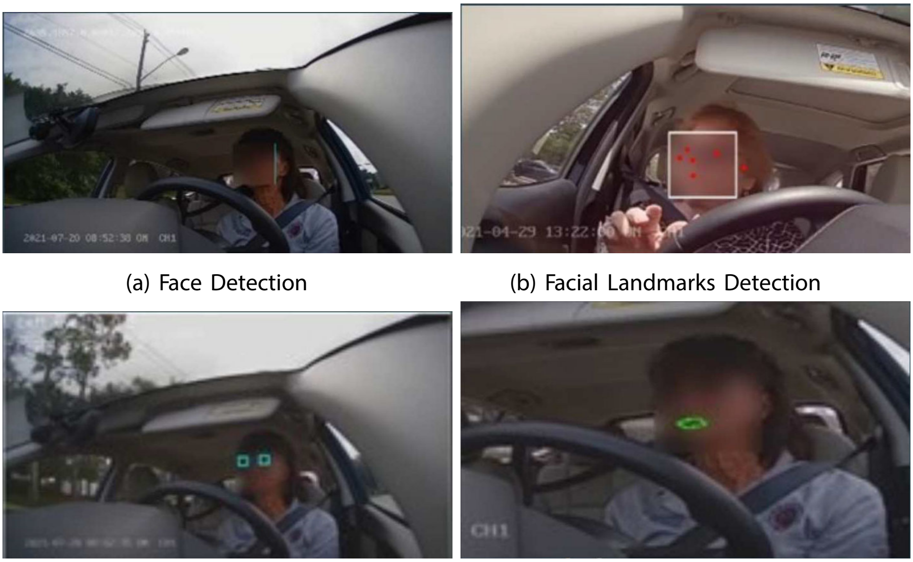
Fig. 6 Data Extraction and Visualization of In-vehicle Sensors

within the vehicle, and data extraction is conducted at three-month intervals. The extracted data undergo meticulous processing for subsequent storage on the cloud server. Simultaneously, a comprehensive analysis is performed, facilitating the preparation of detailed reports. These reports are then visualized on the web-server as discussed in previous works [17, 18], enhancing accessibility and facilitating a comprehensive understanding of the derived insights.

Lane changes are of significance for assessing driving-related cognitive functions. These maneuvers demonstrate the driver's awareness, decision-making, and operational proficiency, involving cognitive functions like attention, reasoning, and control. Thus, studying lane changes provides vital insights into driving behaviors, helping to understand driver performance and safety (Fig. 7).

Figure 8 shows a sequence of views from a vehicle's front-facing camera, recording a lane change maneuver. The first image shows the vehicle in the right lane, with a clear view of the road ahead. The second image captures the vehicle after it has changed lanes, now in

Fig. 7 Front-camera showing the lane departure, left lane change (top) and right-lane change (bottom)[18]



(a) Face Detection

(b) Facial Landmarks Detection

(c) Eyes Detection

(d) Mouth Detection

Fig. 8 Driver-facing Camera Collected Data Indices[18]

the left lane, continuing down the same road. These images are used as evidence of driving behavior and for reviewing the actions taken by the driver during the lane change.

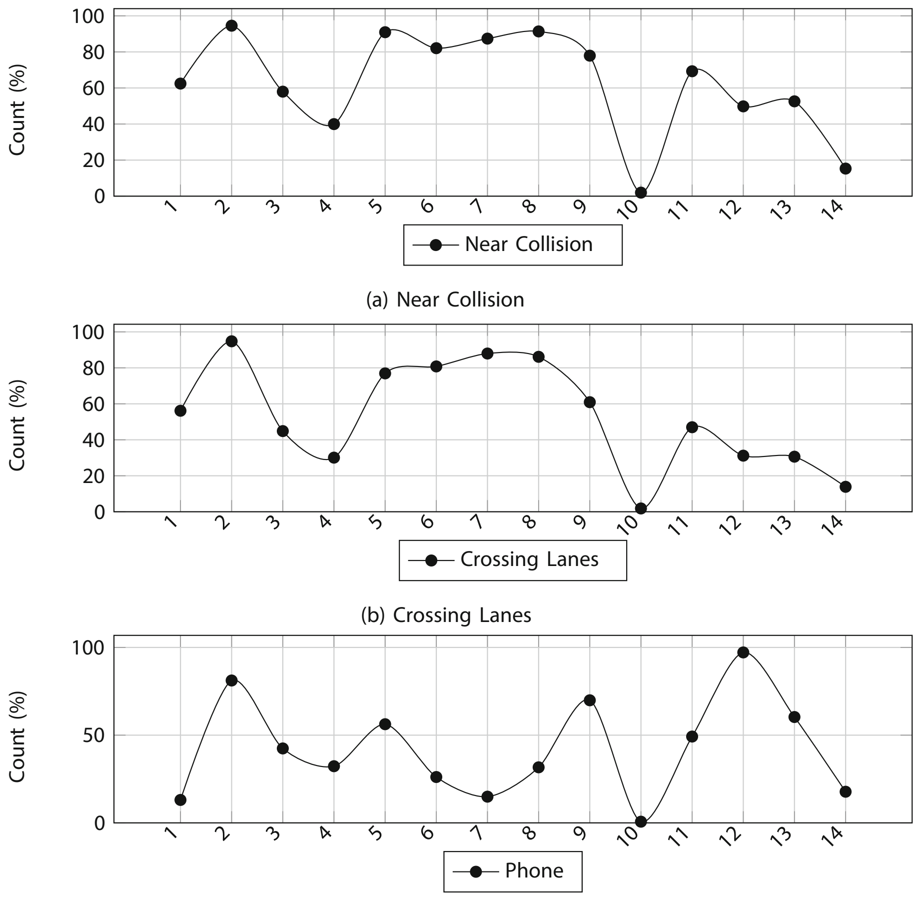
4 Results

4.1 Vision sensors

Two distinct patterns emerge from the analysis of the charts comparing MCI driver Fig. 9 and non-MCI driver Fig. 10. The data is visualized based on monthly basis showing different indices. The data reveals variation in phone usage, near-collision incidents, and lane changes among MCI drivers, suggesting a higher degree of variability in these behaviors. This dynamic pattern suggests that MCI drivers exhibit inconsistent trends in phone engagement and driving maneuvers, possibly indicative of a lack of standardized behavior or varying levels of attention. In contrast, non-MCI drivers exhibit more stable patterns in these metrics, signifying a consistent and predictable driving behavior. These insights underscore the importance of understanding and addressing the specific challenges associated with MCI drivers, potentially contributing to targeted interventions for improving safety and reducing risk on the road.

4.2 Telematic sensors results

In Figs. 11 and 12, this study presented the problematic findings of some Driver Behavior Indicators (DBIs) obtained from real-time telematics data for both MCI and Non-MCI drivers. Observing more swings on plots from different DBIs related to MCI drivers indicates complex



(a) Near Collision

(b) Crossing Lanes

(c) Phone

Fig. 9 Plots for Participant with MCI on Monthly-Basis

driving behavior. Based on this finding, a higher fluctuation in fuel levels among MCI drivers suggests that they may neglect refueling their vehicles consistently. The constant variation in 'RPM' and 'Throttle Positioning' may indicate an aggressive approach, causing more stress on the engine [16]. This assertion can be validated by finding a higher average count of hard acceleration among drivers with MCI.

In this study [21], the problem of anomalous behavior detection is to identify drivers exhibiting significant directional deviations, frequent occurrences of hard braking, and acceleration throughout their trips. Figures 13 and 14 illustrate snapshots of the real dataset where some drivers made long-distance U-turns or repeatedly drove along the same road. These behaviors often suggest drivers might have lost their way or encountered confusion while navigating. In this problem formulation, each trip is represented by a directed graph. Then, this study proposed an Edge-Attributed Matrix to examine various graphs with different

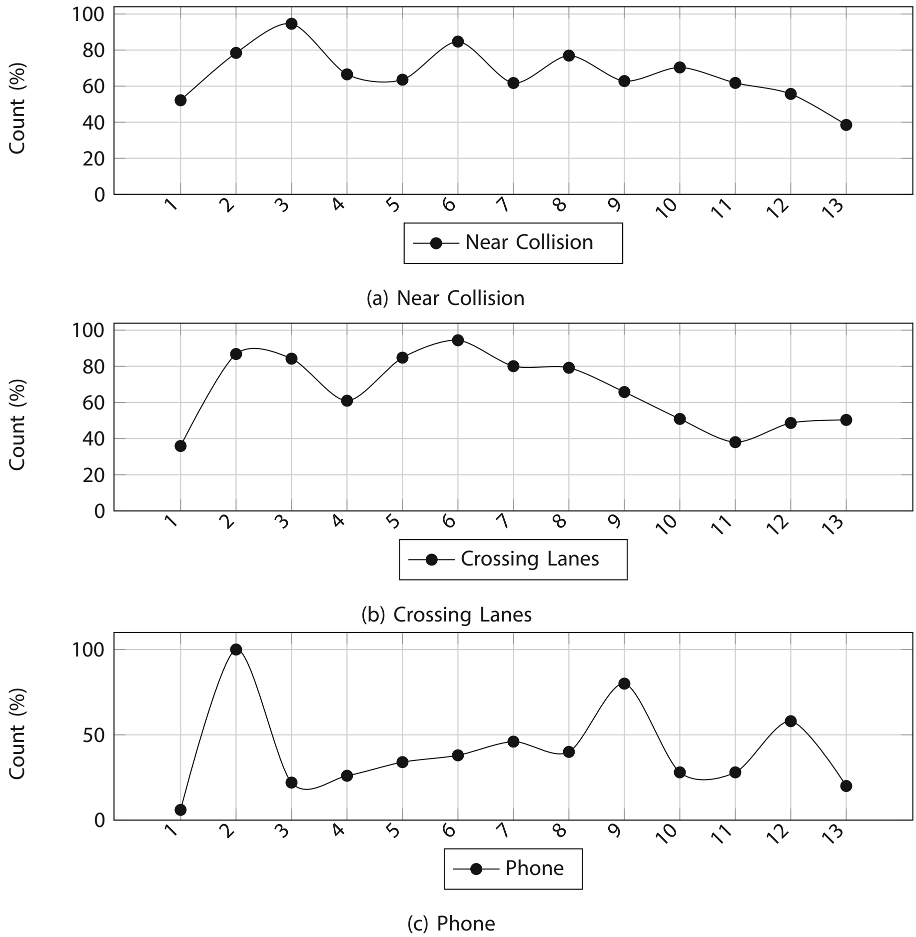


Fig. 10 Plots for Participant with Non-MCI on Monthly-Basis

start and end points and utilized the isolation Forest algorithm to detect anomalous graphs displaying notable differences in their attribute patterns compared to the rest of the dataset.

5 Discussions

The results presented are preliminary. The final results could improve public safety and individual well-being. First, in-vehicle sensor technology seems to detect cognitive changes in older drivers, enabling preventative interventions. Fildes et al. found that early cognitive impairment identification can improve road safety by targeting therapies and support systems. [14] Second, integrating in-vehicle sensor technologies into healthcare and transportation networks may help solve the complicated problems of an aging population. Dingus et al. suggest integrating sensor data into transportation infrastructure to improve road safety and reduce driving dangers [11].

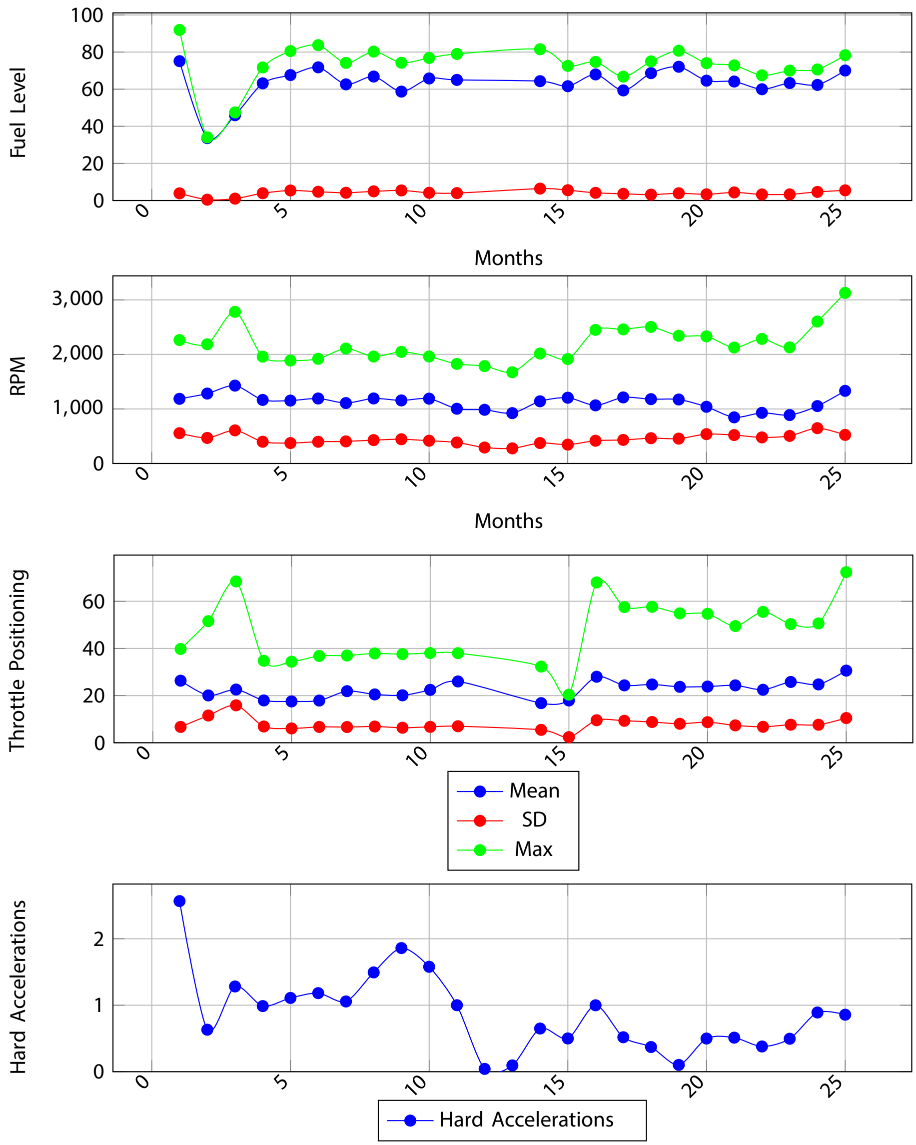


Fig. 11 Plots for Participant with MCI on Monthly-Basis

5.1 Limitations

The dynamic and diverse nature of driving surroundings makes assessing cognitive function in real-world driving scenarios difficult. Clinical cognitive evaluations may not fully capture drivers' complex cognitive demands. Driving requires quick decision-making, navigation, and response to unforeseen situations, which are hard to simulate in testing. Addressing cognitive function performance can be done using both cognitive assessment by clinical evaluation combined with in-vehicle sensors may result in better results. Further studying such results needs to be done in the future.

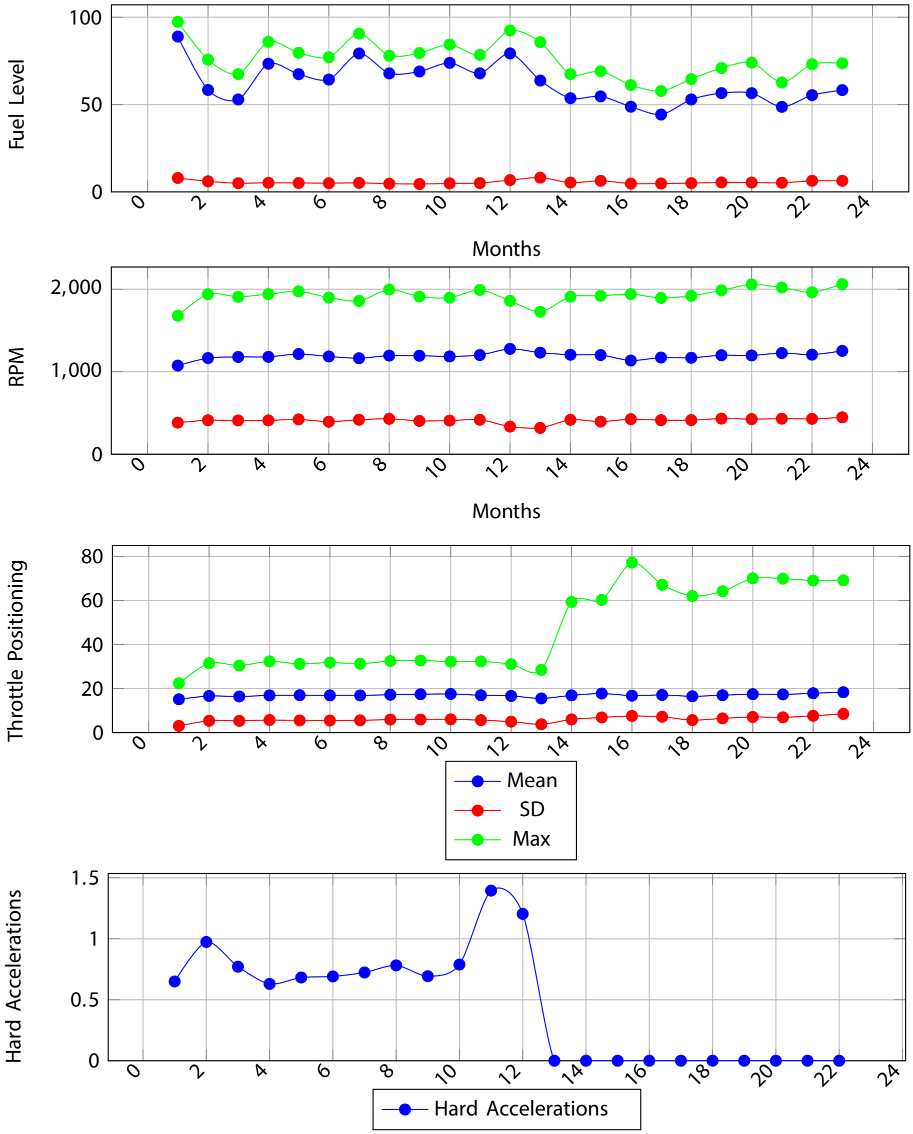


Fig. 12 Plots for Participant with Non-MCI on Monthly-Basis

5.2 Future direction

The advancement of in-vehicle sensor technology represents a pivotal avenue for enhancing driver safety and monitoring. The ongoing refinement of these sensors holds the promise of providing more accurate and comprehensive data on various aspects of driving behavior. As these sensors become more sophisticated, they offer the potential to capture nuanced details, contributing to a deeper understanding of driver actions and responses. Additionally, longitudinal studies assessing the effectiveness of sensor-based monitoring over time are crucial

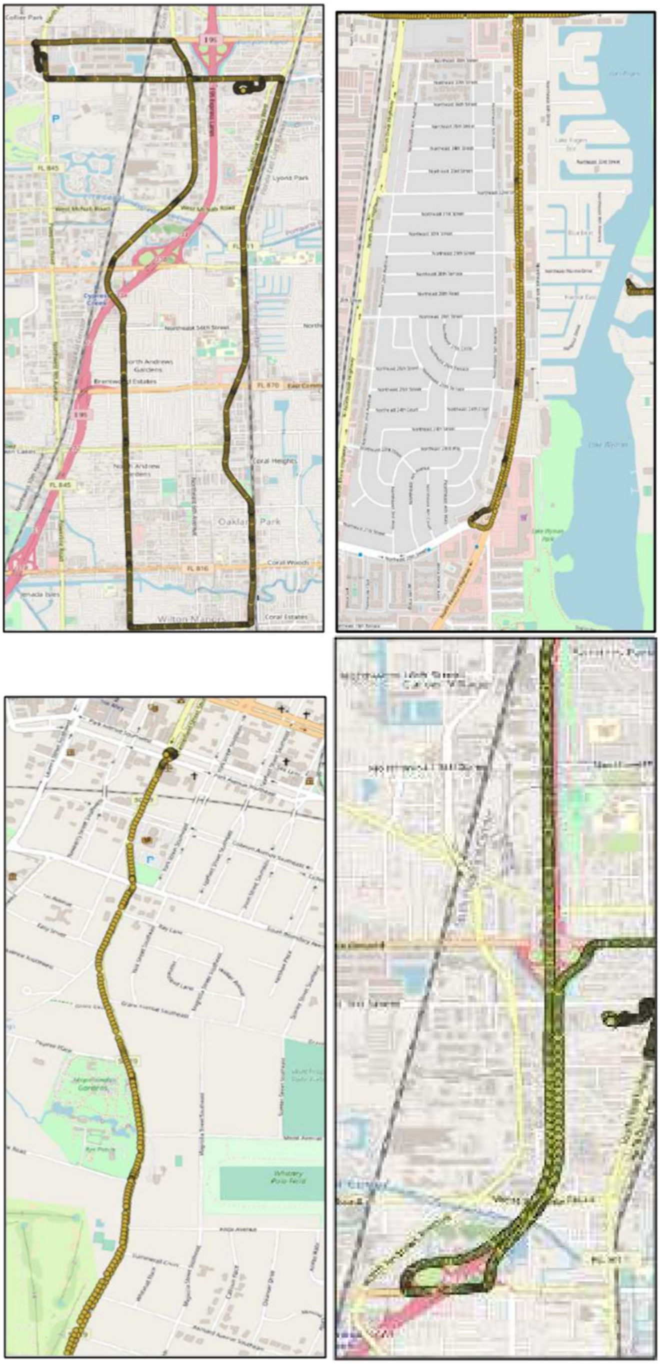


Fig. 13 Long Distance U-Turns for Road Segments [21]

Fig. 14 Cyclic Patterns for Road Segments [21]

for evaluating the sustained impact and reliability of these technologies. Such studies can shed light on the durability of sensor-based assessments, their ability to adapt to evolving driving habits and their long-term contribution to overall road safety. Together, the continued improvement of in-vehicle sensor technology and longitudinal studies can significantly advance thecapabilities in assessing and promoting safer driving practices. Further alongside this, a combination of both the clinical assessment and in-vehicle sensor data can be fused together and assessed to see how well the finding represent. A score-based system should be introduced that evaluates all the data and assigns a performance score to each individual.

6 Conclusion

This study encapsulates key findings at the intersection of aging, cognition, and transportation safety. It reveals notable changes in reaction times, attention spans, and decision-making abilities among older individuals, emphasizing the necessity for targeted interventions to mitigate safety risks. Contributing significantly to the field, the research bridges gaps in understanding how cognitive changes associated with aging impact driving performance, offering crucial insights for researchers, practitioners, and policymakers. The study's recommendations advocate for evidence-based interventions like cognitive training programs and adaptive driving technologies, as well as flexible and inclusive transportation policies to address the diverse needs of aging drivers. Ultimately, this synthesis aims to guide policy and practice in creating a transportation environment that prioritizes both safety and mobility for the aging population.

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Data Availability The data associated with this journal paper will be provided upon request.

Declarations

Conflict of Interest Muhammad Tanveer Jan would like to disclose that Borko Furht is an author of this manuscript and also serves as the Editor-in-Chief of Multimedia Tools and Applications. To ensure transparency, Borko Furht has recused himselve from any editorial decisions regarding the handling and review of this manuscript. All editorial decisions have been made independently by other members of the editorial board.

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