International Journal of Intelligent Transportation Systems Research
https://doi.org/10.1007/s13177-025-00601-w

Structural Brain Biomarker on Driving Safety in Healthy Older Adults: An MRI-Based Review

Kaechang Park[1,2] · **Handityo Aulia Putra**[3]

Received: 13 June 2025 / Revised: 30 November 2025 / Accepted: 2 December 2025
© The Author(s) 2025

Abstract

This review synthesizes current evidence on the relationship between structural brain changes and driving safety in cognitively healthy older adults. Using magnetic resonance imaging (MRI) structural biomarkers—such as white matter hyperintensities (WMH), brain atrophy (BA), and regional gray matter volumes (rGMVs)—recent studies have demonstrated that even mild or asymptomatic alterations are associated with impaired driving behavior and increased crash risk. Emerging machine learning models that incorporate rGMVs have achieved high accuracy and specificity in identifying high-risk drivers, though sensitivity and precision remain limited when relying solely on structural MRI data. Japan's Brain Dock system, an MRI-based brain healthcare screening program developed uniquely in Japan, provides a valuable infrastructure for large-scale neuroimaging-based risk assessment. Importantly, structural MRI biomarkers can be influenced by lifestyle improvements, such as quitting smoking and reducing alcohol consumption, as well as by the treatment of lifestyle-related diseases, including diabetes and hypertension. Overall, this review highlights the potential of neuroimaging-informed approaches to identify at-risk drivers and to support targeted preventive strategies, thereby contributing to both brain healthcare program and traffic safety in aging societies.

Keywords Healthy older drivers · Driving safety performance · MRI · Brain structure · Machine learning

1 Introduction

The global rise in the number of older drivers presents a growing challenge for public health and traffic safety initiatives [1]. Although many older individuals maintain clinically normal cognitive function, they are disproportionately involved in traffic crashes, particularly in scenarios requiring rapid decision-making [2–6]. This discrepancy suggests the presence of latent neurobiological impairments, e.g., asymptomatic or subclinical MRI findings, that are not detectable through standard neuropsychological assessments.

Structural brain abnormalities—such as WMH and BA—can be identified using MRI and may underlie these subtle, undetected impairments (Fig. 1). In this context, Japan's "Brain Dock" system, a population-wide preventive MRI screening initiative, offers a unique opportunity to detect asymptomatic or subclinical cerebral abnormalities [7–12] and assess neurological risk factors relevant to unsafe and dangerous driving behaviors [13–15].

A growing body of evidence has revealed significant associations between structural MRI markers and real-world driving outcomes. Even mild or asymptomatic WMH have been linked to increased rates of traffic collisions, steering instability, and wrong-way driving among cognitively healthy older adults [13–15]. Severe WMH have also been implicated in decisions to cease driving in this population [16]. Furthermore, driving experiments using actual motor vehicles have demonstrated that the combination of mild WMH and BA contributes to unsafe driving behaviors [3,

✉ Kaechang Park
kpark@atr.jp

Handityo Aulia Putra
handityo@vos.nagaokaut.ac.jp

1 Research Organization for Regional Alliance, Kochi University of Technology, 185 Miyanokuchi, Tosayamada-cho, Kami, Kochi 782-0003, Japan

2 Department of Decoded Neurofeedback, Computational Neuroscience Laboratory Group, Advanced Telecommunications Research (ATR) Institute International, Kyoto 619-0288, Japan

3 Department of Electrical, Electronics, and Information Engineering, Nagaoka University of Technology, Nagaoka, Niigata 940-2188, Japan

Published online: 22 December 2025

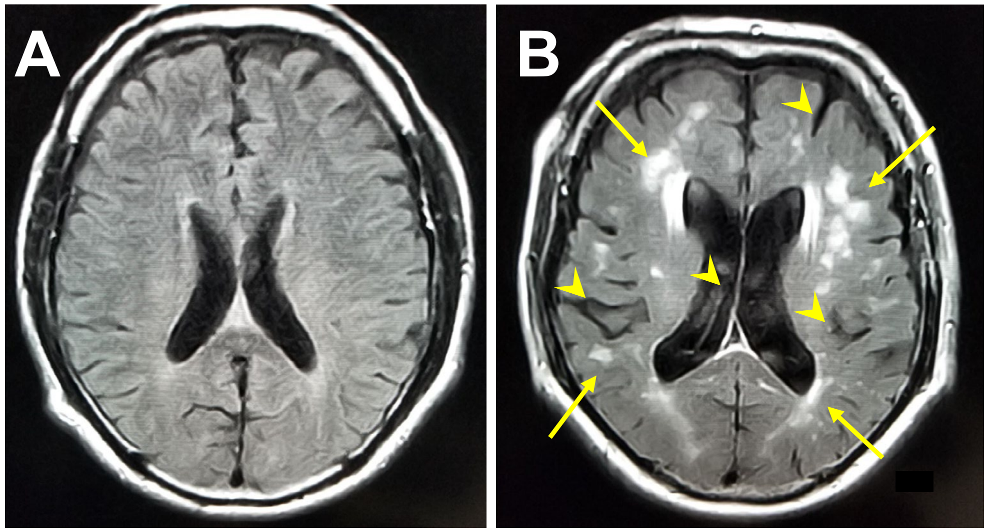

Fig. 1 Cross-sectional brain MRI images from two older adults, both aged 65 years. Image A illustrates normal brain morphology, whereas image B shows widespread white matter hyperintensities (arrows) and brain atrophy (arrowheads), as evidenced by enlarged lateral ventricles and widened cortical sulci. These neuroanatomical differences may be associated with variations in driving safety performance

17]. Importantly, many affected individuals perform competently under routine driving conditions but exhibit deficits under unexpected or rapidly changing situations—suggesting the presence of subclinical impairments that remain undetected by conventional cognitive assessments.

Regarding with regional gray matter volume (rGMV), Toyota research institute pioneeringly reported negative association of supplemental motor area volume with driving behavior estimates using questionnaire [18]. Recent advances in machine learning have enabled the integration of rGMV data with behavioral driving assessments, achieving high classification accuracy in identifying driver safety profiles [19–21]. However, the sensitivity of these models remains limited when based solely on rGMV. In the near future, combining other structural imaging modalities such as WMH and BA may enhance early identification of at-risk individuals.

As summarized in Table 1, this review synthesizes current findings on structural brain biomarkers—specifically WMH, BA, and rGMVs—and their relevance to driving safety performance (DSP) in cognitively healthy older adults (typically age ≥ 65). Table 2 provides a more detailed breakdown of the studies summarized in Table 1, including affiliations, study design, structural neuroimaging factors, and driving performance assessment methods. Our research group reported 10 manuscripts, whereas other groups reported 4. Among our studies, 9 were cross-sectional and 1 was a retrospective longitudinal study. Regarding structural factors, 3 studies examined WMH alone, 3 examined WMH + BA, and 4 examined rGMV, including 1 focusing on cerebral lobe volume. For driving performance assessments, 3 studies used questionnaires and 7 used on-road tests. In contrast, among the other research groups' studies, 2 were cross-sectional and 2 were retrospective longitudinal. Structural factors included 2 WMH studies and 2 rGMV studies, while driving performance assessments consisted of 2 questionnaire-based evaluations and 2 on-road tests.

Interestingly, none of the reviewed studies used driving simulators, despite their advantage of enabling the safe and flexible creation of hazardous traffic scenarios (e.g., sudden bicycle or pedestrian intrusions). One possible explanation is that older adults are prone to simulation sickness, which may discourage their use in research settings.

We highlight recent developments in predictive modeling using machine learning and discuss the implications for clinical screening, preventive interventions, and transportation policy.

2 White Matter Hyperintensities and Driving Risks

White matter hyperintensities (WMH) are widely recognized as ischemic lesions primarily resulting from atherosclerotic degeneration of small cerebral vessels in the white matter [7–12]. Their etiology includes unhealthy lifestyle habits such as smoking and physical inactivity, as well as lifestyle-related diseases such as hypertension, diabetes, dyslipidemia, and metabolic syndrome [12, 26]. The ischemic condition due to WMH can impair neural processing by reducing perfusion in white matter tracts, thereby disrupting long-range neuronal network communication and functional connectivity [27–29]. This disruption of neuronal network may cause unsafe risky driving performances.

The prevalence of WMH increases with age and has been observed in approximately 40–50% of ostensibly healthy adults over 50, with some studies reporting prevalence rates as high as 95% in more advanced age groups [7–10]. While severe WMH is a known contributor to vascular dementia, many affected individuals present with only mild WMH and

Table 1 Summary of studies investigating the relationship between brain MRI structure and driving safety performance

No	First author (Year)	Study design	Purpose/Aim	Structure factors	Driving performance assessment methods	N/Age Mean (SD)	Notable finding
1	Sakai [18]	Cross-sectional	Association between rGMV and two questionnaires	rGMV	Questionnaire concerning risky driving tendencies	*N* = 39 Mean age: 69 (3)	The supplemental motor area volume was associated with risky driving tendencies
2	Park [13]	Cross-sectional	Association between WMH and traffic crashes on crossroads	WMH	Questionnaire Traffic crashes	*N* = 3975 Mean age: 52.5	Multiple WMHs were significantly associated with traffic crashes on crossroads
3	Nakano [14]	Cross-sectional	Association between WMH and driving performance	WMH	Standard licensing road test	Young: *N* = 9/24.7 (3.6) No WMH *N* = 13/70.0 (6.6) WMH *N* = 13/69.5 (6.1)	Older drivers with WMH produced more driving risks and steering entropy than those without WMH
4	Jang [16]	Retrospective Longitudinal	Dectermine if WMH predicts driving cessation over time	WMH	Questionnaire Cessation	Mild *N* = 389:/66.0 (8.7) Mod. *N* = 116:/70.7 (7.4) Severe *N* = 35:/73.4 (6.4)	WMH and severity are associated with driving cessation and faster change in status from'currently driving' to no longer driving
5	Nishiuchi [43]	Cross-sectional	Relationship between Cerebral lobe volume and DSP	Cerebral lobe	Standard licensing road test	*N* = 46 Mean age: 78.5 (3.7)	The occipital lobe volume was significantly associated with DSPs
6	Renge [17]	Cross-sectional	Association between WMH and DSP	WMH	Standard licensing road test	*N* = 92 Mean age: 75.36 (4.78)	WMHs were significantly associated with the duration of signaling and visual research duration
7	Yamamoto [19]	Cross-sectional	The identification of gray matter regions correlated with unsafe braking at an intersection	Regional GM	Standard licensing road test	*N* = 32 Mean age: 74.9 (3.7)	The left precentral sulcus, left sulcus intermedius primus, right inferior frontal gyrus, and right superior frontal sulcus were identified
8	Oba [22]	Cross-sectional	Association between WMH/atrophy and DSP via DVC test	WMH BA	Road test and DVC	*N* = 101 Mean age: 77.88 (3.77)	Brain healthcare in patients with MRI-diagnosed WMH may be particularly useful for the risk management of traffic accidents caused by the elderly in Japan
9	Park [3]	Cross-sectional	Association between WMH/atrophy and DSPs	WMH BA	Standard licensing road test	*N* = 90 Mean age: 75.31 (4.795)	The participant group with more advanced aging brain consisting of brain atrophy and WMH showed lower DSPs
10	Babulal [23]	Retrospective Longitudinal	Association between WMH/atrophy and high risk of driving behaviors	WMH BA	Questionnaire	N = 160 more than 65y.o	WMH and cortical atrophy are standard MRI metrics that are widely available and can be used for screening individuals at higher risk for driving safety risk and decline in community mobility
11	Park [15]	Retrospective Longitudinal	Association between WMH and wrong-way entry on highways	WMH	Questionnaire wrong-way entry on highways	*N* = 11170 Mean age: 52.5	Multiple WMHs were significantly associated with wrong-way entry and near one on highways, not with wrong-way entry on narrow roads
12	Putra [24]	Cross-sectional	Association between ADHD tendency, traffic crash history, and rGMV	Regional GM	Questionnaire Traffic crashes	N = 2548 Mean age: 52.76 (8.632)	Smaller volume of the left precuneus is apt to take more crash risks in ADHD traits
13	Park [25]	Cross-sectional	Association between rGMV and DSPs	Regional GM	Standard licensing road test	*N* = 90 Mean age: 75.31 (4.80)	The participant group with more advanced aging brain consisting of brain atrophy and WMH showed lower SDPs
14	Putra [21]	Cross-sectional	Prediction of driving risk with rGMV and DSPs	Regional GM	Standard licensing road test	N = 94 Mean age: 77.66 (3.67)	Prediction performances are Accuracy: 0.89, F1 score: 0.72, ROC-AUC:0.85, and Specificity:0.94

Table 2 The numbers of cases, study design, structure factors, and assessment methods in Table 1

	No	Study design	Structure factors	Assessment methods
Our groups (2,3,5,6,8,9,11,12,13,14)	10	Cross-sectional: 9	WMH: 3	Questionnaire: 3
		Longitudinal: 1	WMH + BA: 3	Road test: 7
			rGMV: 4	
Other groups (1,4,7,10)	4	Cross-sectional: 2	WMH: 2	Questionnaire: 3
		Longitudinal: 2	WMH + BA: 0	Road test: 1
			rGMV: 2	

remain asymptomatic [12, 26]. These individuals often continue driving, unaware of the underlying neuropathology.

In a population-based cohort of 3,930 drivers aged 21 to 87 years (mean age: 52.7 ± 4.5 years) enrolled through Japan's Brain Dock program, Park et al. reported that even mild WMH was significantly associated with a higher incidence of traffic crashes at intersections—particularly at crossroads [13]. Complementary behavioral studies using real vehicles on closed driving school circuits have validated these findings. In one such study involving 24 healthy older drivers (mean age: 69.9 ± 6.3 years), those with mild WMH demonstrated increased steering entropy—measured using six-axis gyroscopic sensors—while performing secondary cognitive tasks such as mental arithmetic. This indicates unstable vehicle control in cognitively demanding conditions, mental arithmetic, which may not be detectable through visual inspection alone [14].

In a real-world circuit study involving 92 cognitively intact older adults (mean age: 75.4 ± 4.8 years) enrolled by Brain Dock, Renge et al. observed that drivers with WMH were more likely to delay turn signaling compared to those without WMH [17]. In a related analysis, Park et al. grouped 90 dementia-free older adults (mean age: 75.3 ± 4.8 years) based on WMH and BA severity. Participants with elevated levels of both biomarkers received significantly lower scores on the DSP scale—which includes visual search, speed management, signaling, vehicle stability, lane positioning, and steering—during on-road evaluations conducted by certified driving instructors [3]. BA may yield distracted effect like mental arithmetic when old individuals with WMH drive in a closed-circuit, as previously described [14].

A similar trend, poor driving performance by combination of WMH and BA, was observed by researchers at Washington University, who found that among 163 cognitively normal, community-dwelling older adults (age ≥ 65), increased WMH and BA were significantly associated with reduced frequency and distance of naturalistic driving [23]. These results suggest possible behavioral compensation in response to comprehensively structural brain decline such as both WMH and BA. On the other hand, in South Korea, Jang et al. (2018) investigated WMH as a predictor of driving cessation among cognitively healthy older adults. In a cohort of 540 participants, greater WMH severity was significantly associated with transitions from active driving to cessation, independent of cognitive and motor function [16].

These findings collectively highlight WMH as a potential neuroimaging biomarker for driving risk in aging populations. Notably, Oba et al. found that WMH localized in the parietal and occipital lobes—rather than the frontal or temporal regions—were most strongly associated with reduced DSP scores in 101 healthy older adults (mean age: 77.9 ± 3.8 years) [22]. BA was also significantly correlated with diminished DSP. These associations were particularly pronounced during right-turn maneuvers at intersections, which in Japan's left-sided traffic system require complex spatial judgment and heightened visual monitoring. Occipital WMH has also been implicated in deficits in dynamic visual cognition, further impairing situational awareness.

More recently, a retrospective cohort study of 11,170 Brain Dock participants revealed that individuals with multiple or large-multiple WMH had significantly higher odds of wrong-way entries or near-miss incidents on highways, but not on smaller roads [15]. These findings suggest that the rapid decision-making and complex motor responses required for highway driving—such as steering, braking, and accelerating in rapid succession—may be particularly susceptible to disruption by WMH-related neural impairments.

3 Regional Gray Matter Volumes (rGMVs) and Driving Safety Performance (DSP)

Higher-order cognitive functions essential for DSP are known to be localized in specific brain regions—for example, executive function is primarily governed by the prefrontal cortex, spatial cognition by the parietal lobe, and visual information processing by the occipital lobe [30–32]. Recent research has further explored the relationship between DSP and more detailed subregions of the cerebral cortex.

A voxel-based morphometry (VBM) study conducted by Toyota Central Research, involving 39 healthy participants, examined driving-related questionnaire responses rather than actual driving performance. The study found that reduced executive function was significantly associated with decreased gray matter volume in the supplementary motor area—a region within the frontal cortex responsible for planning and coordinating complex, especially bimanual and sequential, movements [19]. However, the study did not investigate other cortical areas.

In general, Drivers diagnosed with attention-deficit/hyperactivity disorder (ADHD) are more likely to cause traffic crashes [33–35]. Handityo et al. examined the relationship between rGMVs, ADHD traits, and traffic crash history in a cohort of 2,548 healthy adults (mean age: 52.76 ± 8.63 years) without clinical ADHD diagnoses [24]. Path analysis revealed that ADHD traits were significantly associated with specific brain regions involved in various cognitive domains. ADHD trait has three categories, inattention, hyperactivity, and impulsivity [33]. Notably, the left precuneus—associated with visuospatial processing—was the only region correlated with all of three ADHD trait dimensions, underscoring its potential relevance to driving safety and crash risk. In a related study, a research team from Honda Motor Co., Ltd. employed an fMRI-compatible driving simulator to evaluate brain activity during traffic signal tasks, comparing professional and non-professional drivers [36]. Their findings showed that the left precuneus exhibited the fastest and most robust activation during driving-related tasks. Taken together, the left cuneus may play an important role to yield driving safety performance.

A team from Keio University used VBM to investigate the association between 74 rGMVs and braking distance at signalized intersections [19, 20]. Employing support vector machines (SVM), a machine learning technique, they analyzed data from 32 healthy older adults (age ≥ 65 years). Their model achieved a classification accuracy of 87.5%, with a sensitivity of 63.6% and a specificity of 100%. Five variables—age and gray matter volumes in four cortical regions (the left superior part of the precentral sulcus, the left sulcus intermedius primus, the right orbital part of the inferior frontal gyrus, and the right superior frontal sulcus)—were consistently selected in the final model. However, this study did not evaluate DSP across its multiple functional categories.

In contrast, Park et al. examined associations between 114 rGMVs and six distinct DSP categories using data from 98 healthy older adults (mean age: 77.72 ± 3.68 years) in a real-world driving circuit experiment [25]. Eighteen brain regions were found to be significantly associated with one or more of the following DSP components: DSP1 (visual search), DSP2 (speed regulation), DSP3 (signaling), DSP4 (vehicle stability), DSP5 (lane positioning), and DSP6 (steering). Notably, each brain region demonstrated a consistent directional association—either positive or negative—with DSP scores across all categories. The authors suggested that this may reflect two opposing neural mechanisms that jointly support DSP, akin to a Yin–Yang dynamic (Fig. 2). The Yin–Yang dynamic, a concept rooted in Eastern traditional philosophy, represents the balance of opposing forces—dark and light, passive and active—interacting in harmony. Each contains the seed of the other, symbolizing constant change and interdependence.

Furthermore, as described in the paper conducted under the same experimental conditions as mentioned above [25], DSP scores falling below the 15th percentile were classified as indicative of a critical decline [21]. Using machine learning of Random Forest classification, the authors achieved high predictive performance as following; Accuracy of 89%, Specificity of 94%, Sensitivity (Recall) of 64%, Precision of 72%, F1 score of 62%, ROC-AUC (receiver operating characteristic curve- area under the curve) of 0.85, and Cross-validation of 0.95. Sensitivity decreases as the number of pseudo-negative (false-negative) cases increases, whereas precision decreases as pseudo-positive (false-positive) cases accumulate. Although F1 score, the harmonic means of sensitivity and precision, are relatively low, these results may be useful as a triage test to identify safe drivers. The final model incorporated 12 variables, including age and gray matter volumes in the following 11 cortical regions: the left angular gyrus, left frontal operculum, left occipital fusiform gyrus, left parietal operculum, left postcentral gyrus, left planum polare, left superior temporal gyrus, right hippocampus, right orbital part of the inferior frontal gyrus, right posterior cingulate gyrus, and right posterior orbital gyrus [21].

Both the Keio and Park studies reported high predictive performance. However, the brain regions identified in their respective models differed entirely except for the right orbital part of the inferior frontal gyrus, which was common to both. This discrepancy highlights the importance of considering experimental context, model design, and potential biases when using machine learning to identify neuroanatomical predictors of driving safety performance (Fig. 3).

4 Limitation and usefulness of functional MRI (fMRI)

This MRI-based review focused on structural biomarkers such as WMH, BA, and rGMV, because functional brain biomarkers (e.g., neuronal connectivity) generally require 3-Tesla MRI, which is more time- and labor-intensive and substantially more costly than the standard 1.5-T MRI commonly used for structural imaging. As a result, the number of participants available for 3-T MRI studies is inevitably smaller [36–39]. In contrast, structural biomarkers can be assessed using conventional 1.5-T MRI, which is easier to implement and more economical, enabling the acquisition of large-scale datasets suitable for machine-learning

Fig. 2 Relationship between regional gray matter volumes and six categories of DSP (driving safety performance): DSP1 = visual search behavior, DSP2 = speeding, DSP3 = signaling, DSP4 = vehicle stability, DSP5 = positioning, and DSP6 = steering. The consistent directional association between rGMVs and specific components of DSP is visualized, reinforcing the hypothesis of region-specific contributions to behavioral regulation. Black and white circles represent positive and negative associations, respectively

Explanatory variable	Driving Safety Performance					
	DSP1	DSP2	DSP3	DSP4	DSP5	DSP6
Gray matter regions						
Rt Inferior Frontal Gyrus		●				
Rt Temporal Gyrus						○
Lt Temporal Gyrus	●					●
Lt Occipital Gyrus			●			
Rt Middle Frontal Gyrus	●					
Lt Middle Frontal Gyrus	○					
Rt Precentral Gyrus		●				
Lt Precentral Gyrus		○				
Rt Angular Gyrus	○	○				
Lt Angular Gyrus	●	●				
Lt Postcentral Gyrus	○	○	○		○	○
Rt Supramarginal Gyrus		○				
Lt Supramarginal Gyrus	●	●				
Rt Entorhinal Area						●
Lt Fusiform Gyrus		●				
Rt Parahippocampus	●	●				
Rt Cuneus			○			
Rt Lingual Gyrus		○				

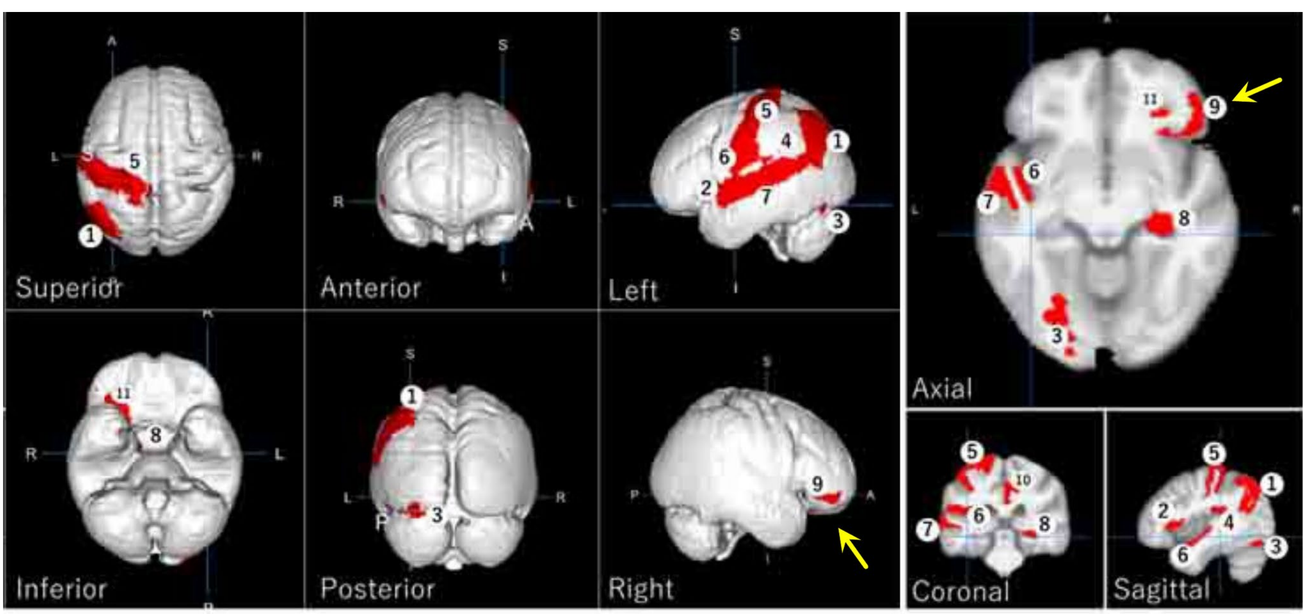

Fig. 3 Gray matter regions associated with driving safety performance (DSP), as identified in the study by Handityo et al. (2025). The selected regions include: (1) left angular gyrus, (2) left frontal operculum, (3) left occipital fusiform gyrus, (4) left parietal operculum, (5) left postcentral gyrus, (6) left planum polare, (7) left superior temporal gyrus, (8) right hippocampus, (9) right orbital part of the inferior frontal gyrus, (10) right posterior cingulate gyrus, and (11) right posterior orbital gyrus. Among these, the orbital part of the inferior frontal gyrus was the only region that overlapped with four regions identified by Yamamoto et al., as indicated by a yellow arrow

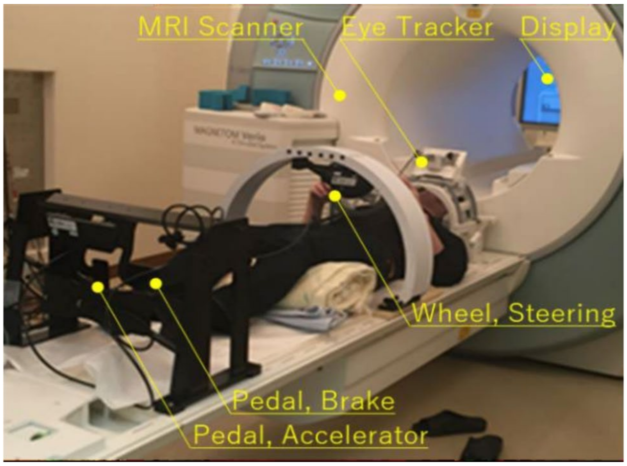

Fig. 4 Steering and pedal-operating posture of a participant in a supine position inside the gantry og MRI, quoted from the Reference No.35

analyses. The predictive performance of machine learning models is highly dependent on the availability of large-scale training data.

Nevertheless, fMRI offers the advantage of capturing real-time functional brain responses, although performing driving-related tasks—such as operating a steering wheel and pedals—in the supine position inside the scanner differs substantially from real-world driving conditions (Fig. 4). Therefore, we believe it would be valuable to corroborate large-scale structural data with smaller-scale but real-time functional data, as demonstrated in the Honda fMRI study with 14 participants that validated our findings with 2,458 participants regarding ADHD traits [24, 36].

5 Interventions for Driving Safety Performance

Real-world driving experiments using actual vehicles on closed- circuit roads have provided empirical evidence for the influence of structural brain MRI biomarkers—specifically WMH, BA, and rGMV—on driving safety performance (DSP) [17, 21, 22, 25]. Importantly, both WMH and BA may be mitigated through lifestyle modifications, such as smoking cessation [40], moderation of alcohol intake [41], and the management of lifestyle-related conditions such as hypertension, diabetes, and dyslipidemia [7–10, 42]. These lifestyle-related interventions have the potential to improve DSP by addressing the underlying neuropathology. Within this context, MRI-based brain health assessments may serve as a foundation for personalized traffic risk management strategies aimed at preventing hazardous driving behaviors such as traffic crashes and wrong-way entry on main roads or highways, and ultimately extending safe driving years in

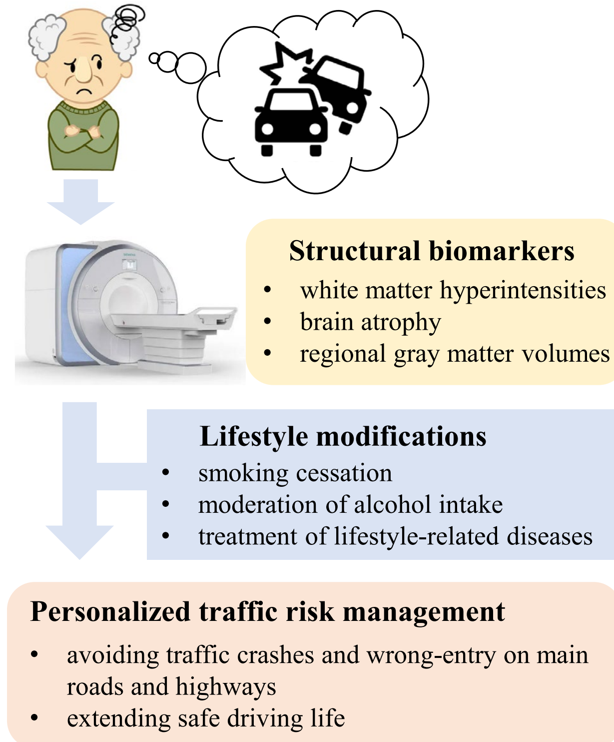

Fig. 5 Brain structural biomarkers and safe driving: Personalized intervention diagram

older drivers. A major challenge in promoting safe driving among the elderly lie in the substantial inter-individual variability of brain aging, including WMH and BA. Therefore, rather than applying a one-size-fits-all approach, it is essential to evaluate each individual's brain status using MRI and design tailored interventions accordingly (Fig. 5).

There are cost-effectiveness concerns when introducing MRI as a measure for driving safety. However, if radiation-free MRI could predict traffic crashes among elderly drivers and help prevent them, it would not only reduce economic losses but also save lives—benefits that are truly incalculable. Fortunately, Japan has already implemented a nationwide brain health screening program known as "Brain Dock," which enables routine MRI evaluations in older adults. As the country with the world's most rapidly aging population, Japan is uniquely positioned to serve as a global pioneer in establishing large-scale, MRI-informed risk management strategies for driving safety. In Japan, drivers aged 75 and older are required to take a closed-circuit driving test and a cognitive function assessment every three years when renewing their driver's license. Within this framework, one possible policy initiative would be to introduce MRI on a trial basis for license renewal, utilizing the Brain Dock system in regions with a high aging rates and limited alternatives to automobile transportation.

6 Machine Learning for Predictive Risk Modeling

A review of the literature indicates that only two research teams to date have attempted to identify high-risk older drivers by using brain volumetric measures and DSP as training inputs for machine learning models. Although both studies reported high overall accuracy and specificity, their sensitivity and precision remained relatively low [19, 21], suggesting a key limitation of relying solely on structural MRI data for predictive modeling. Notably, findings from Honda's fMRI-based driving simulation study with 14 participants and Handityo et al.'s VBM analysis of rGMV with 2,458 participants, both pointed to a common neural correlate: the left precuneus appears to play a pivotal role in supporting safe driving behavior [24, 36]. The involvement of the precuneus is understandable because it lies at the border zone among the frontal, parietal, and occipital lobes and plays a key role in visual cognition and episodic memory. To deepen our understanding the neuronal mechanisms underlying driving behavior and to enable earlier identification of individuals at elevated risk, future models will likely need to incorporate functional neuroimaging data—such as fMRI-derived connectivity and synchronization—alongside structural features. Despite the practical constraints associated with 3 T MRI—including limited sample sizes, substantial time and labor requirements, and higher costs—combining structural and functional brain imaging has the potential to substantially outperform either modality alone in predictive performance. Such multimodal integration could drive major progress in precision-based prevention strategies for both traffic safety and neurocognitive health.

7 Future Directions and Conclusions

The integration of structural brain biomarkers with behavioral assessments of driving performance not only represents a promising frontier in the prevention of traffic accidents among older adults, but also helps reduce economical losses with traffic accidents and supports the efficient functioning road logistics. As the global population continues to age, ensuring driving safety while preserving personal mobility has become an increasingly urgent public health challenge. This review has synthesized growing evidence that WMH and BA—two prevalent age-related changes detectable via MRI—are associated with impairments in driving safety performance (DSP). Additionally, rGMVs have been linked to specific components of driving behavior, and machine learning models leveraging these structural features have demonstrated high predictive accuracy [19, 21].

Despite these advancements, several limitations remain. Most existing studies have relied exclusively on structural MRI data, which may not fully capture the dynamic neural processes involved in real-time driving. In contrast, functional neuroimaging techniques—particularly resting-state and task-based fMRI—offer complementary insights by revealing patterns of connectivity and activation that may underlie subtle deficits in DSP.

Leveraging large-scale structural MRI data in combination with functional imaging data as multimodal inputs for machine learning models is expected to substantially enhance the predictive accuracy, sensitivity, precision and overall performance of these models in identifying individuals at risk of impaired driving. By integrating complementary information from both structural and functional modalities, such an approach can capture not only the anatomical characteristics of the brain but also real-time neural responses associated with cognitive and motor processes that underlie DSP. Furthermore, to elucidate the causal relationships between brain states and driving abilities in older adults, well-designed longitudinal studies are indispensable. These studies are necessary to determine whether early neuroimaging markers, such as WMH, BA, or rGMV, can reliably predict future declines in driving performance. Preventive brain healthcare program, such as Japan's "Brain bock" system, may play a key role in facilitating the feasibility of the longitudinal studies. Additionally, longitudinal research can assess whether targeted interventions—including lifestyle modifications such as exercise, dietary improvements, smoking cessation, and alcohol moderation, as well as cognitive or attentional training—can effectively mitigate these risks, thereby contributing to prolonged safe driving years and improving traffic safety in aging populations.

From a translational perspective, incorporating neuroimaging biomarkers into public health frameworks and transportation policy holds considerable promise. In Japan, drivers aged 70 and older are required to complete a senior driver's course—including practical driving and cognitive function assessments—when renewing their licenses. On the other hand, preventive MRI screening through the "Brain Dock" system is already widespread. Embedding a brain checkup program within this nationwide system could improve the feasibility and cost-effectiveness of MRI implementation, while enabling ethical oversight within government-certified driving schools. However, if incidental brain abnormalities are detected through MRI, establishing a formal referral and collaboration pathway with nearby medical institutions would be essential.

In conclusion, the integration of structural and functional MRI with behavioral data may facilitate a paradigm shift from reactive to preventive approaches in traffic safety. As

Japan pioneers the use of population-wide neuroimaging through the Brain Dock system, its experience may serve as a valuable model for other aging societies seeking to balance mobility, autonomy, and safety in an increasingly older driver population.

Acknowledgements We thank Ms. Mari Takahashi for her contributions to the data collection. The authors declare that financial support was received for the research and/or publication of this article. This study was conducted under the auspices of a research fund of "The General Insurance Association of Japan" and supported by JSPS KAKENHI (Grant Nos. 25H00762, 25K00301, and 23K17330).

Data Availability Data are availability from the corresponding author upon reasonable request.

Declarations

Competing interests The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations This manuscript does not include a separate list of abbreviations. Instead, All abbreviations are defined upon their first appearance in the text

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

References

1. Lin, D., Cui, J.: Transport and mobility needs for an ageing society from a policy perspective: review and implications. Int. J. Environ. Res. Public Health **18**(22), 11802 (2021). https://doi.org/10.3390/ijerph182211802
2. Horikawa, E.: Elderly driver cognitive function and traffic accidents: cognitive assessment utilization and actual vehicle driving assessments. ITARDA workshop report. (2020). Retrieved from: https://www.itarda.jp/
3. Park, K., Renge, K., Nakagawa, Y., Yamashita, F., Tada, M., Kumagai, Y.: Aging brains degrade driving safety performances of the healthy elderly. Front. Aging Neurosci. **13**, 783717 (2022). https://doi.org/10.3389/fnagi.2021.783717
4. Kurita, S., Doi, T., Harada, K., et al.: Motoric cognitive risk syndrome and traffic incidents in older drivers in Japan. JAMA Netw. Open **6**(8), e2330475 (2023). https://doi.org/10.1001/jamanetworkopen.2023.30475
5. Toups, R., Chirles, T.J., Ehsani, J.P., Michael, J.P., Bernstein, J.P.K., Calamia, M., Parsons, T.D., Carr, D.B., Keller, J.N.: Driving performance in older adults: current measures, findings, and implications for roadway safety. Innov. Aging **6**(1), igab051 (2022). https://doi.org/10.1093/geroni/igab051
6. Anstey, K.J., Wood, J., Lord, S., Walker, J.G.: Cognitive, sensory and physical factors enabling driving safety in older adults. Clin. Psychol. Rev. **25**(1), 45–65 (2005). https://doi.org/10.1016/j.cpr.2004.07.008
7. Park, K., Yasuda, N., Toyonaga, S., Yamada, S.M., Nakabayashi, H., Nakasato, M., Shimizu, K.: Significant association between leukoaraiosis and metabolic syndrome in healthy subjects. Neurology **69**(10), 974–978 (2007). https://doi.org/10.1212/01.wnl.0000266562.54684.bf
8. Alkan, E., Taporoski, T.P., Sterr, A., von Schantz, M., Vallada, H., Krieger, J.E., Pereira, A.C., Alvim, R., Horimoto, A.R.V.R., Pompéia, S., Negrão, A.B., Evans, S.L.H.: Metabolic syndrome alters relationships between cardiometabolic variables, cognition, and white matter hyperintensity load. Sci. Rep. **9**, 11752 (2019). https://doi.org/10.1038/s41598-019-40630-6
9. Zhang, Z., Zhang, W.-L., Li, J., Xiao, M.-J.: Metabolic syndrome is associated with white matter hyperintensity in stroke patients. Brain Impairm. **18**(3), 284–291 (2017). https://doi.org/10.1017/BrImp.2017.21
10. Meng, F., Yang, Y., Jin, G.: Research progress on MRI for white matter hyperintensity of presumed vascular origin and cognitive impairment. Front. Neurol. **13**, 865920 (2022). https://doi.org/10.3389/fneur.2022.865920
11. Yang, Y., Hu, Y., Chen, Y., Gu, W., Nie, S.: Identifying leukoaraiosis with mild cognitive impairment by fusing multiple MRI morphological metrics and ensemble machine learning. J. Imaging Inform. Med. **37**, 666–678 (2024). https://doi.org/10.1007/s10278-023-00958-y
12. Debette, S., Markus, H.S.: The clinical importance of white matter hyperintensities on brain magnetic resonance imaging: systematic review and meta-analysis. BMJ (2010). https://doi.org/10.1136/bmj.c3666
13. Park, K., Nakagawa, Y., Kumagai, Y., Nagahara, M.: Leukoaraiosis, a common brain magnetic resonance imaging finding, as a predictor of traffic crashes. PLoS One **8**(2), e57255 (2013). https://doi.org/10.1371/journal.pone.0057255
14. Nakano, K., Park, K., Zheng, R., et al.: Leukoaraiosis significantly worsens driving performance of ordinary older drivers. PLoS One **9**(10), e108333 (2014). https://doi.org/10.1371/journal.pone.0108333
15. Park, K., Nakagawa, Y.: Leukoaraiosis predicts wrong-way entry and near one on highways for healthy drivers. J. Neurol. Disord. **11**(1), 537 (2023). https://doi.org/10.4172/2329-6895.11.1.537
16. Jang, M., Hong, C.H., Kim, H.-C., Choi, S.H., Seo, S.W., Kim, S.Y., Na, D.L., Lee, Y., Chang, K.J., Roh, H.W., Son, S.J.: Subcortical ischemic change as a predictor of driving cessation in the elderly. Psychiatry Investig. **15**(12), 1162–1167 (2018). https://doi.org/10.30773/pi.2018.10.10.3kci.go.kr+3
17. Renge, K., Park, K., Tada, M., et al.: Mild functional decline and driving performance of older drivers without a diagnosed dementia: study of leukoaraiosis and cognitive function. Transp. Res. Part F **75**(202), 160–172 (2020). https://doi.org/10.1016/j.trf.2020.09.016
18. Sakai, H., Takahara, M., Honjo, N.F., Doi, S., Sadato, N., Uchiyama, Y.: Regional frontal gray matter volume associated with executive function capacity as a risk factor for vehicle crashes in normal aging adults. PLoS ONE **7**(9), e45920 (2012). https://doi.org/10.1371/journal.pone.0045920
19. Yamamoto, Y., Yamagata, B., Hirano, J., et al.: Regional gray matter volume identifies high risk of unsafe driving in healthy older people. Front. Aging Neurosci. **12**, 592979 (2020). https://doi.org/10.3389/fnagi.2020.592979
20. Hirano, J., Yamamoto, Y., Yamagata, B., et al.: Machine-learning approach to predict on-road driving ability in healthy older

people. Psychiatry Clin. Neurosci. **75**(10), 352–359 (2021). https://doi.org/10.1111/pcn.13084
21. Putra, H.A., Park, K., Yamashita, F.: Cerebral grey matter volume identifies healthy older drivers with a critical decline in driving safety performance using actual vehicles on a closed-circuit course. Front. Aging Neurosci. **17**, 1462951 (2025). https://doi.org/10.3389/fnagi.2025.1462951
22. Oba, H., Park, K., Yamashita, F., Sato, S.: Parietal and occipital leukoaraiosis due to cerebral ischaemic lesions decrease the driving safety performance of healthy older adults. Sci. Rep. **12**, 21436 (2022). https://doi.org/10.1038/s41598-022-25899-4
23. Babulal, G.M., Chen, L., Carr, D.B., Johnson, A.M., Shimony, J.S., Doherty, J., Murphy, S., Walker, A., Domash, H., Hornbeck, R., Keefe, S., Flores, S., Raji, C.A., Morris, J.C., Ances, B.M., Benzinger, T.L.S.: Cortical atrophy and leukoaraiosis, imaging markers of cerebrovascular small vessel disease, are associated with driving behavior changes among cognitively normal older adults. J. Neurol. Sci. **448**, 120616 (2023). https://doi.org/10.1016/j.jns.2023.120616
24. Putra, H.A., Park, K., Oba, H., Yamashita, F.: Adult attention-deficit/hyperactivity disorder traits in healthy adults associated with brain volumetric data identify precuneus involvement in traffic crashes. Sci. Rep. **13**, 22466 (2023). https://doi.org/10.1038/s41598-023-49907-3
25. Park, K., Putra, H.A., Yoshida, S., Yamashita, F., Kawaguchi, A.: Uniformly positive or negative correlation of cerebral gray matter regions with driving safety behaviors of healthy older drivers. Sci. Rep. **14**, 206 (2024). https://doi.org/10.1038/s41598-023-50895-7
26. Kloppenborg, R.P., Nederkoorn, P.J., Geerlings, M.I., van den Berg, E.: Presence and progression of white matter hyperintensities and cognition: a meta-analysis. Neurology **82**(23), 2127–2138 (2014). https://doi.org/10.1212/WNL.0000000000000505
27. Schwarz, C.G., Dyrba, M., Ewers, M., Hansson, O., Initiative, A.D.N.: Divergent functional connectivity changes associated with white matter hyperintensities. Neuroimage **291**(2024), 120672 (2024). https://doi.org/10.1016/j.neuroimage.2024.120672
28. Lu, T., et al.: Long-range connections damage in white matter hyperintensities affects information processing speed. Hum. Brain Mapp. **45**(2), 512–523 (2024). https://doi.org/10.1002/hbm.26534
29. Rudolph, M.D., et al.: Distributed associations among white matter hyperintensities and structural brain networks with fluid cognition in healthy aging. Cereb. Cortex **34**(3), 1456–1468 (2024). https://doi.org/10.1093/cercor/bhad472
30. Foy, H.J., Runham, P., Chapman, P.: Prefrontal cortex activation and young driver behaviour: a fNIRS study. PLoS One **11**(5), e0156512 (2016). https://doi.org/10.1371/journal.pone.0156512
31. Just, M.A., Keller, T.A., Cynkar, J.: A decrease in brain activation associated with driving when listening to someone speak. Brain Res. **1205**, 70–80 (2008). https://doi.org/10.1016/j.brainres.2007.12.075
32. Schweizer, T.A., Kan, K., Hung, Y., Tam, F., Naglie, G., Graham, S.J.: Brain activity during driving with distraction: an immersive fMRI study. Front. Hum. Neurosci. **7**, 53 (2013). https://doi.org/10.3389/fnhum.2013.00053
33. Chang, Z., Lichtenstein, P., D'Onofrio, B.M., Sjölander, A., Larsson, H.: Serious transport accidents in adults with attention-deficit/hyperactivity disorder and the effect of medication: a population-based study. JAMA Psychiatr. **71**(3), 319–325 (2014). https://doi.org/10.1001/jamapsychiatry.2013.4174
34. Liu, Y.-C., Chen, V.C.-H., Yang, Y.-H., Chen, Y.-L., Gossop, M.: Association of psychiatric comorbidities with the risk of transport accidents in ADHD and methylphenidate treatment. Epidemiol. Psychiatr. Sci. **30**, e14 (2021). https://doi.org/10.1017/S2045796021000032
35. Libutzki, B., Neukirch, B., Kittel-Schneider, S., Reif, A., Hartman, C.A.: Risk of accidents and unintentional injuries in men and women with attention-deficit/hyperactivity disorder across the adult lifespan. Acta Psychiatr. Scand. **146**(2), 135–147 (2022). https://doi.org/10.1111/acps.13524
36. Araya Inc., Honda R&D Co., Ltd.: Development of an AI-based system for early detection of driving risk factors through brain activity analysis. Oral presentation at the 27th enhanced Safety of Vehicles (ESV) Conference, Yokohama, Japan (2023). Retrieved from: https://www.araya.org/publications/news20230410/. Accessed 12 Dec 2025.
37. Yuen, N.H., Tam, F., Churchill, N.W., Schweizer, T.A., Graham, S.J.: Driving with distraction: measuring brain activity and oculomotor behavior using fMRI and eye-tracking. Front. Hum. Neurosci. **15**, 659040 (2021). https://doi.org/10.3389/fnhum.2021.659040
38. Okamoto, Y., Sasaoka, T., Sadato, N., Fukunaga, M., Yamamoto, T., Soh, Z., Nouzawa, T., Yamawaki, S., Tsuji, T.: Is human brain activity during driving operations modulated by the viscoelastic characteristics of a steering wheel? An fMRI study. IEEE Access **8**, 217–229 (2020). https://doi.org/10.1109/ACCESS.2020.3040231
39. Li, Y., Baqapuri, H.I., Keller, M., Wolter, S., Zhang, C., Cong, F., Mathiak, K.: Physiological fingerprinting of audiovisual warnings in assisted driving conditions: an investigation of fMRI and peripheral physiological indicators. Brain Struct. Funct. **230**, 31 (2025). https://doi.org/10.1007/s00429-025-02891-y
40. Power, M.C., Deal, J.A., Sharrett, A.R., Jack, C.R., Jr., Knopman, D., Mosley, T.H., Gottesman, R.F.: Smoking and white matter hyperintensity progression: the ARIC-MRI study. Neurology **84**(8), 841–848 (2015). https://doi.org/10.1212/WNL.0000000000001283
41. Wilson, R.S., et al.: Association of alcohol consumption with brain volume in the Framingham study. JAMA Neurol. **58**(10), 1354–1360 (2000). https://doi.org/10.1001/archneur.58.10.1354
42. Park, K., Nemoto, K., Yamakawa, Y., Yamashita, F., Yoshida, K., Tamura, M., Kawaguchi, A., Arai, T., Sasaki, M.: Cerebral white matter hyperintensity as a healthcare quotient. J. Clin. Med. **8**(11), 1823 (2019). https://doi.org/10.3390/jcm8111823
43. Nichiuchi, H., Park, K., Hamada, S. The relationship between driving behavior and the health conditions of elderly drivers. International journal of intelligent transportation system research **1**, (2021). Retrieved from: https://www.springerprofessional.de/en/international-journal-of-intelligent-transportation-systems-rese/18973468. Accessed 12 Dec 2025.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Kaechang Park obtained his undergraduate degree in 1985 and was awarded a Ph.D. in 1993, from Osaka University. He subsequently joined the Department of Neurosurgery at Kochi University Medical School as an associated professor. He was later appointed as Director of the Medical Transportation and Social Brain Laboratory at Kochi University of Technology. In addition, since 2008, he has been overseeing the Brain Dock program at Kochi Kenshin Clinic in Japan. He is currently affiliated with the Advanced Telecommunications Research Institute International (ATR). His research interests focus on the neural underpinnings of driving behavior and the development of brain–machine interfaces.

Handityo Aulia Putra received his B.Eng. in Electronics Engineering from Bandung Institute of Technology (Indonesia), M.Eng. in IT Convergence from Kumoh National Institute of Technology (Korea), and Dr. Eng. in Engineering from Kochi University of Technology (Japan). He is currently a Research Associate at the Neural Engineering Laboratory, Nagaoka University of Technology, Japan. His research interests include machine learning, neuroimaging, human-computer interaction, and brain-machine interfaces. He has published in leading journals such as Frontiers in Aging Neuroscience and Scientific Reports, and has received external research funding from JSPS (KAKEN: 25K00301).