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The effects of age and physical exercise on multimodal signal responses: Implications for semi-autonomous vehicle takeover requests

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ABSTRACT

The present study examined whether the non-chronological age factor, engagement in physical exercise, affected responses to multimodal (combinations of visual, auditory, and/or tactile) signals differently between younger and older adults in complex environments. Forty-eight younger and older adults were divided into exercise and non-exercise groups, and rode in a simulated Level 3 autonomous vehicle under four different task conditions (baseline, video watching, headway estimation, and video-headway combination), while being asked to respond to various multimodal warning signals. Overall, bi- and trimodal warnings had faster response times for both age groups across driving conditions, but was more pronounced for older adults. Engagement in physical exercise was associated with smaller maximum braking force for younger participants only, and also corresponded to longer average fixation durations, compared to the non-exercise group. Findings from this research can help to guide decisions about the design of warning and information systems for semi-autonomous vehicles.

1. Introduction

The development of vehicles with increasing levels of automation has become a major topic of interest in recent years. One particular demographic expected to benefit from this technology is the worldwide rapidly-growing older adult population, or adults aged 65 years and older, many of whom desire to remain independent throughout later stages of life (Czaja et al., 2019; Erber, 2012). In the United States alone, the number of older adults is predicted to almost double to 95 million by 2060, compared to 49 million in 2016 (Vespa et al., 2018). Self-driving vehicles can promote autonomy and safeguard against the potential for health-related challenges in older adults, most notably social isolation and depression caused by a loss of mobility (Hassan et al., 2015; Molnar et al., 2007).

Fully autonomous vehicles (i.e., SAE Level 5) are not expected to penetrate the market for at least the next 20–30 years (Litman, 2017; Niles, 2019). In the interim, most vehicles will consist of intermediate autonomous functionalities, also known as SAE Levels 1–3, or driver assistance, partial automation, and conditional automation, respectively (SAE International, 2018), where only portions of the driving tasks will be handled by automation, such as speed control and/or lane keeping assistance. In these cases, drivers will need to occasionally take control from the automation and resume manual driving due to unpredictable malfunctioning of the vehicle systems (e.g., resulting from poor visibility or hidden or missing lane markings) (e.g., Eriksson and Stanton, 2017; Körber et al., 2018; Llaneras et al., 2013; Molnar et al., 2017; Zhang et al., 2019).

This takeover process consists of the following steps: (a) perceive and process a vehicle takeover request and prepare for transitioning (i.e., (re)position hands properly on the steering wheel and place feet on brake or accelerator pedals as appropriate), (b) (re)gain environment awareness and select the appropriate course(s) of action, and (c) control the dynamics of the vehicle (e.g., McDonald et al., 2019; Petermeijer et al., 2016; Zeeb et al., 2015). Performance in step (a), the signal response phase (shown in Fig. 1), will primarily dictate the trajectory of the entire takeover process. This step utilizes perceptual, cognitive, and motor resources, and may be challenging for older adults given the increased potential for (any combination of) perceptual, cognitive, and physical difficulties often observed in older age (Anstey et al., 2005; He et al., 1998; Körber et al., 2016; Lemke, 2009; Marottoli et al., 1998; Ni et al., 2010). These changes may result in longer signal perception and response times, as well as slower movement speeds. Given that the signal response phase resembles a reaction time task, it is important to understand age-related differences in responses to stimuli.

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A large body of literature has shown age to be a significant predictor of response time in simple tasks and environments (e.g., Deary and Der, 2005; Der and Deary, 2006; Era et al., 1986; Fozard et al., 1994; Kosinski, 2008; Luchies et al., 2002; Panek et al., 1977; Salthouse, 1998, 2000). These particular studies involve physical responses to abstract signals, comparable to the activities that might be observed in step (a) of the takeover process. For example, Era et al. (1986) compared response times (i.e., reaction time to perceive and process signals + movement time to make responses) to three different auditory frequencies between three age groups, 31–35 years, 51–55 years, and 71–75 years of age. They found response times to significantly increase with each age group. Similarly, Fozard et al. (1994) investigated a large sample of participants whose ages ranged between 17 and 96 years and found that reaction time to auditory tones (measured by button presses) increased by a rate of 5–16 ms (msec) per decade, starting at the age of 20 years. Deary and Der (2005) measured response times to visual cues and found the range of response times to be 373.5–375.1 msec for older adults (approximately 63 years) compared to 294.7–306.0 msec for younger adults (approximately 24 years).

These consistent age-difference findings in response time may not be as robust in more complex settings (such as driving), given the complexity of environmental elements that need to be processed. For example, Stinchcombe and Gagnon (2013) compared age differences in response times during a peripheral detection task under driving conditions with varying levels of complexity (e.g., traffic density and road environment) and found no main effect of age on response time. But with respect to step (a) of the semi-autonomous driving takeover process, to date, very few studies have compared performance in the takeover signal response phase between older and younger drivers, and the results are somewhat conflicting (Clark and Feng, 2017; Körber et al., 2016; Li, Blythe, Guo, & Namdeo, 2018, 2019; Miller et al., 2016; Molnar et al., 2017). For instance, Clark and Feng (2017) and Körber et al. (2016) found no age differences in hands-on/feet-on/takeover times, which is equivelant to signal response time, while Li et al. (2018, 2019) found that older adults took longer to move their hands to the steering wheel and put their feet on pedals compared to the younger group. A few possible explanations exist for the lack of consensus across these studies.

First, all of these studies used different types of sensory signals. Takeover warning signals are generally presented in single visual, auditory, or tactile, or in any combination of these three (see reviews in Eriksson and Stanton, 2017; McDonald et al., 2019). Specifically, Clark and Feng (2017) and Körber et al. (2016) used a single auditory alert, while Li et al. (2018) used a combined visual-auditory signal and Molnar et al. (2017) employed combined visual-verbal-haptic cues. However, research on multimodal signal detection has reported that compared to single visual (V), auditory (A), or tactile (T) signals, multimodal signals (i.e., redundant bi- or trimodal combinations of V, A, and T: VA, VT, AT, and VAT) are often associated with faster response times, and higher detection and response accuracies in simple and complex environments, such as psychology experiments and manual driving tasks, respectively, regardless of age (Gottlob, 2007; Laurienti et al., 2006; Liu, 2001; Pitts and Sarter, 2018).

With respect to age, older adults generally have longer response times compared to younger adults, but the difference is relatively small (e.g., 130–270 msec in Gottlob (2007); 42–91 msec in Laurienti et al. (2006); and 200 msec in Lundqvist and Eriksson (2019)). In some cases, multimodal (compared to unimodal) signals resulted in larger response time reductions for older adults than for their younger counterparts (e.g., Laurienti et al., 2006). To date, no study has directly compared the effects of age and the seven multimodal signal types on response times in the (semi)autonomous driving context to determine whether these results hold true across tasks and environments. This knowledge will be especially important given that in the automated driving environment, the attention allocation of the driver will be different as he/she becomes disengaged from the driving task (Choi et al., 2020; Politis et al., 2017; Yoon et al., 2019, 2021). For instance, in SAE Level 3, drivers may shift their attention away from the driving task and engage in non-driving-related tasks (NDRTs; such as texting, watching a movie, or eating) (Naujoks et al., 2018), and differences may exist in how younger and older drivers allocate their attention. A recent study that focused on age differences in NDRTs selection and takeover (Clark and Feng, 2017) found that younger adults preferred engaging with electronic devices, while older adults enjoyed conversing with others during Level 3 automated driving. Engaging in NDRTs may negatively affect signal response performance. For example, Yoon et al. (2019) varied NDRT type (i.e., phone conversation, phone interaction, and video watching) and occasionally asked participants to takeover after receiving all seven types of multimodal warning signals. They found that response times to takeover alerts varied based on the type of engagement and the sensory modalities occupied by the NDRT. But age was not a factor in their study and, thus, it is unclear how age and attention allocation interact to affect response times to the seven signals.

A second reason for the inconsistent findings among the few studies that measured age differences in responses within the takeover signal response could be that even though the mean age of older adult participants was between 65 and 75 years, which is often referred to as "young old" (Binstock, 1985), the age ranges in these previous studies were different (e.g., 60–81 years of age in Li et al., 2018; 70–81 years of age in Miller et al., 2016). While there are basic biological changes that occur with age, in general, aging is a heterogeneous process in that perceptual, cognitive, and physical abilities deteriorate at varying rates for different people (e.g., Baldock et al., 2007; Czaja et al., 2019). Thus, the findings from these studies may be influenced by co-variates and/or non-chronological age factors (such as physical and cognitive abilities or lifestyle) that might have not been accounted for (e.g., Adrian et al., 2011; Lemke, 2009; National Research Council, 2004; Vipperla et al., 2010). Particularly, physical and cognitive factors may be more predictive of signal response performance in older drivers, and several decades of research has shown that engagement in physical exercise can slow down the rate of age-related perceptual, cognitive, and physical changes (e.g., Ballesteros et al., 2013; Barnes et al., 2003; Gauchard et al., 2003; Marmeleira et al., 2009; Müller et al., 2017; Voss et al., 2010; Zettel-Watson et al., 2017). In fact, a recent review synthesized this literature and reported that physical activity, especially aerobic exercise, e.g., jogging, intense walking, endurance running, swimming, tennis, and basketball, can lessen the negative impacts on perceptual and processing speed, attention, executive control, reaction time, and memory in older adults (Muiños and Ballesteros, 2018). These effects are often assessed using cognitive tests such as the mini-mental state exam (Folstein et al., 1975) or the Trail Making Test (Reitan, 1958). However, currently, no empirical data exists on whether and how aerobic exercise

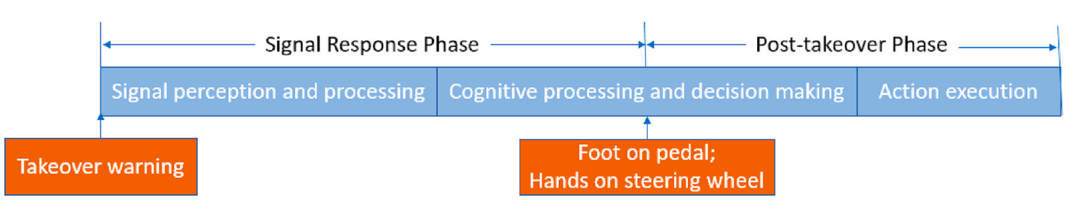

Fig. 1. A vehicle takeover process (adapted from Petermeijer et al. (2016) and Zeeb et al. (2015)).

for older adults can benefit performance in complex environments, such as responses to takeover requests during semi-autonomous vehicles, where attention may be divided.

The goal of this study was to fill the above research gaps in the aging literature by examining whether the non-chronological age factor, engagement in physical exercise, is associated with performance differences in multimodal signal responses (under different attention allocation conditions) between younger and older drivers. Physical exercise and multimodal warning signals (compared to unimodal) were expected to be correlated with shorter response times for all ages, but with a larger reduction in response time for older adults. Given the nature of the task, which more closely resembled a response time task, we also expected any age- and/or exercise-related differences to be relatively small (Ballesteros et al., 2013; Huang et al., 2019; Laurienti et al., 2006; Muiños and Ballesteros, 2018; Petermeijer et al. 2017; Yoon et al., 2019). In this paper, we focus on the first stage of the takeover process, i.e., the signal response phase, because given the complexity of a takeover event, it is necessary to delineate performance at different stages along the takeover continuum. Still, the findings of this study are expected to contribute to the development of theories regarding age-related differencces in performance and may have implications for the design of takeover requests in Level 3 automated vehicles for the signal response phase.

2. Methods

2.1. Participants

Forty-eight participants took part in this study. All participants were evenly recruited into four groups: 12 in a younger exercise group, 12 in a younger non-exercise group, 12 in an older exercise group, and 12 in an older non-exercise group. Younger participants were recruited from Purdue University, while all older participants were healthy residents recruited through Purdue's Center on Aging and the Life Course (CALC), and independent-living communities and senior activity centers in the Lafayette/West Lafayette, Indiana area. For the physical exercise groups, volunteers were required to perform aerobic exercise at least 3 times per week and 45 min per time during the past five years, based on criteria used in previous research on related topics (e.g., Ballesteros et al., 2013; Gauchard et al., 2003; Marmeleira et al., 2009; Voelcker-Rehage et al., 2011; Voss et al., 2010). Participants were assigned to the exercise and non-exercise groups based on self-reported exercising frequency. As shown in Table 1, walking/jogging was the most common aerobic exercise type for both age groups. Both non-exercise groups were individuals who had not exercised regularly during the past 5 years. All participants were required to possess a valid driver's license, have normal or corrected-to-normal vision, and have no impairments to hearing nor the sense of touch. All volunteers were paid $25 for their time. This study was approved by the Purdue University Institutional Review Board (IRB Protocol ID: 1802020214). Demographic information for each group is presented in Table 2.

Table 1
Distribution of aerobic exercises performed by type and age group.

	Walking/ Jogging	Ball sports	Swimming	Biking	Other
Younger adults	9 (75%)	5 (42%)	1 (8%)	2 (17%)	4 (33%)
Older adults	7 (58%)	2 (17%)	5 (42%)	3 (25%)	5 (42%)

Note: the number outside of the parenthesis represents the number of participants who reported performing that activity (out of a total of 12); the percentage inside of the parenthesis is the proportion of people in each group who conducted the respective activity. Also, some participants performed more than one type of exercise. The 'Other' category includes, but is not limited to, exercises such as dancing, high-intensity interval training (HIIT), and trampoline jumping.

2.2. Apparatus/stimulus

2.2.1. Driving simulator

A medium-fidelity fixed-base National Advanced Driving Simulator (NADS), miniSim™ (uiowa.edu), with 138-degree horizontal field-of-view was used for this experiment. This system consists of three 48-inch TV monitors, one 18.5-inch LED monitor as the dashboard, control panel, life-size seat, steering wheel, and foot pedals (Fig. 2). All driving-related metrics were collected at 60 Hz.

2.2.2. Eye tracker

The experiment used an EyeTracking, Inc. FOVIO – FX3 system. This desktop-mounted, contact-free device was located behind the steering wheel, below the main center monitor. Gaze data was collected using the Eye Works Suite (EyeTracking, Inc., USA) and collects data at 60 Hz.

2.2.3. Warning signals

The visual signal was a red circle (200 × 200 pixels) displayed on the center main monitor (presented in Fig. 2). Auditory signals were 6-burst, 400 Hz beeps with a loudness range from 0 to 100 dB. Tactile signals were presented by two 1'' × 0.5'' × 0.25″ piezo-buzzers (called C-2 Tactors developed by Engineering Acoustics, Inc.) at a frequency of 250 Hz with an intensity range of 1–255 gain units. Both Tactors were attached to the lower back center region (e.g., Eriksson et al., 2019; Pitts and Sarter, 2018). The duration of all signals was 1 s. Given the range of ages represented in this study, the intensities of the auditory and tactile signals were chosen by participants through the use of a crossmodal matching procedure (see details in Pitts et al., 2016) conducted prior to the experiment.

2.3. Experimental design

This study employed a 2 (age group: younger and older) × 2 (exercise type: exercise and non-exercise) × 7 (takeover request signal type: V, A, T, VA, VT, AT, and VAT) × 4 (task condition) full factorial design. For signal type, V = visual, A = auditory, and T = tactile. For task condition, participants completed four separate driving sessions/tasks: 1) no task, 2) a video watching task, 3) a headway estimation task, and 4) a video watching and headway estimation (combination) task. Each session consisted of 28 warning signals (i.e., each of the 7 signal types repeated four times in four similar blocks) that were presented randomly throughout each drive. The driving task was designed to represent Level 3 automated driving, where speed and lane position were both controlled by the automation, on a four-lane highway (two adjacent lanes in each traveling direction) with random, and occasional traffic appearing in the two opposite lanes. The average time between warning signals was 25 s, range 15–35 s (e.g., Lundqvist and Eriksson, 2019; Pitts and Sarter, 2018; Politis et al., 2017), and the order of the four

Table 2
Demographic information for each age group.

Factor	Younger adults		Older adults	
	Exercise	Non-exercise	Exercise	Non-exercise
Mean age in years (SD)	21.25 (0.62)	22.58 (1.73)	72.50 (5.71)	70.83 (4.26)
Age range	20–22	20–26	66–84	66–77
Male	8	5	4	4
Female	4	7	8	8
Mean years of driving (SD)	5.33 (1.07)	5.08 (3.12)	54.17 (5.31)	54.09 (4.64)
Mean years of exercise (SD)	5.42 (3.13)	–	18.67 (15.66)	–
Miles driven per year (SD)	8115.86 (7221.66)	7301.00 (7206.90)	6860.91 (4280.07)	7046.36 (5225.77)

Fig. 2. Experimental setup and devices (featured: NADS driving simulator, Fovio eye tracker, and C-2 Tactors).

conditions and signals was counterbalanced.

In the 1) no task (or baseline) condition, participants responded to the seven takeover request (TOR) warning signals by pressing the brake pedal (with their right foot) as soon as they saw/heard/felt any of the multimodal signals (e.g, Dogan et al., 2017). In the 2) video watching task condition (a non-driving-related secondary task that has been used in previous studies (e.g., Carsten et al., 2012; Clark and Feng, 2017; Mok et al., 2015; Yoon et al., 2019), participants were asked to watch a TED talk video related to intelligent technologies, and also respond to the seven TORs as soon as they appeared. This video played on the windshield in the lower right-hand corner of the main display. Here, participants were informed that a video knowledge assessment (or quiz), that contained questions that required recalling of facts spoken by the speaker in the video, would be administered after the driving session. This assessment was used to encourage drivers to focus on the video and disengage from the driving task. In the 3) headway estimation task condition (a driving-related secondary task), the experimenter randomly asked the driver, 12 separate times, "how many seconds to a collision are you behind the car in front of you?" Here, headway was defined as the timing between the leading vehicle and the current/subject vehicle (Yanko and Spalek, 2014). These queries were made in-between, and least 5 s before or after, the presentation of the warning signals to avoid interference with the signal detection task. Participants' options were: 3, 5, or 7 s (i.e., the time to collision), corresponding to a close, medium, and far distance, respectively (see Fig. 3). This condition was created to emulate drivers attending to the forward roadway as they would if automated functions – most notably, Adaptive Cruise Control (ACC) – are deactivated during real-world situations that require takeover. Finally, in the 4) video watching and headway estimation (combination) task condition, participants watched a similar type of video (as in condition 2) while, at the same time, were asked to make headway judgments (as in condition 3) and respond to all TOR signals. The goal was to simulate a more complex situation that could occur in real-life and that requires greater cognitive demands (i.e., video watching, headway judgments, and signal perception) than those in task conditions 2) and 3).

2.4. Procedure

The experiment lasted 90 min. Participants first signed the experimental consent form and then completed a pre-experiment questionnaire that asked about demographic information, driving experiences, and physical exercises. Then, the Montreal Cognitive Assessment (MoCA) was administered to assess capabilities for participating in our study (e.g., Nasreddine et al., 2005). Next, participants were introduced to the experimental setup and asked to perform crossmodal matching. After, a 10-min training session, similar to actual experiment, was conducted. During the actual experiment, since Level 3 automation does not require constant manual control of the vehicle, participants were asked to place their hands in their laps and their feet on the floor (base) of the driving simulator. They were informed that the vehicle could fail due to operational limits and that the study was designed to mimic the moment when such failure occurs. The seven types of TOR warning signals would be presented to signify when the system was failing. They were instructed to respond to the warning signals as quickly as possible after receiving an alert by pressing the brake pedal to deactivate the autonomous driving mode (e.g, Dogan et al., 2017). Since a takeover event was not required, no actual collision would occur if participants missed a signal. This approach was employed to avoid inducing anxiety (especially in older participants) from a vehicle collision. Immediately afterwards, participants needed to reactivate the automation by pressing a button on the steering wheel and then prepare for the next signal(s). A 5-min break was given between each of the four driving conditions. After the experiment, participants filled out a post-experiment questionnaire that asked about their performance and strategies they employed throughout the experiment.

(a) (b) (c)

Fig. 3. Sample scenes for headway estimation and combination (of video watching and headway estimation) task conditions: (a) 3-s, (b) 5-s, and (c) 7-s headway.

2.5. Dependent measures

Dependent measures were classified into three categories: a) driving-related, b) eye movements, and c) secondary task performance.

2.5.1. Driving-related measures

Driving-related measures included brake response time and maximum brake force (Winkler et al., 2018). Brake response time (in milliseconds (msec)) was defined in SAE J2944 as the time between the presentation of any warning signal and the initial contact of the brake pedal (Society of Automotive Engineers, 2015). Maximum brake force (Newtons; N) was defined as the maximum force applied to the brake pedal within the time period between the presentation of a takeover warning signal and the releasing of brake pedal (Winkler et al., 2018), with range of 0–180 N. For maximum brake force, a smaller value indicates better control (Roche and Brandenburg, 2020).

2.5.2. Eye movement measures

Eye tracking metrics included gaze proportion (%) and average fixation duration (seconds) with respect to area of interests (AOIs). We defined one AOI – the video region (size: 10'' × 10″), located in the lower right-hand corner of the main display. Gaze proportion was defined as the percentage of gaze within the AOI. A fixation was defined with a minimum duration of 100 ms in any one location (as used in Caird et al., 2008). Average fixation duration was calculated by dividing the total fixation duration by the total number of fixations (e.g., McPhee et al., 2004).

2.5.3. Secondary task performance

For the video watching (condition 2) and combination (condition 4) task conditions, the video knowledge accuracy was calculated as the percentage of correct answers out of the total number of questions asked after the video. In total, six questions (after each of the two task conditions) were evaluated based on the length of the video and the information extracted from the video. For the headway estimation (condition 3) and combination task conditions, headway estimation accuracy was defined as the percentage of correct responses to the total number of inquiries made during the experiment.

2.6. Data analysis

For driving-related measures, Pearson correlation did not reveal a significant correlation between the brake response time and maximum brake force ($r = -.099$) and thus, two separate 4-way mixed-model Analysis of Variance (ANOVA) tests were conducted for the measures, where age and exercise type were between-subject (quasi-independent) factors, and signal type and task condition were both within-subject factors.

For eye movement measures and secondary task performance, a 3-way mixed-model ANOVA was performed. Signal type was not included in the model because for non-visual signals (i.e., A, T, and AT), participants were not motivated to look at the screen and eye movement data may not be available/accurate in these situations. Likewise, for secondary tasks, performance was not necessarily assessed near a signal presentation. Thus, age and exercise type were between-subject factors, and task condition was a within-subject factor.

For all statistical tests, post-hoc comparisons with Bonferroni corrections were performed to identify significant differences and interactions between means. Also, Greenhouse-Geisser corrections were applied for violations of the assumption of sphericity. All data analysis was completed using SPSS v.26. Significance level was set at $p < 0.05$.

3. Results

3.1. Driving-related measures

There was a significant main effect of age ($F(1,44) = 4.503, p = .040$, $\eta_p^2 = .093$), signal type($F(4.0,177.7) = 517.384$, $p < .001$, $\eta_p^2 = .922$), and task condition ($F(2.5,109.8) = 21.267, p < .001, \eta_p^2 = .326$) on brake response time. For age, post-hoc comparisons revealed that older adults (mean = 1014 msec, standard error of the mean (SEM) = 30) had longer brake response times compared to the younger group (mean = 923 msec, SEM = 30). For signal type, the VAT (mean = 834 msec, SEM = 24) and VT (mean = 837 msec, SEM = 23) signals had the shortest brake response time, followed by AT (mean = 883 msec, SEM = 23) and T (mean = 877 msec, SEM = 26) (see Fig. 4). Finally, for task condition, the headway estimation (mean = 1008 msec, SEM = 24) and combination (mean = 986 msec, SEM = 21) tasks had longer brake response times than the baseline (mean = 926 msec, SEM = 23) and the video watching (mean = 955 msec, SEM = 21) conditions. No main effect of exercise was found (0$F(1,44) = 0.854, p = .360, \eta_p^2 = .019$).

There was a significant age × signal type interaction (F (4.0, 177.7) = 7.260, p < .001, $\eta_p^2 = .142$) on brake response time. Specifically, for single V and A signals, younger adults had shorter response times (for V: mean = 1003 msec, SEM = 28; for A: mean = 1186 msec, SEM = 31) than older adults (for V: mean = 1092 msec, SEM = 28; for A: mean = 1354 msec, SEM = 31). However, no age differences were found between multimodal signals (see Table 3 for summary statistics).

Maximum brake force was significantly affected by age ($F(1,36) = 4.121, p = .050, \eta_p^2 = .103$) and exercise type ($F(1,36) = 4.316, p = .045, \eta_p^2 = .107$). Older adults (mean = 19.359 N, SEM = 1.443) had a larger maximum brake force compared to younger adults (mean = 15.217 N, SEM = 1.443). Also, the non-exercise group (mean = 19.407 N, SEM = 1.443) had a larger maximum brake force compared to the exercise group (mean = 15.168 N, SEM = 1.443). In addition, there was a significant age × exercise type interaction ($F(1,36) = 6.535, p = .015$, $\eta_p^2 = .154$) such that for younger adults, the maximum brake force in the exercise group (mean = 10.489 N, SEM = 2.040) was significantly less than the non-exercise group (mean = 19.944 N, SEM = 2.040), see Fig. 5.

Maximum brake force was not affected by signal type ($F(4.5,161.7) = 1.385, p = .237, \eta_p^2 = .037$) nor task condition ($F(3,108) = 1.781, p = .155, \eta_p^2 = .047$), and there were no interaction effects between the two factors.

3.2. Eye movement measures

Gaze proportion in the video region (AOI) was only analyzed for the video watching and combination task conditions because the video was only played during these two conditions. Age had a significant main effect on gaze proportion in the AOI ($F(1,40) = 8.436, p = .006, \eta_p^2 = .174$). Here, older adults (mean = 24.6%, SEM = 3.062) had a smaller percentage of gaze proportions in the AOI compared to the younger participants (mean = 37.1%, SEM = 3.049) (see an example in Fig. 6). Also, there was a significant main effect of task condition ($F(1,40) = 27.044, p < .001, \eta_p^2 = .403$) on gaze proportion. Post-hoc comparisons indicated that there was a larger percentage of gaze proportions in the video watching task condition (mean = 36.0%, SEM = 2.688) compared to the combination task condition (mean = 25.8%, SEM = 2.007).

Average fixation duration in the video region (AOI) was affected by exercise type ($F(1,35) = 9.204, p = .005, \eta_p^2 = .208$) and only marginally affected by age ($F(1,35) = 3.576, p = .067, \eta_p^2 = .093$). Specifically, the exercise group (mean = 368 msec, SEM = 18) had a longer

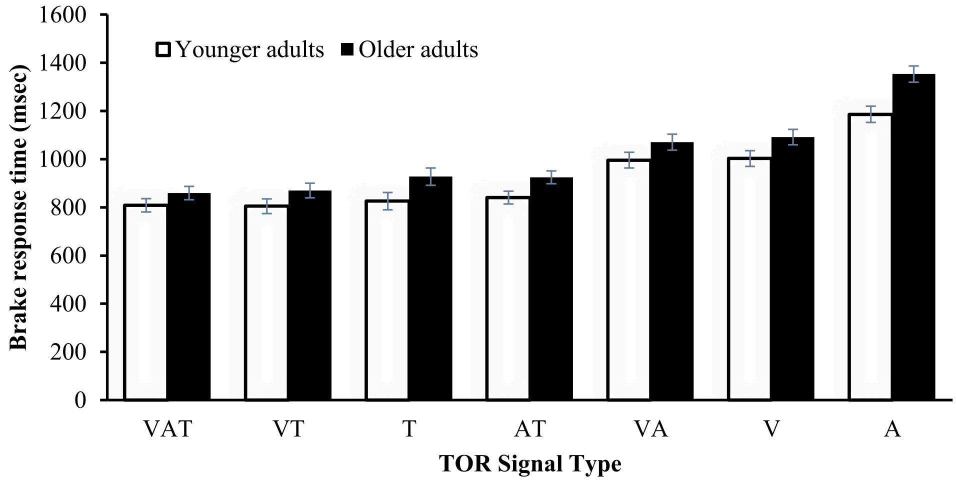

Fig. 4. Brake response time as a function of age and takeover request (TOR) signal type.

average fixation duration in the AOI region compared to the non-exercise group (mean = 288 msec, SEM = 19). Also, younger adults (mean = 353 s, SEM = 18) had a marginally longer average fixation duration in the AOI compared to older adults (mean = 303 msec, SEM = 19). See Fig. 7 for details.

3.3. Secondary task performance

For headway estimation accuracy, there was a significant main effect of age($F(1,44) = 8.167, p = .006, \eta_p^2 = .157$) on headway judgements. Specifically, older adults (mean = 72.7%, SEM = 3.2) had a significantly lower headway estimation accuracy than younger drivers (mean = 85.5%, SEM = 3.2).

For performance on the video knowledge assessment, a significant age × task condition interaction ($F(1,44) = 4.474, p = .040, \eta_p^2 = .092$) was observed. In particular, in the video watching task condition, the difference in accuracy percentage (difference = 0.0%, $p =$ 1.000) between the older (mean = 61.8%, SEM = 3.1) and younger groups (mean = 61.8%, SEM = 3.1) was smaller than in the combined (video watching and headway estimation) task condition (difference = 15.3%, $p =$ .027) between older (mean = 52.8%, SEM = 4.7) and younger adults (mean = 68.1%, SEM = 4.7).

4. Discussion

The goal of this study was to investigate the effects of age and physical exercise on performance differences in multimodal signal responses under different attention allocation conditions. Overall, bi- and trimodal signals were associated with faster brake response times for both age groups, but older adults responded more slowly and also had a higher brake force compared to younger adults. Additionally, engagement in physical exercise was associated with a smaller maximum braking force for younger drivers only, and a longer average fixation duration for everyone.

4.1. Driving-related measures

4.1.1. Brake response time

Somewhat contrary to our expectations, aerobic exercise did not produce a significant main effect on brake response time. Since the response time difference between the younger and older groups is already relatively small (i.e., 91 ms), the effects of physical exercise may not be apparent for our response time measure. The time differences reported in previous studies that found physical exercise to be associated with faster response speeds in older adults were also very small (e.g., 65–78 ms between exercise and non-exercise group in Ballesteros et al. (2013); and 12–69 ms in Marmeleira et al. (2009)) and these effects may be masked by the age effects. However, these studies did not generate data on the gains associated with exercise for younger adults, thus it is difficult to know whether the results are attributable only to exercise. Also, in our study, the signal response phase of a takeover process only included perception, processing, and movement (i.e., contact with the brake pedal). It did not contain significant decision-making components, such as planning for how to deactivate the automation, regaining environment and situation awareness, selecting courses of action (i.e., deciding the dynamic state of the vehicle after resuming control), nor executing actions (deciding how to maneuver). Thus, the benefits of physical exercise might reveal themselves in later, more involved, phases of the vehicle takeover process, such as decision-making regarding space availability in adjacent lanes and/or manual control of longitudinal and lateral accelerations and positions during post-takeover.

With respect to chronological age, older adults had longer brake response times to takeover request (TOR) warning signals than younger adults across the four driving conditions. This finding is consistent with previous studies mostly in manual driving (e.g., Lundqvist and Eriksson, 2019; Pitts and Sarter, 2018) and only a few in autonomous driving (Li et al., 2018, 2019), and potentially points to biological changes in perception, cognition, and physical abilities observed with age (Anstey et al., 2005). We also found both age groups to respond faster to multimodal TORs, compared to single modality signals (Biondi et al., 2017; Huang et al., 2019; Petermeijer et al., 2017; Politis et al., 2017; Yoon et al., 2019). In addition, any signal type that included a tactile component (i.e., T, AT, VT, and VAT) was associated with shorter brake response times for all ages (compared to those that did not; V, A, and VA, as shown in Fig. 4). Lundqvist and Eriksson (2019) explained that the benefits of trimodal warning signals are still debated, but Pitts and Sarter (2018) proposed that the inclusion of the tactile modality (with fastest conduction velocity) is what ultimately dictates the response time to multimodal signals. An additional, and alternative, explanation for why the signals that included the tactile modality had a faster response time compared to signals without a tactile cue may relate to the driving environment. It consisted of constant auditory input (i.e., sounds of the tires-on-the-road, the vehicle engine, and the video) as well as continuous visual information (i.e., monitoring the road elements in baseline condition, video watching and headway estimation in other conditions). Here, the tactile channel was most available (free) for detecting vibration information compared to the already occupied visual and auditory channels (Meng and Spence, 2015; Wickens, 2008).

The advantages of tactile signaling was also found for both age group. Specifically, older adults were only slower than younger adults in

Table 3
Summary statistics of the dependent measures for all independent variables.

	Age		Exercise		Signal Type							Task Condition				Interactions
	YA	OA	E	NE	V	A	T	VA	VT	AT	VAT	T1	T2	T3	T4	
BRT (msec)	923 (30)	1014 (30)	949 (30)	988 (30)	1047 (20)	1270 (22)	877 (26)	1033 (19)	837 (23)	883 (23)	834 (24)	926 (23)	955 (21)	1008 (24)	986 (21)	Age × Signal: F (4.0, 177.7) = 7.260 **p < .001*** η_p^2 = .142
	F (1, 44) = 4.503 **p = .040*** η_p^2 = .093		F (1, 44) = 0.854 p = .360 η_p^2 = .019		F (4.0, 177.7) = 517.384 **p < .001*** η_p^2 = .922							F (2.5, 109.8) = 21.267 **p < .001*** η_p^2 = .326				
MBF (N)	15.22 (1.443)	19.36 (1.44)	15.17 (1.44)	19.41 (1.44)	17.03 (1.05)	17.80 (1.14)	17.25 (.96)	17.04 (1.09)	17.49 (1.01)	16.85 (1.05)	17.56 (1.08)	16.28 (1.04)	18.08 (1.16)	17.20 (1.26)	17.59 (1.07)	Age × Exercise: F (1, 36) = 6.535 **p = .015*** η_p^2 = .154
	F (1, 36) = 4.121 **p = .050** η_p^2 = .103		F (1, 36) = 4.316 **p = .045** η_p^2 = .107		F (4.5, 161.7) = 1.385 p = .237 η_p^2 = .037							F (3, 108) = 1.781 p = .155 η_p^2 = .047				
Gaze (%)	37.4 (3.05)	24.6 (3.06)	32.2 (3.13)	29.6 (2.99)	–							–	36.0 (2.69)	–	25.8 (2.01)	–
	F (1, 40) = 8.436 **p = .006*** η_p^2 = .174		F (1, 40) = .363 p = .550 η_p^2 = .009		–							F (1, 40) = 27.044 **p < .001*** η_p^2 = .403				
AFD (msec)	353 (18)	303 (19)	368 (18)	288 (19)	–							–	332 (16)	–	324 (13)	–
	F (1, 35) = 3.576 p = .067 η_p^2 = .093		F (1, 35) = 9.204 **p = .005*** η_p^2 = .208		–							F (1, 35) = .366 p = .549 η_p^2 = .010				
HEA (%)	85.5 (3.2)	72.7 (3.2)	82.2 (3.2)	76.0 (3.2)	–							–	79.6 (2.4)	–	78.6 (2.6)	–
	F (1, 44) = 8.167 **p = .006*** η_p^2 = .157		F (1, 44) = 1.903 p = .175 η_p^2 = .041		–							F (1, 44) = .189 p = .666 η_p^2 = .004				
VKA (%)	64.9 (3.1)	57.3 (3.1)	64.2 (3.1)	58.0 (3.1)	–							–	61.8 (2.2)	–	60.4 (3.3)	Age × Task: F (1, 44) = 4.474 **p = .040*** η_p^2 = .092
	F (1, 44) = 3.113 p = .085 η_p^2 = .066		F (1, 44) = 2.084 p = .156 η_p^2 = .045		–							F (1, 44) = .148 p = .702 η_p^2 = .003				

Note: YA = younger adults; OA = older adults; T1 = baseline task condition; T2 = video watching task condition; T3 = headway estimation task condition; T4 = combination task condition; BRT = brake response time; MBF = maximum brake force (N = Newtons); GP = gaze proportion; AFD = average fixation duration; HEA = headway estimation accuracy; and VKA = video knowledge accuracy.

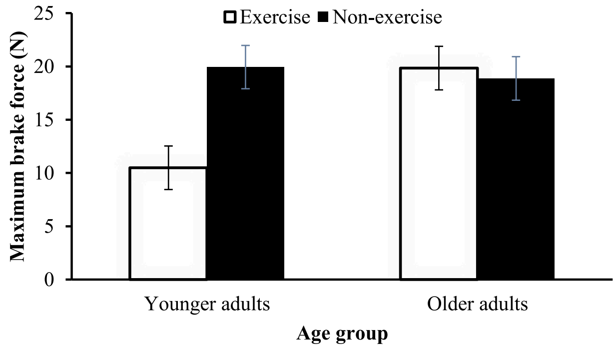

Fig. 5. Maximum brake force as a function of age and exercise type.

responding to single visual and auditory signals, but no differences were found between the two age groups for all other signals. This implies that older adults may benefit from multimodal signals, especially if the signal combination includes tactile information. In other words, age-related declines, resulting in delayed responses to warning signals, may be mitigated by multisensory integration (Laurienti et al., 2006; Peiffer et al., 2007).

For task condition, response times in the headway estimation and combination (of video watching and headway estimation) task conditions were longer compared to the baseline and video watching conditions. One possible explanation for this finding is that a higher level of precision was needed to accurately estimate headway in these conditions. Here, participants might have been performing a complex spatial mental calculation, and when the signals were presented, it took them slightly longer to task switch and recognize the warning signals.

4.1.2. Maximum brake force

Maximum brake force has been used as an indicator of collision risk (Aries, 2019; Dziuk, 2015). In our study, physical exercise and age both affected maximum brake force. Participants who did not perform aerobic exercises had a higher maximum brake force. This finding may be attributed to the fact that aerobic exercise makes use of repetitive leg movement and muscle activation. In this case, those who engage activity of their legs more frequently may benefit from better motor control. This hypothesis may be confirmed by comparing this result to data collected from tasks that utilize arm movements, such as steering while driving, since aerobic exercise also makes use of upper body movements. However, steering metrics were not collected as part of this study.

For age, there was a tendency for older drivers to brake harder than younger adults. This replicates a similar finding in Clark and Feng (2017) and could highlight the uncertain feelings that older adults express about autonomous driving (Abraham et al., 2017). For example, to date, many older adults have not yet had the chance to experience intermediate levels of vehicle automation, and thus their trust in this technology may not be built. Research has found that older adults may be more willing to use automated vehicles once the capabilities of these vehicles are demonstrated to them (Haghzare et al., 2021; Rahman et al., 2019). Therefore, it may take some time to build their trust and for older adults to become comfortable being able to divert their attention from forward driving, to some extent, and perform secondary tasks while in the vehicle. Another possible explanation might be that older participants recognize changes in their cognitive and physical abilities, which may hinder their ability to quickly respond to TOR alerts, and thus may cause them to adopt strategies to compensate for these age-related changes while driving (e.g., Molnar et al., 2015). For example, Marchese (2019) showed that older adults brake harder during manual driving while performing NDRTs to slow down in order to compensate for their slower responses and their attention lost due to the secondary tasks. This behavior may simply be carrying over to semi-autonomous driving.

Finally, there was an interaction effect between age and exercise on maximum brake force. Here, younger participants in the exercise group had a lower maximum brake force compared to older adults in the exercise group, while no difference was found between the two age groups in the non-exercise category. One possibility for this phenomenon is that the benefits of physical exercise, in terms of braking control, may not be determined only by aerobic exercise. In other words, in addition to aerobic exercises, many younger participants in this study also likely regularly performed anaerobic exercises (such as weightlifting), as well as other high intensity workouts that make use of leg and overall body strength.

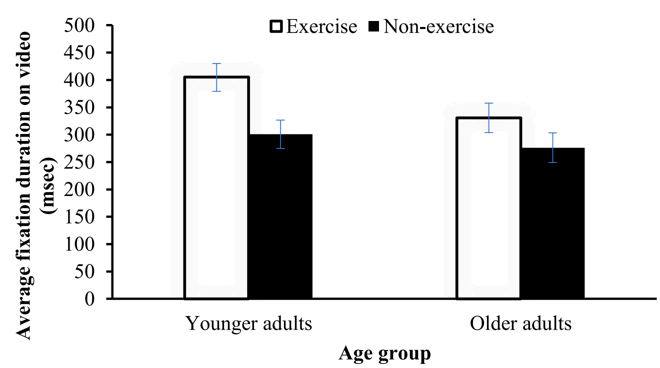

Fig. 7. Average fixation duration in the video region (AOI) as a function of age and exercise type.

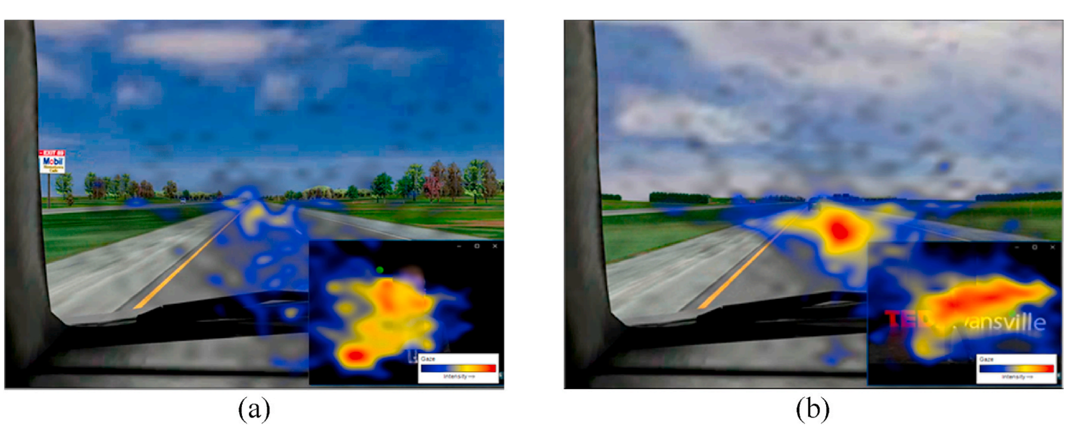

Fig. 6. Example gaze distributions for: (a) younger adults and (b) older adults. Video region (AOI) located in lower right-hand corner of the main display.

4.2. Eye movement measures

With respect to attention allocation, older participants had a lower percentage of gaze proportion on the video compared to younger adults. This suggests that older drivers focused their attention more on the driving environment than the video, even though they did not have to control the vehicle and knew that they would be asked a series of questions after the driving session. One likely reason for this observation could be self-regulatory practices enacted by older adults, which results in them being more conservative in manual driving and prioritizing safety over entertainment. Driving self-regulation, i.e., the changing of one's driving behavior in response to the acknowledgment of declines in abilities critical for driving (Charlton et al., 2006; Gwyther and Holland, 2012; Meng and Siren, 2012), usually includes actions such as driving at slower speeds, avoiding night time driving, and limiting in-vehicle distractions (Charlton et al., 2006; Molnar et al., 2015). Similar to the brake force effects discussed previously, this self-regulatory behavior may be being transferred to the semi-autonomous driving context.

Another possible explanation is that older adults could have lower trust level in automated vehicles (especially lower levels, such as SAE Levels 2–3) (Abraham et al., 2017; Rovira et al., 2019; Schoettle and Sivak, 2016). For example, a survey of 618 respondents showed that when asked if semi-autonomous vehicles were the only available option, roughly 62% of older adults were moderately or very concerned about riding in these vehicles, compared to only 36% of younger adults (Schoettle and Sivak, 2016). However, the authors did not provide explanations for this finding. Abraham et al. (2017) proposed that older adults' lifetime of driving experiences may make them uncomfortable in relinquishing control to the vehicle. This lack of trust may drive them to pay more attention to the road.

In addition, participants in the physical exercise group had a longer average fixation duration in the video region compared to those in the non-exercise group. This finding may infer that exercise helps with concentration, which is one aspect of inhibitory cognitive control in executive function (Ballesteros et al., 2013; Kao et al., 2017; Levin and Netz, 2015).

4.3. Secondary task performance

Older adults had worse performance on the headway estimation task, which is consistent with previous work (DeLucia et al., 2003) that reports lower accuracy in estimating time-to-collision in older adults. Boot, Stothart, and Charness (2014) and Czaja et al. (2019) explained that older drivers, in general, have difficulty judging headway distances, such as when turning across opposing traffic to make a left-hand turn. They explain that headway estimations require use of visual resources, spatial processing, and working memory, and that age-related decrements in any of these abilities will limit such judgment abilities (Boot et al., 2014; Czaja et al., 2019; DeLucia et al., 2003; Scialfa et al., 1991; Sekuler et al., 1980).

For the video knowledge assessment, as expected, older adults recalled fewer facts about the video (compared to younger adults) when they had to watch the video and estimate headway at the same time (combination task condition). Also, consistent with previous studies, while no age-related performance difference was found in the video watching condition alone, this observation may further highlight the relative difficulty older adults experience when divided attention is required to complete multiple unrelated tasks – a phenomenon highlighted by several decades of research (e.g., Erber, 2012; Horberry et al., 2006; Kemper et al., 2011; McDowd and Craik, 1988; McKnight and McKnight, 1993; Somberg and Salthouse, 1982; Son et al., 2011). In our study, older drivers performed worse on both the video knowledge assessment and the headway estimation task (in the combination task condition) when multiple tasks needed to be conducted simultaneously. Here, older participants seemed to prioritize tasks related to safety, i.e., focusing more attention on the road and the warning signals (as indicated by eye tracking data), which is in accordance with previous studies in terms of a safety prioritization strategy (e.g., Horberry et al., 2006; Son et al., 2011).

4.4. Limitations

One potential limitation of this study is the manner in which participants who exercise were recruited. Participants were grouped based on their self-reported exercising frequency. However, there was no upper limit (so some participants might have exercised daily) and engagement in particular types of physical activities (per person) might have changed within the past 5 or more years. These factors could have caused variability even within the exercise groups. Future research should explore ways to collect more precise data on exercise frequency and type, and/or conduct longitudinal studies over a specific timeframe to compare performance before and after an intervention of physical exercise (Marottoli et al., 2007). For instance, a longitudinal study with interventions of physical exercise could help to determine whether exercise leads to improvements in task performance (compared to only correlation effects). Similarly, some participants performed different types of aerobic exercises, and previous work (Diamond, 2015; Peruyero et al., 2017) suggests that enhancements to cognition are a function of exercise type, intensity, and duration. Thus, future work may attempt to control these variables.

In our experiment, we did not measure baseline maximum brake force, which could have helped to support explanations of our findings regarding muscle control and braking intensity. Similarly, steering wheel-related measures were not collected, which may reflect benefits of physical activities with respect to upper body functionality. Instead, we focused on brake pedal behavior because deciphering when the signal response phase stops and the post-takeover phase starts can be difficult when using steering wheel activity. Finally, this study focused on the signal response phase of the takeover process as a starting point. However, given the complexity of the task, follow-up work should examine the effects of physical exercise on the entire takeover process using timing between signals that is more representative of an actual takeover.

5. Conclusion

The non-chronological age factor, engagement in physical activity, was associated with better brake pedal control for younger adults, but did not help older adults as originally expected. However, chronological age differences were observed in that, compared to younger individuals, older adults had longer response times to warnings, larger maximum brake force, more gaze proportions on the driving environment, and poorer secondary task performance.

This research fills gaps in the aging and (vehicle) automation literature by taking first steps to generate empirical data on the effects that signaling modality and physical activity have on performance in the signal response phase of the takeover process. Results may contribute to the development of frameworks in this area. In terms of application, the findings may be beneficial to designers of next-generation (in-vehicle) warning systems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Abraham, H., Lee, C., Mehler, B., Reimer, B., 2017. Autonomous vehicles and alternatives to driving: trust, preferences, and effects of age learning to use technology view project. Transp. Res. Board 96th Annu. Meet.

Adrian, J., Postal, V., Moessinger, M., Rascle, N., Charles, A., 2011. Personality traits and executive functions related to on-road driving performance among older drivers. Accid. Anal. Prev. 43, 1652–1659. https://doi.org/10.1016/j.aap.2011.03.023.

Anstey, K.J., Wood, J., Lord, S., Walker, J.G., 2005. Cognitive, sensory and physical factors enabling driving safety in older adults. Clin. Psychol. Rev. 25, 45–65. https://doi.org/10.1016/j.cpr.2004.07.008.

Aries, K., 2019. Why monitor harsh braking and acceleration? | verizon connect. URL. https://www.verizonconnect.com/resources/article/harsh-braking-acceleration-why-monitor/. accessed 12.8.19.

Baldock, M.R.J., Mathias, J., McLean, J., Berndt, A., 2007. Visdual attention as a predictor of on-road driving performance of older drivers. Aust. J. Psychol. 59, 159–168. https://doi.org/10.1080/00049530701458035.

Ballesteros, S., Mayas, J., Reales, J., 2013. Does a physically active lifestyle attenuate decline in all cognitive functions in old age? Curr. Aging Sci. 6, 189–198. https://doi.org/10.2174/18746098112059990001.

Barnes, D.E., Yaffe, K., Satariano, W.A., Tager, I.B., 2003. A longitudinal study of cardiorespiratory fitness and cognitive function in healthy older adults. J. Am. Geriatr. Soc. 51, 459–465. https://doi.org/10.1046/j.1532-5415.2003.51153.x.

Binstock, R.H., 1985. The oldest old: a fresh perspective or compassionate ageism revisited? Milbank Meml. Fund Q. - Health & Soc. https://doi.org/10.2307/3349887.

Biondi, F., Strayer, D.L., Rossi, R., Gastaldi, M., Mulatti, C., 2017. Advanced driver assistance systems: using multimodal redundant warnings to enhance road safety. Appl. Ergon. 58, 238–244. https://doi.org/10.1016/j.apergo.2016.06.016.

Boot, W.R., Stothart, C., Charness, N., 2014. Improving the safety of aging road users: a mini-review. Gerontology 60, 90–96. https://doi.org/10.1159/000354212.

Caird, J.K., Chisholm, S.L., Lockhart, J., 2008. Do in-vehicle advanced signs enhance older and younger drivers' intersection performance? Driving simulation and eye movement results. Int. J. Hum. Comput. Stud. 66, 132–144. https://doi.org/10.1016/j.ijhcs.2006.07.006.

Carsten, O., Lai, F.C.H.H., Barnard, Y., Jamson, A.H., Merat, N., 2012. Control task substitution in semiautomated driving: does it matter what aspects are automated? Hum. Factors 54, 747–761. https://doi.org/10.1177/0018720812460246.

Charlton, J.L., Oxley, J., Fildes, B., Oxley, P., Newstead, S., Koppel, S., O'Hare, M., 2006. Characteristics of older drivers who adopt self-regulatory driving behaviours. Transport. Res. F Traffic Psychol. Behav. 9, 363–373. https://doi.org/10.1016/j.trf.2006.06.006.

Choi, D., Sato, T., Ando, T., Abe, T., Akamatsu, M., Kitazaki, S., 2020. Effects of cognitive and visual loads on driving performance after take-over request (TOR) in automated driving. Appl. Ergon. 85, 103074. https://doi.org/10.1016/j.apergo.2020.103074.

Clark, H., Feng, J., 2017. Age differences in the takeover of vehicle control and engagement in non-driving-related activities in simulated driving with conditional automation. Accid. Anal. Prev. 106, 468–479. https://doi.org/10.1016/j.aap.2016.08.027.

Czaja, S.J., Boot, W.R., Charness, N., Rogers, W.A., 2019. Designing for Older Adults: Principles and Creative Human Factors Approaches, Designing for Older Adults. CRC Press. https://doi.org/10.1201/b22189.

Deary, I.J., Der, G., 2005. Reaction time, age, and cognitive ability: longitudinal findings from age 16 to 63 years in representative population samples. Aging Neuropsychol. Cognit. 12, 187–215. https://doi.org/10.1080/13825580590969235.

DeLucia, P.R., Bleckley, M.K., Meyer, L.E., Bush, J.M., 2003. Judgments about collision in younger and older drivers. Transport. Res. F Traffic Psychol. Behav. 6, 63–80. https://doi.org/10.1016/S1369-8478(02)00047-5.

Der, G., Deary, I.J., 2006. Age and sex differences in reaction time in adulthood: results from the United Kingdom health and lifestyle survey. Psychol. Aging 21, 62–73. https://doi.org/10.1037/0882-7974.21.1.62.

Diamond, A., 2015. Effects of physical exercise on executive functions: going beyond simply moving to moving with thought. Ann. Sport. Med. Res. 2, 1011.

Dogan, E., Rahal, M.C., Deborne, R., Delhomme, P., Kemeny, A., Perrin, J., 2017. Transition of control in a partially automated vehicle: effects of anticipation and non-driving-related task involvement. Transport. Res. F Traffic Psychol. Behav. 46, 205–215. https://doi.org/10.1016/j.trf.2017.01.012.

Dziuk, B., 2015. Why you should monitor hard braking and acceleration. URL. https://info.rastrac.com/blog/monitor-hard-braking-and-acceleration. accessed 12.8.19.

Era, P., Jokela, J., Heikkinen, E., 1986. Reaction and movement times in men of different ages: a population study. Percept. Mot. Skills 63, 111–130. https://doi.org/10.2466/pms.1986.63.1.111.

Erber, J.T., 2012. Aging and Older Adulthood 466. Wiley-Blackwell.

Eriksson, A., Petermeijer, S.M., Zimmermann, M., De Winter, J.C.F., Bengler, K.J., Stanton, N.A., 2019. Rolling out the red (and Green) Carpet: supporting driver decision making in automation-to-manual transitions. IEEE Trans. Human-Machine Syst. 49, 20–31. https://doi.org/10.1109/THMS.2018.2883862.

Eriksson, A., Stanton, N.A., 2017. Takeover time in highly automated vehicles: noncritical transitions to and from manual control. Hum. Factors 59, 689–705. https://doi.org/10.1177/0018720816685832.

Folstein, M., Folstein, S., McHugh, P., 1975. Mini-mental state (MMSE). J. Psychiatr. Res.

Fozard, J.L., Vercruyssen, M., Reynolds, S.L., Hancock, P.A., Quilter, R.E., 1994. Age differences and changes in reaction time: the Baltimore Longitudinal Study of Aging. Journal of gerontology.

Gauchard, G.C., Gangloff, P., Jeandel, C., Perrin, P.P., 2003. Physical activity improves gaze and posture control in the elderly. Neurosci. Res. 45, 409–417. https://doi.org/10.1016/S0168-0102(03)00008-7.

Gottlob, L.R., 2007. Aging and capacity in the same-different judgment. Aging Neuropsychol. Cognit. 14, 55–69. https://doi.org/10.1080/138255890969528.

Gwyther, H., Holland, C., 2012. The effect of age, gender and attitudes on self-regulation in driving. Accid. Anal. Prev. 45, 19–28. https://doi.org/10.1016/j.aap.2011.11.022.

Haghzare, S., Campos, J.L., Bak, K., Mihailidis, A., 2021. Older adults' acceptance of fully automated vehicles: effects of exposure, driving style, age, and driving conditions. Accid. Anal. Prev. 150, 105919. https://doi.org/10.1016/j.aap.2020.105919.

Hassan, H., King, M., Watt, K., 2015. The perspectives of older drivers on the impact of feedback on their driving behaviours: a qualitative study. Transport. Res. F Traffic Psychol. Behav. 28, 25–39. https://doi.org/10.1016/J.TRF.2014.11.003.

He, N., Dubno, J.R., Mills, J.H., 1998. Frequency and intensity discrimination measured in a maximum-likelihood procedure from young and aged normal-hearing subjects. J. Acoust. Soc. Am. 103, 553–565. https://doi.org/10.1121/1.421127.

Horberry, T., Anderson, J., Regan, M.A., Triggs, T.J., Brown, J., 2006. Driver distraction: the effects of concurrent in-vehicle tasks, road environment complexity and age on driving performance. Accid. Anal. Prev. 38, 185–191. https://doi.org/10.1016/j.aap.2005.09.007.

Huang, G., Steele, C., Zhang, X., Pitts, B.J., 2019. Multimodal cue combinations: a possible approach to designing in-vehicle takeover requests for semi-autonomous driving. Proc. Hum. Factors Ergon. Soc. Annu. Meet. 63, 1739–1743. https://doi.org/10.1177/1071181319631053.

Kao, S.C., Westfall, D.R., Soneson, J., Gurd, B., Hillman, C.H., 2017. Comparison of the acute effects of high-intensity interval training and continuous aerobic walking on inhibitory control. Psychophysiology 54, 1335–1345. https://doi.org/10.1111/psyp.12889.

Kemper, S., Schmalzried, R., Herman, R., Mohankumar, D., 2011. The effects of varying task priorities on language production by young and older adults. Exp. Aging Res. 37, 198–219. https://doi.org/10.1080/0361073X.2011.554513.

Körber, M., Gold, C., Lechner, D., Bengler, K., 2016. The influence of age on the take-over of vehicle control in highly automated driving. https://doi.org/10.1016/j.trf.2016.03.002, 39, 19-32.

Körber, M., Prasch, L., Bengler, K., 2018. Why do I have to drive now? Post hoc explanations of takeover requests. Hum. Factors 60, 305–323. https://doi.org/10.1177/0018720817747730.

Kosinski, R.J., 2008. A literature review on reaction time. Clemson University 10 (1). http://www.cognaction.org/cogs105/readings/clemson.rt.pdf.

Laurienti, P.J., Burdette, J.H., Maldjian, J.A., Wallace, M.T., 2006. Enhanced multisensory integration in older adults. Neurobiol. Aging 27, 1155–1163. https://doi.org/10.1016/j.neurobiolaging.2005.05.024.

Lemke, U., 2009. The challenges of aging – sensory, cognitive, socio-emotional and health changes in old age. In: Hearing Care for Adults 2009—The Challenge of Aging. Proceedings of the 2nd International Adult Conference. Phonak AG, Stäfa, Switzerland, pp. 33–43.

Levin, O., Netz, Y., 2015. Aerobic training as a means to enhance inhibition: what's yet to be studied? Eur. Rev. Aging Phys. Act. 12, 1–4. https://doi.org/10.1186/s11556-015-0160-9.

Li, S., Blythe, P., Guo, W., Namdeo, A., 2019. Investigating the effects of age and disengagement in driving on driver's takeover control performance in highly automated vehicles. Transport. Plann. Technol. 42, 470–497. https://doi.org/10.1080/03081060.2019.1609221.

Li, S., Blythe, P., Guo, W., Namdeo, A., 2018. Investigation of older driver's takeover performance in highly automated vehicles in adverse weather conditions. IET Intell. Transp. Syst. 12, 1157–1165. https://doi.org/10.1049/iet-its.2018.0104.

Litman, T., 2017. Autonomous Vehicle Implementation Predictions: Implications for Transport Planning. Transport Policy Institute, Victoria, Canada.

Liu, Y.C., 2001. Comparative study of the effects of auditory, visual and multimodality displays on drivers' performance in advanced traveler information systems. Ergonomics 44, 425–442. https://doi.org/10.1080/00140130010011369.

Llaneras, R.E., Salinger, J., Green, C.A., 2013. Human factors issues associated with limited ability autonomous driving systems: drivers' allocation of visual attention to the forward roadway. Proc. Seventh Int. Driv. Symp. Hum. Factors Driv. Assessment, Training, Veh. Des. 92–98 https://doi.org/10.17077/drivingassessment.1472.

Luchies, C.W., Schiffman, J., Richards, L.G., Thompson, M.R., Bazuin, D., DeYoung, A.J., 2002. Effects of age, step direction, and reaction condition on the ability to step quickly. Journals Gerontol. - Ser. A Biol. Sci. Med. Sci. 57, M246–M249. https://doi.org/10.1093/gerona/57.4.M246.

Lundqvist, L.M., Eriksson, L., 2019. Age, cognitive load, and multimodal effects on driver response to directional warning. Appl. Ergon. 76, 147–154. https://doi.org/10.1016/j.apergo.2019.01.002.

Marchese, C., 2019. Distracted Driving and Crash Responsibility in Fatal USA Collisions 1991-2015.

Marmeleira, J.F., Godinho, M.B., Fernandes, O.M., 2009. The effects of an exercise program on several abilities associated with driving performance in older adults. Accid. Anal. Prev. 41, 90–97. https://doi.org/10.1016/j.aap.2008.09.008.

Marottoli, R., Richardson, E., Stowe, M., Miller, E., Brass, L., Cooney, L., Tinetti, M., 1998. Development of a test battery to identify older drivers at risk for self-reported adverse driving events. J. Am. Geriatr. Soc. 46, 562–568. https://doi.org/10.1111/j.1532-5415.1998.tb01071.x.

Marottoli, R.A., Allore, H., Araujo, K.L.B., Iannone, L.P., Acampora, D., Gottschalk, M., Charpentier, P., Kasl, S., Peduzzi, P., 2007. A randomized trial of a physical conditioning program to enhance the driving performance of older persons. J. Gen. Intern. Med. 22, 590–597. https://doi.org/10.1007/s11606-007-0134-3.

McDonald, A.D., Alambeigi, H., Engström, J., Markkula, G., Vogelpohl, T., Dunne, J., Yuma, N., 2019. Toward computational simulations of behavior during automated driving takeovers: a review of the empirical and modeling literatures. Hum. Factors. https://doi.org/10.1177/0018720819829572.

McDowd, J.M., Craik, F.I.M., 1988. Effects of aging and task difficulty on divided attention performance. J. Exp. Psychol. Hum. Percept. Perform. 14, 267–280. https://doi.org/10.1037/0096-1523.14.2.267.

McKnight, A.J., McKnight, A.S., 1993. The effect of cellular phone use upon driver attention. Accid. Anal. Prev. 25, 259–265. https://doi.org/10.1016/0001-4575(93)90020-W.

McPhee, L.C., Scialfa, C.T., Dennis, W.M., Ho, G., Caird, J.K., 2004. Age differences in visual search for traffic signs during a simulated conversation. Hum. Factors 46, 674–685. https://doi.org/10.1518/hfes.46.4.674.56817.

Meng, A., Siren, A., 2012. Cognitive problems, self-rated changes in driving skills, driving-related discomfort and self-regulation of driving in old drivers. Accid. Anal. Prev. 49, 322–329.

Meng, F., Spence, C., 2015. Tactile warning signals for in-vehicle systems. Accid. Anal. Prev. 75, 333–346. https://doi.org/10.1016/j.aap.2014.12.013.

Miller, D., Johns, M., Ive, H.P., Gowda, N., Sirkin, D., Sibi, S., Mok, B., Aich, S., Ju, W., 2016. Exploring transitional automation with new and old drivers. SAE Tech. Pap. https://doi.org/10.4271/2016-01-1442.

Mok, B., Johns, M., Lee, K.J., Miller, D., Sirkin, D., Ive, P., Ju, W., 2015. Emergency, automation off: unstructured transition timing for distracted drivers of automated vehicles. In: IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC. IEEE, pp. 2458–2464. https://doi.org/10.1109/ITSC.2015.396.

Molnar, L., Eby, D., Zhang, L., Zanier, N., Louis, R., Kostyniuk, L., 2015. Self-regulation of driving by older adults: a synthesis of the literature and framework. Aging (Albany. NY) 20, 227–235.

Molnar, L.J., Eby, D.W., St Louis, R.M., Neumeyer, A.L., 2007. Promising Approaches for Promoting Lifelong Community Mobility. Ann Arbor.

Molnar, L.J., Pradhan, A.K., Eby, D.W., Ryan, L.H., St Louis, R.M., Zakrajsek, J., Ross, B., Lin, B.T., Liang, C., Zalewski, B., Zhang, L., St Louis, R.M., Zakrajsek, J., Ross, B., Lin, B.T., Liang, C., Zalewski, B., Zhang, L., 2017. Age-Related Differences in Driver Behavior Associated with Automated Vehicles and the Transfer of Control between Automated and Manual Control: A Simulator Evaluation. Umtri 2017-4.

Muiños, M., Ballesteros, S., 2018. Does physical exercise improve perceptual skills and visuospatial attention in older adults? A review. Eur. Rev. Aging Phys. Act. https://doi.org/10.1186/s11556-018-0191-0.

Müller, P., Rehfeld, K., Schmicker, M., Hökelmann, A., Dordevic, M., Lessmann, V., Brigadski, T., Kaufmann, J., Müller, N.G., 2017. Evolution of neuroplasticity in response to physical activity in old age: the case for dancing. Front. Aging Neurosci. 9 https://doi.org/10.3389/fnagi.2017.00056.

Nasreddine, Z.S., Phillips, N.A., Bédirian, V., Charbonneau, S., Whitehead, V., Collin, I., Cummings, J.L., Chertkow, H., 2005. The Montreal Cognitive Assessment, MoCA: a brief screening tool for mild cognitive impairment. J. Am. Geriatr. Soc. 53, 695–699. https://doi.org/10.1111/j.1532-5415.2005.53221.x.

National Research Council, 2004. Technology for Adaptive Aging. Steering Committee for the Workshop on Technology for Adaptive Aging. National Academies Press.

Naujoks, F., Befelein, D., Wiedemann, K., Neukum, A., 2018. A review of non-driving-related tasks used in studies on automated driving. Adv. Intell. Syst. Comput. 597, 525–537. https://doi.org/10.1007/978-3-319-60441-1_52.

Ni, R., Kang, J.J., Andersen, G.J., 2010. Age-related declines in car following performance under simulated fog conditions. Accid. Anal. Prev. 42, 818–826. https://doi.org/10.1016/j.aap.2009.04.023.

Niles, J., 2019. Automated Vehicles Have Arrived: what' S a Transit Agency to Do?.

Panek, P.E., Barrett, G.V., Sterns, H.L., Alexander, R.A., 1977. A review of age changes in perceptual information processing ability with regard to driving. Exp. Aging Res. 3, 387–449. https://doi.org/10.1080/03610737708257117.

Peiffer, A.M., Mozolic, J.L., Hugenschmidt, C.E., Laurienti, P.J., 2007. Age-related multisensory enhancement in a simple audiovisual detection task. Neuroreport 18, 1077–1081. https://doi.org/10.1097/WNR.0b013e3281e72ae7.

Peruyero, F., Zapata, J., Pastor, D., Cervelló, E., 2017. The acute effects of exercise intensity on inhibitory cognitive control in adolescents. Front. Psychol. 8 https://doi.org/10.3389/fpsyg.2017.00921.

Petermeijer, S., Bazilinskyy, P., Bengler, K., de Winter, J., 2017. Take-over again: investigating multimodal and directional TORs to get the driver back into the loop. Appl. Ergon. 62, 204–215. https://doi.org/10.1016/j.apergo.2017.02.023.

Petermeijer, S.M., De Winter, J.C.F., Bengler, K.J., 2016. Vibrotactile displays: a survey with a view on highly automated driving. IEEE Trans. Intell. Transport. Syst. https://doi.org/10.1109/TITS.2015.2494873.

Pitts, B.J., Riggs, S.L., Sarter, N., 2016. Crossmodal matching: a critical but neglected step in multimodal research. IEEE Trans. Human-Machine Syst. 46, 445–450. https://doi.org/10.1109/THMS.2015.2501420.

Pitts, B.J., Sarter, N., 2018. What you don't notice can harm you: age-related differences in detecting concurrent visual, auditory, and tactile cues. Hum. Factors 60, 445–464. https://doi.org/10.1177/0018720818759102.

Politis, I., Brewster, S., Pollick, F., 2017. Using multimodal displays to signify critical handovers of control to distracted autonomous car drivers. Int. J. Mobile Hum. Comput. Interact. 9, 1–16. https://doi.org/10.1016/j.bbapap.2014.08.013.

Rahman, M.M., Deb, S., Strawderman, L., Burch, R., Smith, B., 2019. How the older population perceives self-driving vehicles. Transport. Res. F Traffic Psychol. Behav. 65, 242–257. https://doi.org/10.1016/j.trf.2019.08.002.

Reitan, R.M., 1958. Validity of the Trail making test as an indicator of organic brain damage. Percept. Mot. Skills 8, 271–276. https://doi.org/10.2466/pms.1958.8.3.271.

Roche, F., Brandenburg, S., 2020. Should the urgency of visual-tactile takeover requests match the criticality of takeover situations. IEEE Trans. Intell. Veh. 5, 306–313. https://doi.org/10.1109/TIV.2019.2955906.

Rovira, E., McLaughlin, A.C., Pak, R., High, L., 2019. Looking for age differences in self-driving vehicles: examining the effects of automation reliability, driving risk, and physical impairment on trust. Front. Psychol. 10, 800. https://doi.org/10.3389/fpsyg.2019.00800.

SAE International, 2018. Sae J3016: taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. SAE Int 1.

Salthouse, T.A., 2000. Aging and measures of processing speed. Biol. Psychol. 54, 35–54. https://doi.org/10.1016/S0301-0511(00)00052-1.

Salthouse, T.A., 1998. Relation of successive percentiles of reaction time distributions to cognitive variables and adult age. Intelligence 26, 153–166. https://doi.org/10.1016/S0160-2896(99)80059-2.

Schoettle, B., Sivak, M., 2016. Motorists' Preferences for Different Levels of Vehicle Automation (Umtri-2015-22).

Scialfa, C.T., Guzy, L.T., Leibowitz, H.W., Garvey, P.M., Tyrrell, R.A., 1991. Age differences in estimating vehicle velocity. Psychol. Aging 6, 60–66. https://doi.org/10.1037/0882-7974.6.1.60.

Sekuler, R., Hutman, L.P., Owsley, C.J., 1980. Human aging and spatial vision. Science 209, 1255–1256. https://doi.org/10.1126/science.7403884, 80.

Society of Automotive Engineers, 2015. Operational Definitions of Driving Performance Measures and Statistics. SAE, Warrendale, PA.

Somberg, B.L., Salthouse, T.A., 1982. Divided attention abilities in young and old adults. J. Exp. Psychol. Hum. Percept. Perform. 8, 651–663. https://doi.org/10.1037/0096-1523.8.5.651.

Son, J., Lee, Y., Kim, M.H., 2011. Impact of traffic environment and cognitive workload on older drivers' behavior in simulated driving. Int. J. Precis. Eng. Manuf. 12, 135–141. https://doi.org/10.1007/s12541-011-0017-8.

Stinchcombe, A., Gagnon, S., 2013. Aging and driving in a complex world: exploring age differences in attentional demand while driving. Transport. Res. F Traffic Psychol. Behav. 17, 125–133. https://doi.org/10.1016/j.trf.2012.11.002.

Vespa, J., Armstrong, D.M., Medina, L., 2018. *Demographic turning points for the United States: Population projections for 2020 to 2060*. Washington, DC: US Department of Commerce, Economics and Statistics Administration, US Census Bureau.

Vipperla, R., Renals, S., Frankel, J., 2010. Ageing voices: the effect of changes in voice parameters on ASR performance. EURASIP J. Audio Speech Music Process. https://doi.org/10.1155/2010/525783, 2010.

Voelcker-Rehage, C., Godde, B., Staudinger, U.M., 2011. Cardiovascular and coordination training differentially improve cognitive performance and neural processing in older adults. Front. Hum. Neurosci. 5, 26. https://doi.org/10.3389/fnhum.2011.00026.

Voss, M.W., Erickson, K.I., Prakash, R.S., Chaddock, L., Malkowski, E., Alves, H., Kim, J. S., Morris, K.S., White, S.M., Wójcicki, T.R., Hu, L., Szabo, A., Klamm, E., McAuley, E., Kramer, A.F., 2010. Functional connectivity: a source of variance in the association between cardiorespiratory fitness and cognition? Neuropsychologia 48, 1394–1406. https://doi.org/10.1016/j.neuropsychologia.2010.01.005.

Wickens, C.D., 2008. Multiple resources and mental workload. Hum. Factors J. Hum. Factors Ergon. Soc. 50, 449–455. https://doi.org/10.1518/001872008X288394.

Winkler, S., Kazazi, J., Vollrath, M., 2018. How to warn drivers in various safety-critical situations – different strategies, different reactions. Accid. Anal. Prev. 117, 410–426. https://doi.org/10.1016/j.aap.2018.01.040.

Yanko, M.R., Spalek, T.M., 2014. Driving with the wandering mind: the effect that mind-wandering has on driving performance. Hum. Factors 56, 260–269. https://doi.org/10.1177/0018720813495280.

Yoon, S.H., Kim, Y.W., Ji, Y.G., 2019. The effects of takeover request modalities on highly automated car control transitions. Accid. Anal. Prev. 123, 150–158. https://doi.org/10.1016/j.aap.2018.11.018.

Yoon, S.H., Lee, S.C., Ji, Y.G., 2021. Modeling takeover time based on non-driving-related task attributes in highly automated driving. Appl. Ergon. 92, 103343. https://doi.org/10.1016/j.apergo.2020.103343.

Zeeb, K., Buchner, A., Schrauf, M., 2015. What determines the take-over time? An integrated model approach of driver take-over after automated driving. Accid. Anal. Prev. 78, 212–221. https://doi.org/10.1016/j.aap.2015.02.023.

Zettel-Watson, Laura, Suen, Meagan, Wehbe, Lara, Rutledge, Dana, Cherry, Barbara, 2017. Aging well: Processing speed inhibition and working memory related to balance and aerobic endurance. Geriatrics and Gerontology International.

Zhang, B., de Winter, J., Varotto, S., Happee, R., Martens, M., 2019. Determinants of take-over time from automated driving: a meta-analysis of 129 studies. Transport. Res. F Traffic Psychol. Behav. 64, 285–307. https://doi.org/10.1016/j.trf.2019.04.020.