TRB Annual Meeting

THE IMPACT OF WORKING MEMORY CAPACITY ON TAKEOVER PERFORMANCE AMONG OLDER DRIVERS IN SAE LEVEL 2 VEHICLES

--Manuscript Draft--

Full Title:	THE IMPACT OF WORKING MEMORY CAPACITY ON TAKEOVER PERFORMANCE AMONG OLDER DRIVERS IN SAE LEVEL 2 VEHICLES
Abstract:	Advanced Driver Assistance Systems (ADAS) can enhance the mobility of older adults by compensating for cognitive and physical declines, thereby alleviating transportation poverty associated with driving cessation. Older adults often experience reduced working memory capacity (WMC) due to diminished resting-state functional connectivity. However, whether WMC decline affects takeover performance remains unclear, especially when drivers are distracted by non-driving-related tasks (NDRT). With 24 participants, we examined takeover and NDRT performance among older adults with varying WMC levels and compared to younger drivers. Results indicate that older drivers with lower WMC exhibited significantly poorer post-takeover performance than both younger drivers and older drivers with higher WMC. Notably, older drivers with high WMC performed comparably to younger drivers. These findings suggest that cognitive tests are still needed for the licensure process of older drivers, even with driving automation and targeted cognitive training may help older drivers to use ADAS more effectively.
Additional Information:	
Question	**Response**
The total word count limit is 7500 words including tables. Each table equals 250 words and must be included in your count. Papers exceeding the word limit may be rejected. My word count is:	5176
Manuscript Classifications:	Safety, Human Factors, Pedestrians, Bicycles; Cognitive Workload; Driver Distraction; Driver Performance; Advanced Driver Assistance Systems (ADAS); Older Driver Safety
Manuscript Number:	TRBAM-26-01567
Article Type:	Presentation
Order of Authors:	Jing Yan, Mphil
	Zhixiong Wang, Mphil
	Dengbo He

THE IMPACT OF WORKING MEMORY CAPACITY ON TAKEOVER PERFORMANCE AMONG OLDER DRIVERS IN SAE LEVEL 2 VEHICLES

Jing Yan ,Co-first Author[1]
[1]Intelligent Transportation Thrust, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China
Email: jyan856@connect.hkust-gz.edu.cn
ORCID: 0009-0001-8501-4932
Zhixiong Wang ,Co-first Author[2]
[2]Robotics and Autonomous Systems Thrust, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China
Email: zwang477@connect.hkust-gz.edu.cn
ORCID: 0009-0005-9346-465X
Dengbo He ,Corresponding Author[1,2,3]
[1]Intelligent Transportation Thrust, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China
[2]Robotics and Autonomous Systems Thrust, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China
[3]Hong Kong University of Science and Technology Shenzhen-Hong Kong Collaborative Innovation Research Institute, Shenzhen, China
Email: dengbohe@hkust-gz.edu.cn
ORCID: 0000-0003-4359-4083

Word Count: 4426 words + 3 table(s) × 250 = 5176 words

Submission Date: July 31, 2025

ABSTRACT

Advanced Driver Assistance Systems (ADAS) can enhance the mobility of older adults by compensating for cognitive and physical declines, thereby alleviating transportation poverty associated with driving cessation. Older adults often experience reduced working memory capacity (WMC) due to diminished resting-state functional connectivity. However, whether WMC decline affects takeover performance remains unclear, especially when drivers are distracted by non-driving-related tasks (NDRT). With 24 participants, we examined takeover and NDRT performance among older adults with varying WMC levels and compared to younger drivers. Results indicate that older drivers with lower WMC exhibited significantly poorer post-takeover performance than both younger drivers and older drivers with higher WMC. Notably, older drivers with high WMC performed comparably to younger drivers. These findings suggest that cognitive tests are still needed for the licensure process of older drivers, even with driving automation and targeted cognitive training may help older drivers to use ADAS more effectively.

Keywords: Advanced Driver Assistance Systems, Takeover performance, SAE level 2 vehicles, Working memory capacity, Non-driving-related tasks, Older adults

INTRODUCTION

Advanced Driver Assistance Systems (ADAS) are designed to support drivers by providing warnings to reduce risk exposure or by autonomously executing certain control tasks to ease the burden of manual control. Typical ADAS functions available on the market include adaptive cruise control (ACC), lane centering control (LCC), blind spot detection (BSD), and automatic emergency braking (AEB) (*1*). All ADAS functions available on the market at this stage can be categorized as SAE Level 2 automation according to the Society of Automotive Engineers (SAE). With SAE Level-2 functions (*2*), drivers are freed from constant control of vehicles. Previous research found that ADAS bring numerous benefits, offering the potential to reduce road traffic accidents (*3*). However, as the level of automation increases, drivers can become too dependent on the system, which can lead to potential attention lapses when manual intervention is needed (*4*). Furthermore, the interaction between human drivers and ADAS is not always perfect, especially in complex or unpredictable situations. This can increase driver stress or anxiety, particularly when the system response does not meet drivers' expectations (*5*). These behavioral changes may impair the overall safety of the human-ADAS system, especially for vulnerable groups (*6*).

Population aging is emerging as a major societal challenge. By 2050, adults aged 55 and older are projected to become one of the primary groups in the labor force (*7*). This trend calls for an urgent need to prolong the active lives of older people to meet their expectations and to enable them to live actively with high quality. However, reduced physical and cognitive abilities may cause involuntary driving cessation in older adults, leading to a significant loss of independence.

In addition, transportation poverty has been identified as a key factor in social isolation among older adults. For example, previous research found that people who do not drive tend to engage in fewer social activities (*8*). Moreover, although public transportation remains available in some areas, a large proportion of older adults live in rural regions where access to public and community transit is further limited. This is often due to factors such as population migration, a shortage of working-age residents, economic stagnation, and cuts to public services (*9, 10*). Furthermore, social isolation among older adults has been shown to reduce access to goods and services, which is closely associated with a decline in their self-perceived well-being (*11*). ADAS have the potential to enhance mobility for older driver (*12, 13*), and can also significantly boost their driving confidence, particularly in complex scenarios (*14*). Moreover, by providing supplementary driving information, ADAS can effectively reduce the cognitive workload of older drivers and thereby enhance overall driving safety (*15*). However, older drivers often show poorer takeover performance when interacting with ADAS (*13*). Engaging in non-driving-related tasks (NDRT) has been found to further affect takeover performance and increase the risk of collisions (*13*). Despite these findings, limited research has explored the underlying factors contributing to the decline in takeover performance among older adults.

Working memory refers to a cognitive system responsible for the temporary storage and manipulation of information (*16, 17*). Drivers with higher working memory capacity (WMC) possess greater cognitive resources, allowing them to allocate attention more effectively and manage multiple tasks with increased flexibility (*18*). In addition, a robust relationship between age and WMC has been well documented. older adults typically exhibit reduced resting-state functional connectivity, which has been significantly linked to age-related declines in WMC (*19*). Previous studies have highlighted the importance of treating older drivers as a heterogeneous group when using ADAS, given their generally poorer takeover performance compared to younger drivers (*6*). However, little research has investigated the underlying factors contributing to this heterogeneity among older adults. This study aims to examine whether WMC is one of the key factors that accounts for the variability in takeover performance within older adults. Accordingly, the following RQs are proposed:

- Does working memory capacity affect takeover performance?
- Can high working memory capacity mitigate age-related differences in takeover performance during NDRT in SAE level 2 vehicles?

LITERATURE REVIEW

Challenges for older adults in Driving

It is widely known that one's cognitive abilities and physical health gradually decline with the increase of age, and this can ultimately lead to driving cessation. Physically, the reduction in muscle strength may impair their ability to perform emergency maneuvers, while declining vision may affect their ability to drive at night (*20*). Shih et al. (*21*) found that older drivers' weaker hip and knee muscles cause them to react more slowly at medium and high speeds, increasing their probability of an accident. Cognitively, Vardaki et al.(*22*) examined the differences of challenges between older drivers with and without moderate cognitive impairment (MCI). They found that MCI drivers reacted more slowly and struggled with distractions, particularly when they had to multitask or switch among different jobs. The results indicate that cognitive decline can negatively influence driving performance among older drivers. As a result, some older drivers may choose to avoid driving when possible, and driving cessation can impair one's independence in mobility and negatively affect one's sense of well-being (*8*).

Takeover Performance Among Older Drivers in Interaction with ADAS

Older drivers often exhibit poorer takeover performance when using ADAS (*6*). A previous study shows that compared to younger drivers, older drivers perform worse in visual scanning, vehicle control stability, and takeover timing, and they also tend to react more slowly (*13*). In addition, research has explored how aging affects drivers' perception of the surrounding environment during takeovers, which found that older drivers have longer hazard perception times, indicating greater difficulty in responding quickly to unexpected situations (*23*). Moreover, Li et al. (*24*) found that older adults performed significantly worse than younger drivers in terms of takeover quality, particularly in operating the steering wheel and pedals. They also required more time to make decisions and execute actions during takeovers.

The Impact of WMC on Driving Performance

Working memory plays an important role in driving, as drivers have to continuously integrate and dynamically update information from both internal and external traffic environments (*25*). For example, Wood et al. (*26*) linked higher WMC with better visual attention control and reduced distraction across various driving tasks. Certain driving situations have also been associated with increased working memory demands. However, working memory is a limited-capacity system (*17*), and overload can deteriorate driving performance (*27*). A previous study shows that increasing working memory load with secondary tasks affects lane-change performance. This effect was more distinct in individuals with lower WMC (*28*). Furthermore, age-related declines in WMC have been associated with reduced plasticity in the frontoparietal network among older drivers. They are more likely to exhibit attentional failures and slower decision-making during driving tasks with high cognitive load conditions. (*29*). Therefore, it is necessary to explore whether age-related decreases in WMC may impact older drivers' takeover performance when using ADAS.

METHOD

Participants

To be eligible to participate in this study, these criteria are applied when recruiting participants: older drivers were required to be 55 years or older, while younger drivers had to be between 18 and 35 years old (*30*). All participants needed to hold a valid Chinese driver's license and be active drivers at the time of participation in the study. Participants were initially assessed using the AD8 Dementia Screening Questionnaire to exclude individuals exhibiting signs of cognitive impairment (cut-off score ≥ 2) (*31*). All of them were recruited from social media platforms and Nansha senior university. In total, 24 valid participants (mean age = 42.42 years, SD = 18.94 years; max = 67 years, min = 21 years; 14 female, 10 male) participated in the study. Among them, 12 were from the younger driver (mean age = 24.08 years, SD = 2.50 years; max = 28 years, min = 21 years; 6 female, 6 male), and 12 were from the older driver (mean age = 60.75 years, SD = 3.19 years; max = 67 years, min = 56 years; 8 female, 4 male).

Apparatus

The experiment was conducted using a stationary driving simulator by WIVW GmbH consisting of three 43-inch displays located in front and to the sides, with a horizontal viewing angle of 150 degrees and a vertical viewing angle of 47 degrees (Figure 1). Additionally, a 15.6-inch touchscreen display was located on the right side of the steering wheel. The simulator was equipped with ACC and LCC, achieving a SAE Level 2 automation according to the standards set by the SAE. ACC can automatically adjust vehicle speed to ensure a safe distance from the vehicle in front. However, the limitations of this function are that it cannot brake the vehicles sharply and detect stationary objects on the road. LCC can manage the vehicle's lateral movements to ensure it remains centered within its lane. This function generally depends on the presence of clear lane markings to operate properly. If such markings are obscured or absent, LCC may fail to navigate the vehicle correctly, necessitating the driver to take over steering control. The combination of ACC and LCC functions can be activated and deactivated in three ways: dragging the button upward on the touchscreen, turning the steering wheel, or pressing the brake pedal. The driving data, including various vehicle dynamics measures such as driving speed, steering angles, acceleration, and braking, was recorded at a rate of 60 Hz.

FIGURE 1 The driving simulator.

Driving Scenario

As shown in Figure 2, participants operated an SAE Level 2 vehicle in a highway driving simulation. The scenario began with the driver starting the engine. The system prompted participants to activate the assisted driving function at a fixed location. Once engaged, the automation system took control of both longitudinal and lateral movements, maintaining a constant speed of 90 km/h (25.00 m/s) in the center of the right-hand lane.

During Level 2 automated driving, participants were allowed to remove their hands from the steering wheel and feet from the pedals, fully disengaging from driving. They were also instructed to perform a series of mandatory auditory 1-back tasks as NDRT. Each task consisted of a sequence of 35 numbers, presented at 1.5-second intervals. Participants were required to verbally repeat the number that had occurred one step earlier. Throughout the four rounds of the 1-back task, participants encountered four takeover scenarios without Takeover Requests (TOR). They had to decide for themselves when to take control based on their experience. The automation system transferred control to the driver upon detecting active input (at least 2 degrees of steering wheel movement and/or 10% pressure on the accelerator or brake pedals). Once the takeover was initiated, the driver had to execute lane changes, acceleration, or deceleration to respond to hazardous situations. This scenario has been widely used in previous studies on Level 2 automated vehicles and has been shown to be effective in assessing takeover performance (*32*). Participants were allowed to discontinue the 1-back task whenever they felt it was too overwhelming to simultaneously manage both NDRT and driving. After each takeover, the system asked the driver to turn automation back on in the next road section. When all four takeover scenarios were finished, participants reactivated the assisted driving function and continued under automation until the end of the scenario.

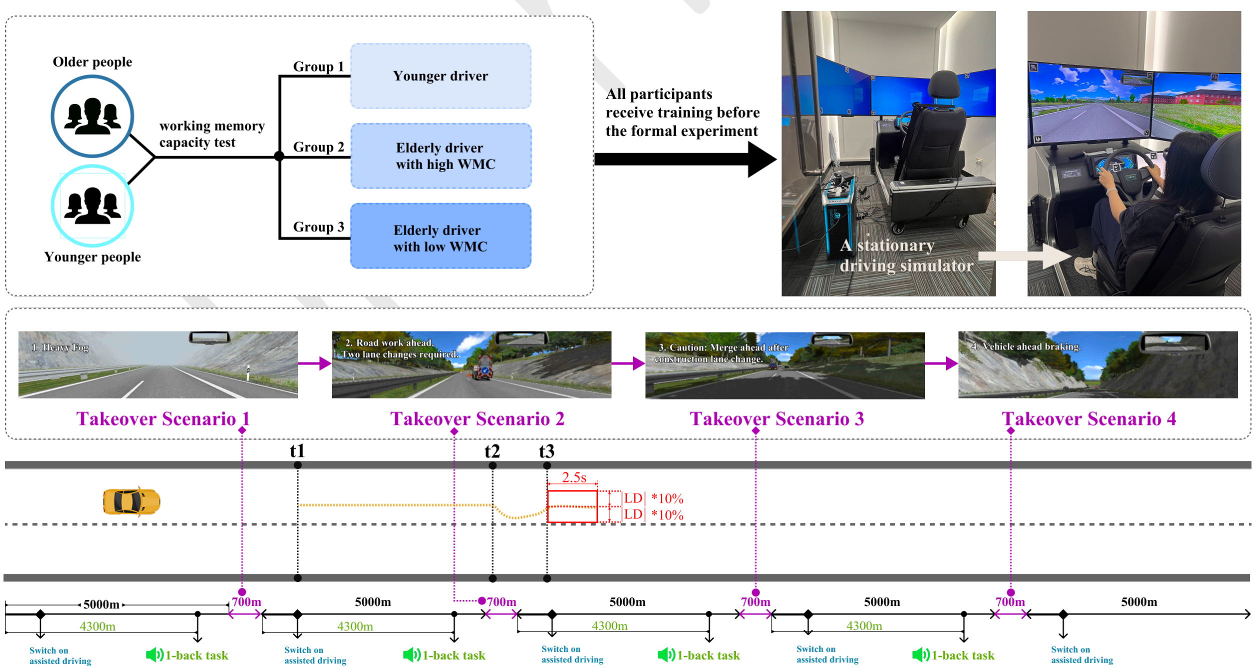

FIGURE 2 Illustration of the experimental design and level 2 automated driving scenario. 't1' represents Driver activates the assisted driving system; 't2' represents Driver takes over control; 't3' represents Vehicle reaches a stable manual control state.

To establish a standardized data processing pipeline, this study focuses on identifying key temporal markers in driver behavior, segmenting the takeover process into distinct behavioral phases, and extracting multi-dimensional performance metrics for each phase. We first identify three critical time points, as illustrated in Figure 2: t_1 marks the initiation of the automated driving assistance system; t_2 represents the moment the driver first engages in manual control. The identification of t_2 is based on thresholds such as steering torque exceeding 1.5 Nm or steering angle changing by more than 2 degrees (*33*), brake pedal travel increasing by more than 10% or the presence of significant braking force (*34*), and accelerator pedal travel exceeding 5% or the onset of evident vehicle acceleration (*35*).

The time point t_3 indicates the driver's transition into a stable manual control state. This is determined by identifying a 2.5-second window after t_2 during which lateral deviation remains within 10% of its current value, and variations in steering, throttl (*36*), and brake inputs remain within defined thresholds, indicating that control has stabilized (*37*).

Building on the identification of these time points, and informed by existing research and behavioral characteristics, the takeover process is segmented into three analytical phases. The first is the *Trust Assessment & Risk Perception phase* (from t_1 to t_2), which captures two key dimensions: system trust, reflected in how long the driver is willing to allow the automation to remain in control, and risk perception, indicating whether the driver recognizes potential hazards and chooses to takeover. Previous studies have shown that the timing of takeover is closely related to environmental risk awareness (*38*), and that risk perception significantly influences takeover performance (*39*). Moreover, Walch et al. (*40*) found that the time between hazard recognition and the driver's takeover action may offer insights into their internal risk assessment process.

The *Control phase* (from t_2 to t_3) encompasses the driver's transition from initiating control to reaching a stable driving state. This phase is essential for evaluating both the quality of control and the consistency of the takeover process (*41*).

In addition, we define the *N-back task phase*, which starts from the onset of the auditory task and ends when the driver completes the required response. This phase is critical for analyzing changes in driving behavior under the influence of NDRT. Meteier et al. (*42*) reported that during the execution of a 1-back task, drivers experience increased physiological load and behavioral variability, particularly with diminished consistency in longitudinal control and speed management. Thus, driving behavior during the 1-back phase serves as a key indicator of dual-task interference in the context of automated driving.

Procedures and data analysis

After verifying participant eligibility, each individual provided written informed consent and completed a pre-experiment questionnaire to collect demographic information. Participants then underwent a pretest, which included the Operation Span Task (Ospan) to measure accuracy and response time, which has been proven to be effective in measuring working memory capacity (*43*). Based on their Ospan scores, participants were categorized into three distinct WMC groups (YD means younger driver, EDH means older driver with high WMC, EDL means older driver with low WMC) using *k*-means clustering analysis (Figure 3). The centroids of each cluster (marked with "+") represent the mean performance along these dimensions.

Before the experiment, participants received standardized training on the assisted driving system, including ACC and LCC. They were informed of system limitations (e.g., failure to detect

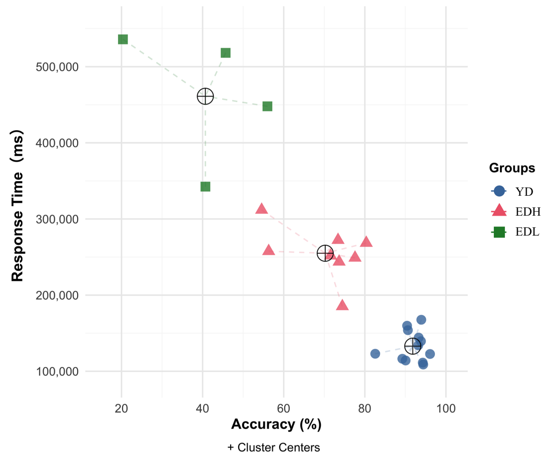

FIGURE 3 K-means Three-Class Clustering Results.

stationary objects) and reminded that they remained fully responsible for driving safety. To ensure understanding, participants were required to verbally repeat these limitations. Additional clarification was provided when necessary. They also received instruction on the auditory 1-back task and completed at least two supervised practice rounds. After becoming familiar with the driving simulator and practicing automation controls, participants completed a brief practice drive before beginning the formal session.

During the experiment, participants encountered four takeover events without TOR and had to decide independently when to intervene. They were allowed to change lanes, accelerate, or decelerate as needed and could stop the 1-back task if necessary. After each takeover, the system prompted them to reactivate automation. The session concluded after all four events. All participants were compensated 80 RMB per hour.

All statistical analyses were conducted using Python and RStudio software. A linear mixed-effects model with random intercepts was fitted for each participant to examine the relationship between the independent variable (cluster group) and the dependent variables (as shown in Table 1). Statistical significance was determined at $p < .05$. For all variables with significant main effects, post-hoc analyses were systematically conducted using Tukey's HSD for general pairwise comparisons, Bonferroni-corrected t-tests for targeted contrasts, and Dunn's test with Bonferroni-Holm adjustment in non-parametric cases, ensuring thorough exploration of between-group differences. This study evaluates driver performance based on indicators of takeover quality and control smoothness. These indicators collectively capture the driver's control quality and behavioral variability during task-switching scenarios.

Pretest cluster analysis

To analyze working memory performance, this study applied *k*-means clustering to Ospan test data from 24 participants (12 younger driver, 12 older driver). Accuracy rate, response time, and age were used as clustering features, resulting in three distinct participant clusters. A one-way analysis of variance (ANOVA) was conducted to examine accuracy differences across the three clusters. The robustness of these differences was supported by large effect sizes (Cohen's d) and narrow confidence intervals.

A one-way ANOVA was conducted to compare cluster characteristics across four dimensions:

Accuracy. Significant differences were observed among the three groups, $F(2,21) = 178.45$, $p < .001$. As depicted in Figure 4 (a), YD (M = 91.82%, SD = 3.51) achieved significantly higher accuracy than both EDH (M = 70.23%, SD = 8.29, Δ = 21.59%, 95% CI: [16.71, 26.47], $p < .001$, $d = 2.97$) and EDL (M = 40.67%, SD = 14.94, Δ = 51.15%, 95% CI: [43.49, 58.81], $p < .001$, d = 4.67). Additionally, EDH outperformed EDL (Δ = 29.56%, 95% CI: [21.90, 37.22], $p < .001$, d = 2.67).

Response Time. As shown in Figure 4 (b), there was a significant group difference in response time, $F(2,21) = 129.63$, $p < .001$. YD (M = 132,964.50 ms, SD = 20,334.45) completed the task significantly faster than both EDH (M = 255,000.25 ms, SD = 38,558.21, Δ = −122,035.75 ms, 95% CI: [−150,065.30, −94,006.20], $p < .001$, $d = 3.97$) and EDL (M = 461,133.50 ms, SD = 91,277.11, Δ = −328,169.00 ms, 95% CI: [−374,227.80, −282,110.20], $p < .001$, $d = 4.86$). Furthermore, EDH was significantly faster than EDL (Δ = −206,133.25 ms, 95% CI: [−252,192.05, −160,074.45], $p < .001$, $d = 2.87$).

Age. Figure 4 (c) indicates significant age differences among the groups, $F(2,21) = 222.10$, $p < .001$. YD (M = 24.08 years, SD = 2.57) was significantly younger than both EDH (M = 60.12 years, SD = 3.59, Δ = −36.04, 95% CI: [−38.81, −33.27], $p < .001$, $d = 11.33$) and EDL (M = 62.00 years, SD = 3.16, Δ = −37.92, 95% CI: [−40.69, −35.15], $p < .001$, $d = 13.45$). However, no significant age difference was observed between the two older subgroups (p = .368).

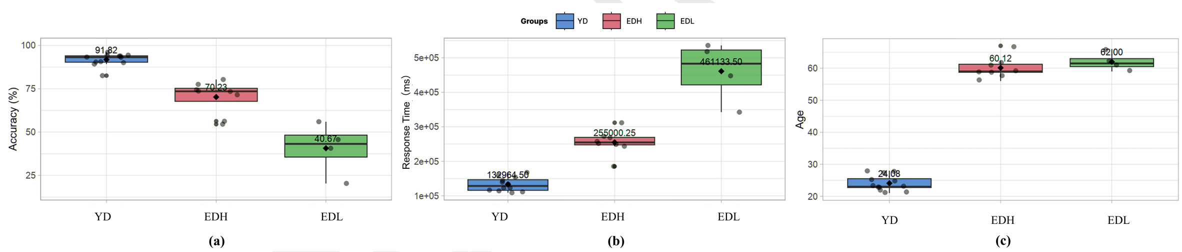

FIGURE 4 Comparison of cluster characteristics across four metrics: (a) Accuracy (%) shows that YD significantly outperformed both older subgroups; (b) Response Time (ms) indicates faster performance in YD; (c) Age distribution confirms the demographic separation between clusters;

Through k-means clustering, this study identified three cognitively distinct participant groups. As shown in Figures 3–4, YD exhibited stronger working memory performance, while the older group was further divided into high and low WMC subgroups. These results support the presence of individual differences in cognitive abilities among older adults and highlight the heterogeneity of working memory capacity in this population. The clustering results provide a solid foundation for subsequent group-based comparisons in driving performance.

RESULTS

As shown in Table 2 and 3, participants' driving behavior varied significantly across cluster groups and each experimental phases, reflecting the impact of cognitive capacity on risk perception, control strategy, and behavioral stability.

TABLE 1 Overview of Dependent Variables

Dependent Variable	Unit	Definition	Data Collection Phase
Trust Assessment & Risk Perception Duration	s	Time interval from t1 to t2	Trust Assessment & Risk Perception
Min Time-to-Collision (MinTTC)	s	Minimum TTC during the phase	Control, N-back task
Min Time-to-Lane-Crossing (MinTCL)	s	Minimum TCL during the phase	Control, N-back task
Mean Lane Offset	m	Mean absolute lane center offset	Control, N-back task
Max Lane Offset	m	Maximum absolute lane center offset	Control, N-back task
Max Steering Angle Velocity	°/s	Maximum steering angle velocity	Control, N-back task
Count of Steering Angle Reversals	count	Number of steering direction changes	Control, N-back task
Rate of Steering Angle Reversals	count/s	Frequency of steering direction changes per second	Control, N-back task
Control Phase Duration	s	Duration of the control phase	Control
Control Phase Distance	m	Distance driven during the control phase	Control
Mean Longitudinal Speed	m/s	Average longitudinal speed	Control, N-back task
SD of Longitudinal Speed	m/s	Standard deviation of longitudinal speed	Control, N-back task
Mean Longitudinal Acceleration	m/s^2	Average longitudinal acceleration	Control, N-back task
SD of Longitudinal Acceleration	m/s^2	Standard deviation of longitudinal acceleration	Control, N-back task
Mean Lateral Acceleration	m/s^2	Mean absolute value of lateral acceleration	Control, N-back task
SD of Lateral Acceleration	m/s^2	Standard deviation of lateral acceleration	Control, N-back task
Max Resulting Jerk	m/s^3	Maximum combined jerk (lateral + longitudinal)	Control, N-back task
SD of Lane Offset	m	Standard deviation of lane center offset	Control, N-back task
SD of Steering Angle Velocity	°/s	Standard deviation of steering angle velocity	Control, N-back task
SD of Steering Angle Acceleration	$°/s^2$	Standard deviation of steering angle acceleration	Control, N-back task

Note: Variables 1–10 belong to the *Takeover Quality* dimension; variables 11–20 belong to the *Smoothness* dimension.

TABLE 2 Statistical Results for K-means-Derived Clusters (Takeover Quality Indicators)

Dependent Variable	F-value	p-value	YD	EDH	EDL	Significant Group Differences
Trust Assessment & Risk Perception Phase						
Trust Assessment & Risk Perception Duration (s)	$F(2,1126) = 14.39$	$< .0001$	158.32 ± 12.27	142.75 ± 13.19	80.00 ± 14.27	YD–EDL*; EDH–EDL*
Control Phase						
Min Time-to-Collision (s)	$F(2,754) = 10.97$	$< .0001$	8.26 ± 2.15	16.89 ± 3.98	38.10 ± 5.94	YD–EDL*; EDH–EDL*
Min Time-to-Lane-Crossing (s)	$F(2,754) = 6.32$	0.002	3.41 ± 0.85	4.12 ± 0.98	7.55 ± 1.42	YD–EDL*
Mean Lane Offset (m)	$F(2,1126) = 6.12$	0.0023	0.031 ± 0.002	0.032 ± 0.003	0.094 ± 0.044	YD–EDL*; EDH–EDL*
Max Lane Offset (m)	$F(2,1126) = 4.84$	0.0082	0.13 ± 0.04	0.15 ± 0.03	0.36 ± 0.13	YD–EDL*
Max Steering Angle Velocity (°/s)	$F(2,1126) = 5.01$	0.0069	0.022 ± 0.010	0.078 ± 0.044	0.207 ± 0.113	YD–EDL*
Count of Steering Angle Reversals	$F(2,1126) = 4.14$	0.0161	466.48 ± 75.31	507.91 ± 80.90	851.31 ± 196.13	YD–EDL*
Rate of Steering Angle Reversals (count/s)	$F(2,1126) = 4.14$	0.0161	0.016 ± 0.003	0.017 ± 0.003	0.028 ± 0.007	YD–EDL*

TABLE 3 Statistical Results for K-means-Derived Clusters (Smoothness Indicators)

Dependent Variable	F-value	p-value	YD	EDH	EDL	Significant Group Differences
Mean Longitudinal Speed (m/s)	$F(2,1126) = 7.64$	0.0005	25.25 ± 0.01	24.81 ± 0.34	22.99 ± 1.22	YD–EDL*; EDH–EDL*
SD of Longitudinal Speed (m/s)	$F(2,1126) = 8.71$	0.0002	0.04 ± 0.01	0.27 ± 0.12	1.21 ± 0.63	YD–EDL*; EDH–EDL*
Mean Longitudinal Acceleration (m/s^2)	$F(2,1126) = 6.89$	0.0011	-0.001 ± 0.0003	0.005 ± 0.006	0.034 ± 0.020	YD–EDL*; EDH–EDL*
SD of Longitudinal Acceleration (m/s^2)	$F(2,1126) = 9.47$	< .0001	0.01 ± 0.002	0.04 ± 0.01	0.15 ± 0.07	YD–EDL*; EDH–EDL*
SD of Lateral Acceleration (m/s^2)	$F(2,1126) = 4.23$	0.0149	0.17 ± 0.09	0.26 ± 0.11	0.72 ± 0.33	YD–EDL*
Max Resulting Jerk (m/s^3)	$F(2,1126) = 4.16$	0.0159	337.66 ± 228.75	546.74 ± 310.49	1664.31 ± 718.50	YD–EDL*
SD of Lane Offset (m)	$F(2,1126) = 6.71$	0.0013	0.035 ± 0.007	0.046 ± 0.010	0.104 ± 0.035	YD–EDL*; EDH–EDL*
SD of Steering Angle Velocity (°/s)	$F(2,1126) = 3.90$	0.0207	0.004 ± 0.001	0.010 ± 0.006	0.020 ± 0.010	ns
SD of Steering Angle Acceleration ($°/s^2$)	$F(2,1126) = 4.05$	0.0176	0.264 ± 0.034	0.467 ± 0.144	0.669 ± 0.199	ns

During the Trust Assessment & Risk Perception Phase Results

During the *Trust Assessment & Risk Perception phase*, a significant group difference was observed, $F(2,1126) = 14.39$, $p < .00001$. YD (M = 158.32 s, SE = 12.27) and EDH (M = 142.75 s, SE = 13.19) spent significantly more time assessing the automated system compared to EDL (M = 80.00 s, SE = 14.27). This finding suggests that EDL are more inclined toward manual control and may demonstrate lower trust in ADAS, choosing to take control sooner at the first signs of perceived risk, thereby suspending automation. Their shortened evaluation time reflects a higher sensitivity to uncertainty and a tendency to avoid system reliance.

Control Phase Results

In the *Control Phase* (t_2 to t_3), MinTTC revealed group disparities, $F(2,754) = 10.97$, $p < .00001$. EDL maintained a markedly higher MinTTC ($M = 38.10$ s, $SE = 5.94$) compared to EDH ($M = 16.89$ s, $SE = 3.98$) and YD ($M = 8.26$ s, $SE = 2.15$). The extended MinTTC observed in EDL indicates a strongly conservative braking pattern and suggests they maintain larger headway distances to compensate for perceived cognitive limitations or reduced confidence in reacting to road hazards. This aligns with previous research indicating risk-averse behavior in drivers with diminished executive function (*26*). Mean longitudinal speed demonstrated a graded decline from YD ($M = 18.13$ m/s) to EDH ($M = 15.42$ m/s) to EDL ($M = 11.94$ m/s), $F(2,754) = 6.32$, $p = .002$. This progressive reduction suggests that WMC not only influences driving under cognitive load but also impacts baseline driving dynamics in non-demanding conditions. Drivers with lower WMC may lack the cognitive capacity to simultaneously monitor speed, maintain situational awareness, and process environmental changes, leading them to adopt slower, more cautious driving patterns as a self-regulatory strategy.

N-back task Phase Results

According to the results summarized in Table 2 and 3, the cognitively demanding *N-back task phase* elicited pronounced behavioral differences across WMC groups, especially in terms of stability, control precision, and dynamic modulation. SD of longitudinal speed was significantly affected by distinct WMC, $F(2,1126) = 8.71$, $p = 0.002$. EDL exhibited the greatest speed variability ($M = 1.21$ m/s, $SE = 0.63$), markedly higher than both EDH ($M = 0.27$ m/s, $SE = 0.12$) and YD ($M = 0.04$ m/s, $SE = 0.01$). These results indicate reduced consistency in longitudinal control among EDL, suggesting that cognitive load disproportionately disrupts their ability to maintain stable driving behavior. SD of lane offset differed significantly across groups, $F(2,1126) = 6.71$, $p = .0013$. EDL deviated more substantially from the lane center ($M = 0.104$ m, $SE = 0.035$) compared to EDH ($M = 0.046$ m, $SE = 0.010$) and YD ($M = 0.035$ m, $SE = 0.007$), indicating poorer lateral control under cognitive demand. Regarding operational smoothness, max resulting jerk, which represents a composite measure of abrupt acceleration, was significantly greater for EDL ($M = 1664.31$ m/s^3, $SE = 718.50$) compared to YD ($M = 337.66$ m/s^3, $SE = 228.75$), $F(2,1126) = 4.16$, $p = .0159$. Likewise, count of steering angle reversals was higher in EDL ($M = 851.31$, $SE = 196.13$) than in YD ($M = 466.48$, $SE = 75.31$), $F(2,1126) = 4.14$, $p = .0161$. These findings reflect increased corrective steering activity, indicative of unstable and less confident control. Notably, EDH continued to perform comparably to YD across speed variability, jerk magnitude, and lateral stability, underscoring the protective role of high WMC in maintaining performance under dual-task cognitive load.

DISCUSSION

In SAE Level 2 vehicles, WMC has a significant impact on takeover performance among older drivers, particularly in areas such as control quality, risk perception, and driving strategy (*44*). The results showed that EDL performed significantly worse than both YD and EDH, with less stable lane-keeping, more abrupt steering or braking, and a higher frequency of corrective maneuvers, indicating degraded lateral control. In contrast, EDH performed comparably to YD across most key indicators, including trust assessment & risk perception duration, MinTTC, mean lane offset, SD of longitudinal speed, SD of longitudinal acceleration, and SD of lane offset.

Our findings align with prior research showing that older drivers tend to struggle more than younger drivers during takeover transitions, often exhibiting slower responses and reduced control stability. These deficits are commonly linked to age-related cognitive and motor decline, such as diminished working memory and slower information processing (*13*). The unstable lane-keeping and erratic steering seen in EDL support this interpretation (*44*).

Furthermore, EDL also adopted a notably conservative driving strategy, characterized by earlier takeover and the maintenance of larger safety margins. This is consistent with findings that older drivers often compensate for reduced abilities through cautious behavior (*44*). In non-urgent takeover scenarios, this self-initiated early intervention may reflect a trade-off between caution and control stability.

Importantly, these results highlight the moderating role of WMC. EDH performed considerably better than EDL, in some cases performing at a level comparable to YD. This aligns with emerging evidence on cognitive heterogeneity in aging, where stronger executive function buffers against age-related decline (*45*). For example, older drivers with higher cognitive capacity tend to exhibit more stable lane changes and smoother transitions. Thus, our study reinforces the idea that not all older drivers are equally affected by aging. Cognitive capacity, particularly WMC, plays a critical role in takeover performance.

In addition, Differences in takeover performance across age and WMC groups likely reflect underlying cognitive mechanisms related to attention and control. EDH can manage cognitive load better, maintain situation awareness, and smoothly transition from automated to manual control (*45*). In contrast, EDL often struggle with divided attention, leading to early takeover, abandonment of NDRT, and unstable vehicle control. These behaviors suggest cognitive overload and limited capacity to integrate perception, decision-making, and motor actions under pressure (*44*). As a result, they compensate with overly cautious strategies but still exhibit erratic inputs. EDH, by comparison, demonstrate more organized and adaptive responses, consistent with prior findings on the role of executive function in supporting smooth and effective takeovers.

Overall, WMC impacts takeover performance in older drivers highlights important practical considerations. It emphasizes the value of integrating cognitive assessments into driver training or licensing for semi-automated vehicles, enabling targeted interventions for those with lower cognitive capacity. Cognitive training and practice may improve takeover skills, especially in high-risk groups.

CONCLUSION

This study investigated how WMC affects older drivers' takeover performance in SAE Level 2 vehicles while performing NDRT. Results showed EDL had poorer takeover performance, including reduced lane control, less consistent speed, and more variable steering, especially during NDRT. EDH performed similarly to YD on most measures, suggesting cognitive reserve helps maintain safe driving behavior. These findings highlight the importance of considering individual cognitive differences among older drivers. Cognitive ability, particularly WMC, appears crucial for effective interaction with ADAS. As such systems become more widespread, providing support based on individual cognitive abilities may improve system safety and usability. Future research should explore tailored cognitive training, adaptive interface designs, and feedback systems suitable for drivers with varying WMC. Incorporating cognitive screening into licensing processes could also identify drivers who may benefit from additional support, helping ensure safer automated driving for older users.

REFERENCES

1. Piao, J. and M. McDonald, Advanced Driver Assistance Systems from Autonomous to Cooperative Approach. *Transport Reviews*, Vol. 28, No. 5, 2008, pp. 659–684.
2. Trypuz, R., P. Kulicki, and M. Sopek, Ontology of autonomous driving based on the SAE J3016 standard. *Semantic Web*, Vol. 15, No. 5, 2024, pp. 1837–1862.
3. Masello, L., G. Castignani, B. Sheehan, F. Murphy, and K. McDonnell, On the road safety benefits of advanced driver assistance systems in different driving contexts. *Transportation Research Interdisciplinary Perspectives*, Vol. 15, 2022, p. 100670.
4. He, D. and B. Donmez, Influence of Driving Experience on Distraction Engagement in Automated Vehicles. *Transportation Research Record*, Vol. 2673, No. 9, 2019, pp. 142–151.
5. Vogelpohl, T., M. Kühn, T. Hummel, and M. Vollrath, Asleep at the automated wheel—Sleepiness and fatigue during highly automated driving. *Accident Analysis & Prevention*, Vol. 126, 2019, pp. 70–84, 10th International Conference on Managing Fatigue: Managing Fatigue to Improve Safety, Wellness, and Effectiveness”.
6. Gasne, C., L. Paire-Ficout, S. Bordel, S. Lafont, and M. Ranchet, Takeover performance of older drivers in automated driving: A review. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 87, 2022, pp. 347–364.
7. Kotschy, R. and D. E. Bloom, *Population Aging and Economic Growth: From Demographic Dividend to Demographic Drag?* Working Paper 31585, National Bureau of Economic Research, 2023.
8. Kovacs, F. S., S. McLeod, and C. Curtis, Aged mobility in the era of transportation disruption: Will autonomous vehicles address impediments to the mobility of ageing populations? *Travel Behaviour and Society*, Vol. 20, 2020, pp. 122–132.
9. Shirgaokar, M., B. Dobbs, L. Anderson, and E. Hussey, Do rural older adults take fewer trips than their urban counterparts for lack of a ride? *Journal of Transport Geography*, Vol. 87, 2020, p. 102819.
10. Han, D., Y. Lee, J. Yu, and C. Dejno, How does driving status affect trip patterns among older adults in suburban and rural communities? *Journal of Transport & Health*, Vol. 21, 2021, p. 101052.
11. Nguyen, N. and Z. Lin, SOCIAL ISOLATION AND SUBJECTIVE WELL-BEING AMONG OLDER ADULTS: AN EXAMINATION BY RACE/ETHNICITY AND GENDER. *Innovation in Aging*, Vol. 8, No. Supplement_1, 2024, pp. 783–783.
12. Gong, J., X. Guo, L. Pan, C. Qi, and Y. Wang, Impact of Age on Takeover Behavior in Automated Driving in Complex Traffic Situations: A Case Study of Beijing, China. *Sustainability*, Vol. 14, No. 1, 2022.

13. Pan, H., W. Payre, J. Xu, and S. K. and, Age-related differences in takeover performance: A comparative analysis of older and younger drivers in prolonged partially automated driving. *Traffic Injury Prevention*, Vol. 25, No. 7, 2024, pp. 968–975, pMID: 38860883.
14. Liang, D., N. Lau, S. A. Baker, and J. F. Antin, Examining Senior Drivers' Attitudes Toward Advanced Driver Assistance Systems After Naturalistic Exposure. *Innovation in Aging*, Vol. 4, No. 3, 2020, p. igaa017.
15. Souders, D. J., N. Charness, N. A. Roque, and H. Pham, Aging: Older Adults' Driving Behavior Using Longitudinal and Lateral Warning Systems. *Human Factors*, Vol. 62, No. 2, 2020, pp. 229–248, pMID: 31361158.
16. Jarrold, C. and J. Towse, Individual differences in working memory. *Neuroscience*, Vol. 139, No. 1, 2006, pp. 39–50, cognitive Neuroscience of Working Memory.
17. Baddeley, A., *Working Memory, Thought, and Action*. Oxford University Press, 2007.
18. Prochnow, A., A. Bluschke, A. Weissbach, A. Münchau, V. Roessner, M. Mückschel, and C. Beste, Neural dynamics of stimulus-response representations during inhibitory control. *Journal of Neurophysiology*, Vol. 126, No. 2, 2021, pp. 680–692, pMID: 34232752.
19. Pläschke, R. N., K. R. Patil, E. C. Cieslik, A. D. Nostro, D. P. Varikuti, A. Plachti, P. Lösche, F. Hoffstaedter, T. Kalenscher, R. Langner, and S. B. Eickhoff, Age differences in predicting working memory performance from network-based functional connectivity. *Cortex*, Vol. 132, 2020, pp. 441–459.
20. Yang, J. and J. F. Coughlin, In-vehicle technology for self-driving cars: Advantages and challenges for aging drivers. *International Journal of Automotive Technology*, Vol. 15, No. 2, 2014, pp. 333–340.
21. Shih, H.-Y., I.-H. Chu, C.-C. Wang, L.-J. Liaw, H.-T. Hsu, and W.-L. Wu, Cognitive and Physical Factors Affecting High-Speed Driving Ability in Older Adults. *Topics in Geriatric Rehabilitation*, Vol. 35, No. 4, 2019.
22. Vardaki, S., A. E. Dickerson, I. Beratis, G. Yannis, and S. G. P. and, Driving difficulties as reported by older drivers with mild cognitive impairment and without neurological impairment. *Traffic Injury Prevention*, Vol. 20, No. 6, 2019, pp. 630–635, pMID: 31246098.
23. Ding, W., Y. Murzello, S. Samuel, and S. Cao, Examining Driver Situation Awareness in the Takeover Process of Conditionally Automated Driving With the Effect of Age. *IEEE Access*, Vol. 12, 2024, pp. 96169–96178.
24. Li, S., P. Blythe, W. Guo, and A. N. and, Investigating the effects of age and disengagement in driving on driver's takeover control performance in highly automated vehicles. *Transportation Planning and Technology*, Vol. 42, No. 5, 2019, pp. 470–497.
25. Zhang, H., Y. Guo, W. Yuan, and K. Li, On the importance of working memory in the driving safety field: A systematic review. *Accident Analysis & Prevention*, Vol. 187, 2023, p. 107071.
26. Wood, G., G. Hartley, P. Furley, and M. Wilson, Working Memory Capacity, Visual Attention and Hazard Perception in Driving. *Journal of Applied Research in Memory and Cognition*, Vol. 5, No. 4, 2016, pp. 454–462, working Memory in the Wild: Applied Research in Working Memory.
27. Yun, R. J., J. H. Krystal, and D. H. Mathalon, Working Memory Overload: Fronto-Limbic Interactions and Effects on Subsequent Working Memory Function. *Brain Imaging and Behavior*, Vol. 4, No. 1, 2010, pp. 96–108.

28. Scheunemann, J., A. Unni, K. Ihme, M. Jipp, and J. Rieger, Demonstrating Brain-Level Interactions Between Working Memory Load and Lateral Control Demands While Driving Using Functional Near Infrared Spectroscopy (fNIRS). *Frontiers in Neuroscience*, Vol. 12, 2019, p. 542.
29. Li, L., Z. Chen, L. Zhang, M. Zhang, H. Liu, D. Wu, P. Ren, and Z. Zhang, Dynamic reconfiguration of brain coactivation states that underlying working memory correlates with cognitive decline in clinically unimpaired older adults. *Cerebral Cortex*, Vol. 34, No. 2, 2024, p. bhad546.
30. Robertsen, R., H. W. Lorås, R. Polman, O. Simsekoglu, and H. Sigmundsson, Aging and Driving: A Comparison of Driving Performance Between Older and Younger Drivers in an On-Road Driving Test. *SAGE Open*, Vol. 12, No. 2, 2022, p. 21582440221096133.
31. Wang, Y., T. Liu, Y. Cai, Y. Wu, Y. Nie, W. Kuang, P. Qiu, and Y. Wan, The Chinese version of informant AD8 for mild cognitive impairment and dementia screening in community-dwelling older adults. *Public Health Nursing*, Vol. 40, No. 2, 2023, pp. 258–265.
32. Doubek, F., E. Loosveld, R. Happee, and J. de Winter, Takeover Quality: Assessing the Effects of Time Budget and Traffic Density with the Help of a Trajectory-Planning Method. *Journal of Advanced Transportation*, Vol. 2020, No. 1, 2020, p. 6173150.
33. Körber, M., C. Gold, D. Lechner, and K. Bengler, The influence of age on the take-over of vehicle control in highly automated driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 39, 2016, pp. 19–32.
34. Morales-Alvarez, W., O. Sipele, R. Léberon, H. H. Tadjine, and C. Olaverri-Monreal, Automated Driving: A Literature Review of the Take over Request in Conditional Automation. *Electronics*, Vol. 9, No. 12, 2020.
35. Kim, J. W. and J. H. Yang, Understanding Metrics of Vehicle Control Take-Over Requests in Simulated Automated Vehicles. *International Journal of Automotive Technology*, Vol. 21, No. 3, 2020, pp. 757–770.
36. Chen, H., X. Zhao, Z. Li, H. Li, J. Gong, and Q. Wang, Study on the influence factors of takeover behavior in automated driving based on survival analysis. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 95, 2023, pp. 281–296.
37. Wang, A., J. Wang, C. Huang, D. He, and H. Yang, Exploring How Physio-Psychological States Affect Drivers' Takeover Performance in Conditional Automated Vehicles. *Accident Analysis & Prevention*, 2024, in Press.
38. Gold, C., M. Körber, D. Lechner, and K. Bengler, Taking Over Control From Highly Automated Vehicles in Complex Traffic Situations: The Role of Traffic Density. *Human Factors*, Vol. 58, No. 4, 2016, pp. 642–652.
39. Petersen, L., L. Robert, X. J. Yang, and D. Tilbury, Situational Awareness, Drivers Trust in Automated Driving Systems and Secondary Task Performance. *SAE International Journal of Connected and Automated Vehicles*, Vol. 2, 2019.
40. Walch, M., K. Lange, M. Baumann, and M. Weber, Autonomous driving: investigating the feasibility of car-driver handover assistance. In *Proceedings of the 7th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, Association for Computing Machinery, New York, NY, USA, 2015, AutomotiveUI '15, p. 11–18.
41. Zhang, T., D. Tao, X. Qu, X. Zhang, R. Lin, and W. Zhang, The roles of initial trust and perceived risk in public's acceptance of automated vehicles. *Transportation Research Part C: Emerging Technologies*, Vol. 98, 2019, pp. 207–220.

42. Meteier, Q., E. De Salis, M. Capallera, M. Widmer, L. Angelini, O. Abou Khaled, A. Sonderegger, and E. Mugellini, Relevant Physiological Indicators for Assessing Workload in Conditionally Automated Driving, Through Three-Class Classification and Regression. *Frontiers in Computer Science*, Vol. 3, 2022.
43. Richmond, L. L., L. K. Burnett, A. B. Morrison, and B. H. Ball, Performance on the processing portion of complex working memory span tasks is related to working memory capacity estimates. *Behavior Research Methods*, Vol. 54, No. 2, 2022, pp. 780–794.
44. Peng, Q., Y. Wu, N. Qie, and S. Iwaki, Age-related effects of executive function on takeover performance in automated driving. *Scientific reports*, Vol. 12, No. 1, 2022, p. 5410.
45. Zhang, H., Y. Guo, W. Yuan, and K. Li, On the importance of working memory in the driving safety field: A systematic review. *AccidentAnalysis & Prevention*, Vol. 187, 2023, p. 107071.