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High-speed curve negotiation: Can differences in expertise account for the different effects of cognitive load?

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ABSTRACT

The role of expertise in the relationship between cognitive load (CL) and driving performance has received little scientific attention. This real-world study included 8 expert race car drivers and 10 non-expert drivers, who were driving on a racetrack while simultaneously performing cognitively distracting secondary tasks. The experiment examined whether the effects of CL on high-speed driving performance of hairpin, compound, and reverse curves are influenced by drivers' expertise. In general, we found that non-expert drivers were not any more vulnerable to CL-induced performance decrements than skilled expert drivers, although the relationship between driving expertise and CL appeared to be task- and curve type-dependent. While between-group differences in secondary task performance were not obtained, speed was found to decrease in CL conditions but only in sharp hairpin curves. Additionally, CL affected experts' and non-experts' lateral performance in all curve types, although a clear relationship between trajectory deviations and steering corrections was not obtained. While the effects of CL appear to be the most prominent in sharp hairpin curves, the findings of this study suggest curve geometry as a variable that needs greater attention in future studies.

1. Introduction

That better driving skills are crucial for traffic safety has been confirmed in many earlier studies, demonstrating that, for instance, less experienced drivers more often fail to slow down appropriately when challenges of the driving task increase, such as when navigating a curve or driving in adverse weather (Abdel-Aty & Radwan, 2000; Clarke et al., 2006; McKnight & McKnight, 2003). While the ubiquitous addition of modern in-vehicle systems has worsened this state in recent years, leading to increased engagement in non-driving related activities, scientific research has predominantly focused on the negative effects of these systems rather than finding preventive measures to mitigate their impact. Although driving expertise has been recognized as a critical factor for driving safety (Durso & Dattel, 2006; van Leeuwen et al., 2017), whether and to what extent it benefits cognitively challenging situations remains largely a matter of theoretical discussions without solid empirical evidence.

Even though extensive research has been conducted on cognitive distraction, which takes drivers' mind off the road and away from safe driving performance, the entire scope of safety implications caused by activities which increase drivers' cognitive load (CL) without redirecting their gaze from the road ahead, is yet unknown. Although there is no single accepted theory of CL, it is generally

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believed that CL is proportional to the “amount” of cognitive control that a secondary activity, commonly not related to driving, requires of the driver (Engström et al., 2017; Fuller, 2005). Engström and colleagues (2017) analyzed existing findings on the effects of CL on driving performance and concluded that CL does not affect automatized activities, while selectively impairs components of driving that rely on cognitive control, i.e., unfamiliar, or fundamentally challenging activities. However, driving literature shows that even vehicle control skills, which are believed to be easily automatized (de Waard, 1996; Michon, 1985), do not always exhibit pure automatic behavior under CL (de Waard, 1996; Engström et al., 2017). For instance, CL has been shown to affect drivers' speed management, sometimes resulting in significantly reduced vehicle speeds, and other times leading to significantly higher and more variable speeds (Engström et al., 2017). Similarly, many driving simulator studies have shown that cognitively loaded drivers tend to drive closer to the centreline, which is believed to be the result of CL-induced gaze concentration towards the road centre and consequent guidance of steering movements (Engström et al., 2005; Kountouriotis et al., 2015; Li et al., 2018). However, evidence of this behaviour from naturalistic studies is scarce (e.g., Chen et al., 2019; Engström et al., 2005; Östlund et al., 2006), and Chen and colleagues (2019) concluded that while there was no clear relationship between CL and lane keeping performance in their real-world study, the relationship between CL and speed appeared to be bidirectional. Namely, speed significantly increased drivers' CL while the increase in CL reduced their ability to manage and maintain speed. This is consistent with Young and colleagues' (2015) conclusion that CL is not only determined by performers' capabilities but also by task demands, both of which can be potentially influenced by context. Indeed, road alignment and curve characteristics are recognized as one of the factors that define the complexity of the driving task and, implicitly, the workload it imposes on drivers (Onate-Vega et al., 2020; Theeuwes, 2010; Theeuwes, 2021), and its adverse effects on driving performance are more pronounced among less skilled drivers (Abdel-Aty & Radwan, 2000; Clarke et al., 2006; McKnight & McKnight, 2003). This was shown by Onate-Vega and colleagues (2020) who found that curved roads reduced driving speeds and increased variation in speed and lateral position compared to straight segments and tunnels. Moreover, the effect of road geometry was stronger than the effect of secondary cognitive activity, whose impact on longitudinal and lateral performance was not obtained (Onate-Vega et al., 2020). Oviedo-Trespalacios and colleagues (2017), on the other hand, found that cognitively loaded drivers reduced their speed more while driving on sharp bends than on curved roads or straight segments.

As task demands are thought to be inversely proportional to the degree of automatic processes one develops through experience (Fitts & Posner, 1967; Logan, 1985; Wheatley & Wegner, 2001), drivers who become more adept at controlling the vehicle, eventually achieving automaticity, get their cognitive resources freed up for observing the environment (Patten et al., 2006), adapting their behavior (Durso & Dattel, 2006), or even performing different non-driving related activities (Engström et al., 2017; Patten et al., 2006). Identical task requirements, therefore, may place different demands on novice, experienced, and highly trained experts, and the less resources are required for a certain activity, the less performance will be affected (de Waard, 1996; Engström et al., 2017; Fuller, 2005). However, expertise is not a factor commonly investigated in driving studies, and many times it is cofounded with experience, with both concepts often being quantified by either average annual mileage or the number of years operating the vehicle. This might be one of the reasons why several studies have shown that experts do not necessarily outperform less experienced individuals (Ericsson & Lehmann, 1996; McKenna & Farrand, 1999), suggesting that for certain driving subtasks experience is no guarantee of expertise. Although these two terms are often used interchangeably, it is plausible to conclude that most drivers who have been driving for years might be considered experienced, but they can hardly be considered experts. Experience, however, can be seen as an important element of expertise (Duncan et al., 1991; Simons-Morton & Ehsani, 2016) which, according to Ericsson and colleagues (1993; Helton, 2008; Lappi, 2018; Simons-Morton & Ehsani, 2016), is the outcome of a prolonged period of learning that occurs through extensive and deliberate practice. This has been confirmed by studies on expert racing drivers which show that their superior performance is based on broad knowledge and skills that have been refined over many years of practice (Lappi, 2018; Lappi, 2022).

To the best of our knowledge, there are no studies on the effects of CL on experts' and non-experts' driving performance while navigating high-speed curves. Based on existing theoretical models (Engström et al., 2017; Fuller, 2005), when compared to expert drivers, non-experts should be more vulnerable to interruptions from a cognitively demanding task, but as some actions become automated rather quickly, there should be a substantial task dependence in the relationship between driving expertise and CL (Engström et al., 2017). Therefore, this real-world study was designed to determine if CL exerts a different influence on the longitudinal and lateral driving performance of expert and non-expert drivers while negotiating hairpin, compound, and reverse curves at high speeds. Expert drivers were expected to reach and maintain higher driving speeds in all curve types, and to demonstrate lower deviations from the optimal line, irrespective of CL. Due to CL-induced gaze concentration (Engström et al., 2017), steering smoothness was expected to decrease while corrections were expected to increase, particularly in low visibility hairpin curves. However, a decrease in smoothness under CL was expected for experts, as they are believed to rely more on far-road information and peripheral steering corrections, while non-experts, relying on near-road information, were expected to make more small steering corrections when cognitively loaded (Lappi et al., 2017; Lehtonen et al., 2014).

2. Method

2.1. Participants

Eighteen male participants (M_{age} = 32.55, SD = 8.51) were recruited for this study. The inclusion criteria assured that all participants held a valid driving license for at least 10 years, drove at least 15,000 km per year, and reported zero racing experience (non-experts) or at least 10 years of racing experience together with a valid FIA (Fédération Internationale de l'Automobile) driver's license (experts). All participants were recruited through the Rimac Automobili Participant Pool. For this study, the final combination of participants included 10 non-expert drivers (M_{age} = 29.10, SD = 5.61) who had no previous real-world or virtual motorsport experience and had their driving licenses for 13.20 years (SD = 4.19) and 8 expert drivers (M_{age} = 36.88, SD = 9.45) who had on average 11.50 years (SD = 1.48) of racing experience and held their licenses for 19.13 years (SD = 9.21). All participants drove regularly, with non-experts reporting 2.4 h (SD = 0.77) driving on an average weekday, compared to experts who reported 5.38 h (SD = 2.54). Before taking part in the study, they all supplied written informed consent. Participants did not receive monetary compensation for participation in the study.

2.2. Driving environment

The study was conducted at NAVAK, a 2800 m long racetrack (Fig. 1) with seven horizontal curves and without any vertical curvature or superelevation. The width of the track was 8 m in curves and 12 m in straight segments, bordered by wide run-off areas. All but one curve was preceded by a straight segment. Three curves were reverse curves (i.e., S-shape curves, where two adjacent curves, one left and one right, are divided by a short tangent), two were compound curves – one right and one left, and two were right-hand hairpin curves (i.e., U-shape curves). The track surface was dry, and the temperature was between 15 and 20 °C.

Curves were defined based on an optimal racing line, contrary to the common approach where curve elements (entry and exit points) and geometry, such as radius or length, are described using a centreline. Studies have shown that curve-cutting strategy is the most frequent strategy that drivers use while negotiating different curves (especially small radius curves), while behaviour assumed in the design standards that corresponds to a symmetrical curve path within a narrow area along the centre of the lane was hardly ever found (Spacek, 2005; Yu et al., 2021; Yuan-Yuan et al., 2012). As shown in Fig. 1, whether the curves are defined based on the centreline or optimal line is not the same, since, for example, the optimal line radius is greater than the centreline radius and curve entry/exit points are different which, consequently, affects curve length. It is believed that the optimal line better represents the data of this study since curve cutting is a common strategy in racing as it allows curve negotiation at higher speeds (this can also be seen in Figure 13, Appendix A, showing mean lateral performance with respect to the optimal line). Curved segments were, therefore, defined in a way that curvature[1] was calculated for every point along the optimal line (P_i; every 20 cm) to get the points where the curves started and ended or the points where the curvature changed, such as in s-shape or compound curves. While the straight-line distance between these points was used to calculate the curve radius, the curve length was measured along the arc. The geometric characteristics of curves and preceding segments can be seen in Fig. 1.

2.3. Data acquisition and analysis

The test vehicle was a Kia Stinger GT, equipped with a 368-hp twin-turbo 3.3-liter V-6 front engine and an eight-speed automatic transmission. The front brake pads were replaced with Ferodo DS Uno endurance race pads and tyres were replaced with Michelin Pilot Sport Cup 2 track day tyres, with both being replaced with a new set every 12 laps. No other components or systems were modified. The vehicle was outfitted with an Nvidia Drive AGX Pegasus high-performance computer that acquired data from the vehicle, one internal and eleven external cameras, and several motion and localization sensors. Therefore, the data from different sources were recorded on the same computer, ensuring a common timeframe across all data. Vehicle telemetry, such as speed, brake, throttle, or steering signals, was logged via CAN bus, at a sample rate of 5 ms (200 Hz). To get a precise heading and a centimetre level position accuracy an SBG Ellipse-D Inertial Navigation System was used along with two antennas mounted on the vehicle's top, and both GNSS and IMU data were logged via CAN bus. These systems were also used to get the coordinates for left and right track borders. Because the racetrack barely changes altitude by about half a metre, the left and right track borders as well as the optimal line were rendered in XY plane. To calculate the optimal line the IPOPT solver was utilised to solve a non-linear optimization problem based on a non-linear parametrized model of the test vehicle. Track borders were introduced as constraints and the main target was to minimize the lap time. The multi-channel audio system was connected to drivers' headphones and a voice recorder, and it was used to broadcast secondary task stimuli while, at the same time, recording both the stimuli and the drivers' responses. Timestamps were recorded for every stimulus and logged together with the vehicle telemetry. Although the data was logged in the time domain, to be able to compare different participants in a particular location, the entire dataset as well as the optimal line were transformed to the distance domain, with 0.20 m being a new space sampling rate. More specifically, a centreline with points 20 cm apart was generated, and the closest points measured in Euclidean distance were found for each participant and for the optimal line.

2.4. Secondary tasks

The target matching form of the auditory n-back task (Lenneman & Backs, 2009; Mehler et al., 2011; Nilsson et al., 2020) was used to examine the effects of CL on driving performance. The task required a decision whether a certain number matches the one presented ***n*** numbers before and its construct and face validity has been confirmed in several earlier studies (e.g., Jaeggi et al., 2010; Kane et al., 2007). The task items were pre-recorded auditory stimuli (single digits; 0–9), presented to participants via headphones one at a time at regular intervals of 1 every 2.25 s. As the baseline drive did not include any secondary task, two levels of difficulty of the n-back task were used to present drivers with moderate (1-back) and high (2-back) levels of CL. At the moderate level (1-back), participants were

[1] MATLAB function was used to find the radius R and the centre of the circumscribed circle of a triangle in 3D space. The function calls circumcentre for every triplet $P_{i\text{-}1}$, P_i, P_{i+1} of neighbouring points along the curve. The curvature is defined as $\kappa_i = 1/R_i$and the curvature vector is $k_i = \varepsilon_i/R_i$, where $\in_i$ is the unit vector in the direction from to the centre of the circle (Mjaavatten, 2024).

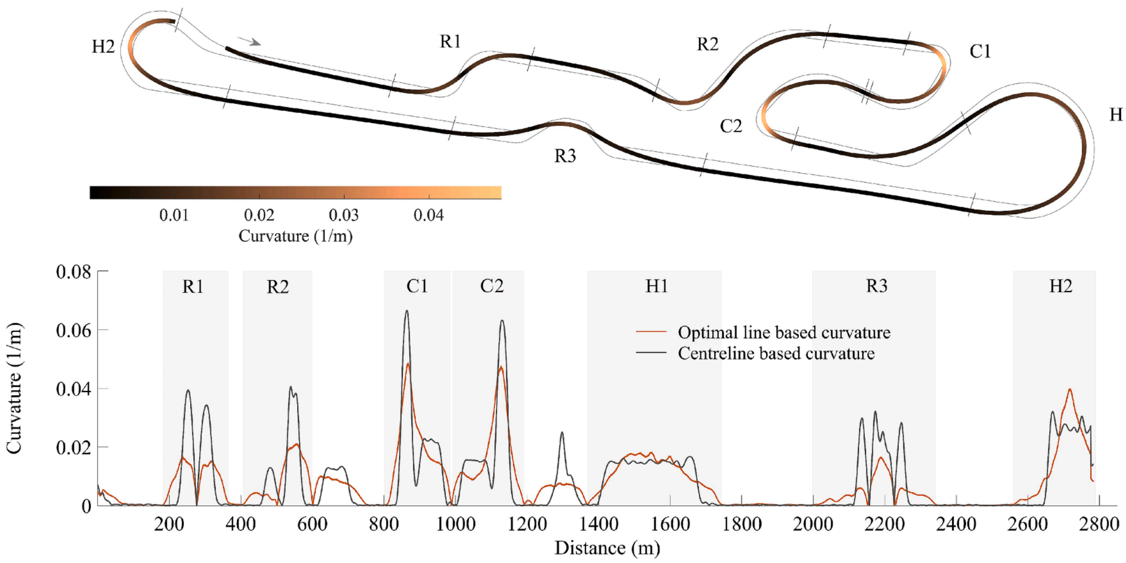

Fig. 1. NAVAK circuit with optimal line-based corner curvatures and curve entry/exit points (top panel) and comparison between optimal line- and centreline-based curvatures (bottom panel)Note. R = Reverse (S-shape) curve, C = Compound curve, H = Hairpin (U-shape) curve.

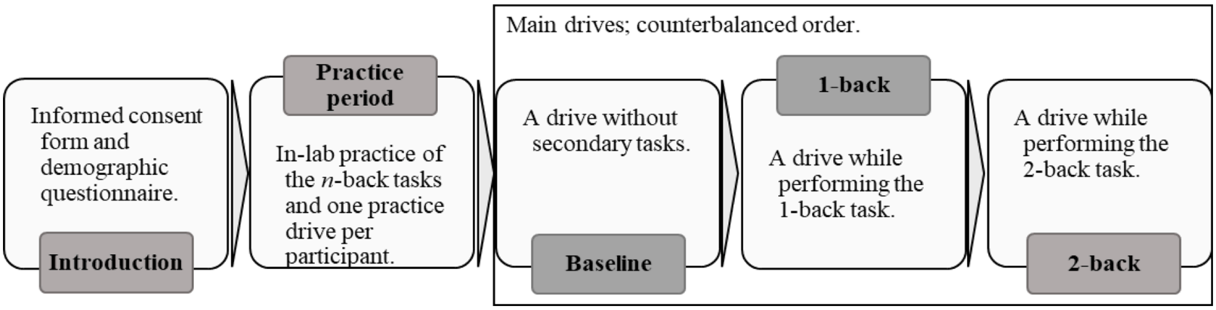

Fig. 2. A scheme of the experimental procedure.

required to verbally respond by saying either “Yes” or “No” depending on whether the last number they heard was the same as or different to the second-to-last number. Similarly, in the most difficult level (2-back), the last number presented needed to be compared with the third-to-last number in the sequence. At the beginning of each drive, verbal instruction was given to participants to indicate whether they were required to complete the 1- or 2-back task.

2.5. Experimental design

The study followed a mixed model design, where driving expertise (Experts, Non-experts) was a between-group independent variable, while CL (Baseline, 1-back, 2-back) was a within-subject factor. As every participant drove all the scenarios (Baseline, 1-back, and 2-back), they were counterbalanced among participants to control for the order effect. Therefore, a total of 3 experimental drives per participant were included, with each drive consisting of one lap around the track.

2.6. Procedure

Upon arrival at the racetrack, every participant received a brief overview of the experimental procedure and filled out a demographic questionnaire about their age, gender, and driving/racing experience. All participants reviewed the information sheet, signed the informed consent form, and went through a 5-minute-long introductory n-back training, where they practised the 1- and 2-back tasks. After the practice session, both the participant and the researcher moved into the car, with the researcher seated in the back of the vehicle to monitor the driver’s ability to maintain safe control, to give instructions, and to answer potential questions. Before the main drives, every participant experienced one practice drive, i.e., one lap that lasted ~2 min. The following three laps (one lap for every experimental condition – baseline, 1-back, and 2-back, counterbalanced among participants), lasting approximately 2 min each, were recorded. There was a brief pause between laps when participants received instructions about the difficulty level of the n-back task (if any) for the following experimental drive. For the baseline drive, participants were told to complete the lap as fast as possible, while for the 1- and 2-back drives, the instruction was to complete the lap as quickly as possible while also performing the n-back tasks as accurately and as quickly as possible. The complete session lasted ~30 min per participant. The experimental procedure is outlined in Fig. 2.

2.7. Metrics

To capture two distinct parts of a participant's intra-individual speed distribution, two longitudinal performance indicators, max speed and average speed, were used. Root Mean Square Error (RMSE) was used as a measure of trajectory error relative to the optimal line, and its sensitivity to both strategic and unintentional changes in lateral position was confirmed in previous studies (Engström et al., 2017). Since both near- and far-road information was shown to be necessary for steering control (Salvucci & Gray, 2004), two additional lateral performance indicators were collected. Steering smoothness was calculated as an average of absolute difference between the raw and smoothed steering wheel angle,[2] with the lower value being indicative of smoother steering (Lehtonen et al., 2014). Steering wheel reversal rate (SWRR) was used as a measure of corrective steering and it was calculated as the total number of steering reversals greater than 0.1 degrees, divided by the signal's total length in minutes (Markkula & Engström, 2006). The speed and steering data, as well as vehicle trajectories used for calculating the metrics can be found in Appendix B.

In terms of secondary task performance measures, miss rates were manually calculated for the two n-back tasks and they were later divided into errors (i.e., wrong answers) and omissions (i.e., missed answers within the response window, up to 2500 ms from stimulus onset). While errors have often been investigated as indicators of secondary task performance (e.g., Harvey et al, 2005; Miller et al, 2009), increased omissions are either not reported or generically classed as errors. Increased omissions are interpreted as an indication of the difficulty to sustain attention and inhibit distraction (Damaso et al., 2022), and there is evidence that omissions are more frequent than errors in n-back tasks (Meule, 2017). In addition, omissions, but not errors, are associated with working memory capacity (Oberauer, 2005), suggesting that there might be extra psychological insights to be gained by considering them separately. The percentage of misses, errors, and omissions were calculated for each participant and these values were used in further analyses.

3. Results

To test the effects of CL and Expertise on driving performance, 2 (Non-experts, Experts) x 3 (Baseline, 1-back, 2-back) mixed-model ANOVAs with a Bonferroni correction were conducted. Since hairpin, compound, and reverse curves were different in terms of length, radii, speed, etc., and these differences would most likely increase variability and impact the results, curve type was not included as an additional within-subject variable. Instead, ANOVAs were done separately for the three types of curves and the results are provided based on average performance in each curve type (see Appendix C for ANOVA summary tables). Outliers were identified using Tukey's method (Tukey, 1977) and box plots, with two detected in the 2-back condition: one in experts' maximum speed and one in non-experts' steering smoothness. Since these were not error outliers and their exclusion did not affect the results, they were retained in the analysis (Aguinis et al., 2013). Additionally, as complete counterbalancing of conditions could not be achieved due to the smaller number of participants, the order effect was tested, but as no significant differences were found for any curve type, the order was not included in further analyses as one of the factors. The Greenhouse-Geisser correction was applied when the sphericity assumption was violated, however, adjusted degrees of freedom are only reported in Tables 1 and 2 (Appendix C) for clarity. The Kolmogorov-Smirnov test showed significant deflection from normality for 3 distributions, with two of them being positively skewed (RMSE in 2-back condition for expert drivers for reverse and compound curves) and one negatively skewed (max speed in 1-back condition for non-expert drivers for hairpin curves). Out of five dependent variables, Levene's tests showed that the error variance was unequal across groups but only in the case of max speed in baseline conditions for reverse ($p = 0.04$) and compound ($p = 0.01$) curves. According to the results of Box's tests, the assumption of homogeneity of the variance–covariance matrices is violated only in the case of RMSE for simple curves ($p = 0.005$). As proposed by Quach and colleagues (2022), post-hoc power analysis was calculated using a Monte Carlo simulation with a two-sided alpha of 0.05. Effect sizes of 0.02, 0.05, and 0.08 yielded power values of 0.161, 0.349, and 0.711, respectively.

3.1. Hairpin curves

3.1.1. Longitudinal performance

A mixed-model ANOVA showed a significant main effect of Expertise ($F(1,16) = 8.86$, $p = 0.009$, $\eta_p^2 = 0.36$) and a significant main effect of CL ($F(2,32) = 4.43$, $p = 0.02$, $\eta_p^2 = 0.22$) on max speed. As expected, the max speed of experts ($M = 136.65$, $SE = 2.72$) was significantly higher than non-experts' ($M = 125.79$, $SE = 2.43$). The post hoc analysis for the main effect of CL showed a significant decrease in max speed from baseline to 2-back condition ($p = 0.05$) while baseline – 1-back ($p = 0.15$) and 1-back – 2-back ($p = 0.92$) comparisons were not statistically significant (Fig. 3). When the mixed-model ANOVA was run on average speed, it showed only a significant main effect of Expertise ($F(1,16) = 8.08$, $p = 0.01$, $\eta_p^2 = 0.37$), with experts' average speed being higher ($M = 90.82$, $SE = 2.59$) than non-experts' ($M = 85.18$, $SE = 2.32$).

[2] MATLAB function (smoothdata) was used. The function determines the moving window size, computing an average over the elements within each window.

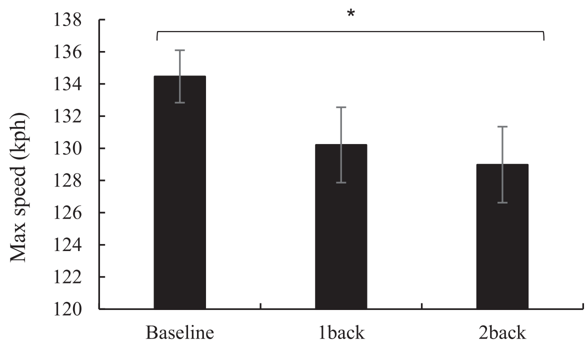

Fig. 3. The main effects of CL on Max speed (error bars = SE)Note. * = p < 0.05.

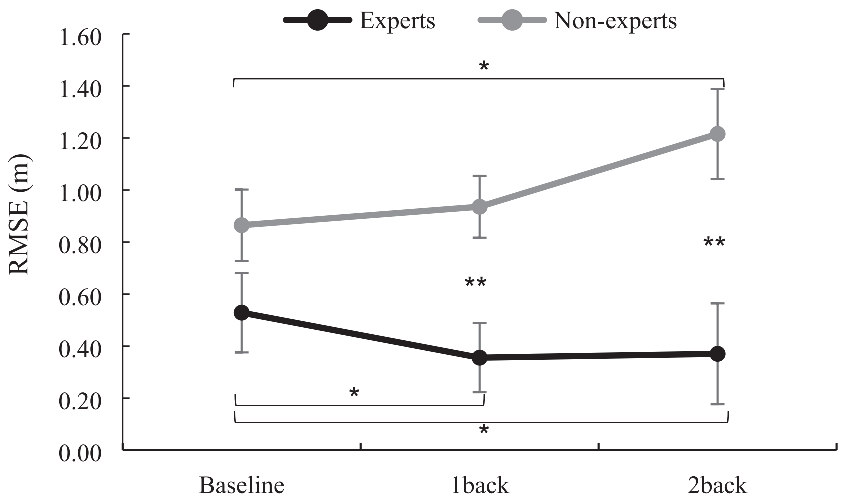

Fig. 4. The Expertise x CL interaction effect on RMSE (error bars = SE)Note. * = p < 0.05, ** = p < 0.01.

3.1.2. Lateral performance

The significant main effect of Expertise ($F(1,16) = 11.31$, $p = 0.004$, $\eta_p^2 = 0.41$), and significant Expertise x CL interaction effect ($F(2,32) = 3.98$, $p = 0.05$, $\eta_p^2 = 0.14$) were obtained when mixed-model ANOVA was run on RMSE. As expected, expert drivers had smaller deviations from the optimal line ($M_E = 0.42$, $SE = 0.13$; $M_{NE} = 1.02$, $SE = 0.12$). However, simple effect analysis of the two-way interaction showed that the main effect of Expertise was only true for secondary task conditions ($p_{baseline} = 0.12$, $p_{1back} = 0.005$, $p_{2back} = 0.005$). Expert drivers' RMSE values, when compared to baseline, decreased significantly in the 1-back ($p = 0.05$) and 2-back ($p = 0.05$) conditions while this was found to be in the opposite direction for non-experts, whose RMSE values increased significantly in the 2-back condition ($p = 0.05$). The Expertise x CL effect on RMSE is displayed in Fig. 4, while the mean lateral position of expert and non-expert drivers for different CL conditions is displayed in Fig. 5. No significant main or interaction effects were obtained for SWRRs.

Significant main effects of Expertise ($F(1,16) = 11.72$, $p = 0.003$, $\eta_p^2 = 0.42$), CL ($F(2,32) = 5.52$, $p = 0.02$, $\eta_p^2 = 0.26$), and Expertise x CL interaction effect ($F(2,32) = 9.65$, $p = 0.002$, $\eta_p^2 = 0.38$) on steering smoothness were obtained. While it was shown that experts' steering performance ($M = 7.79$, $SE = 0.30$) was less smooth than non-experts' ($M = 6.40$, $SE = 0.27$), the post-hoc analysis of the interaction effect (Fig. 6) showed that this difference was significant only for the 2-back condition ($p < 0.001$). Also, steering smoothness decreased in the 2-back condition, compared to baseline ($p < 0.001$) and 1-back conditions ($p = 0.01$), but only for expert drivers, since changes in steering smoothness across CL conditions were not obtained for non-experts. The raw and smoothed steering signals for expert and non-expert drivers and for the three CL conditions are shown in Figure 16 (see Appendix D).

3.1.3. Secondary task performance

Mixed-model ANOVAs showed significant main effects of CL on misses ($F(1,16) = 15.42$, $p = 0.001$, $\eta_p^2 = 0.85$), errors ($F(1,16) = 8.84$, $p = 0.009$, $\eta_p^2 = 0.62$), and omissions ($F(1,16) = 7.29$, $p = 0.02$, $\eta_p^2 = 0.35$), indicating an increase in all three indicators as the CL increased (Fig. 7). No other main or interaction effects were obtained, however, the Expertise x CL interaction effect is shown in Figure 17 (see Appendix E).

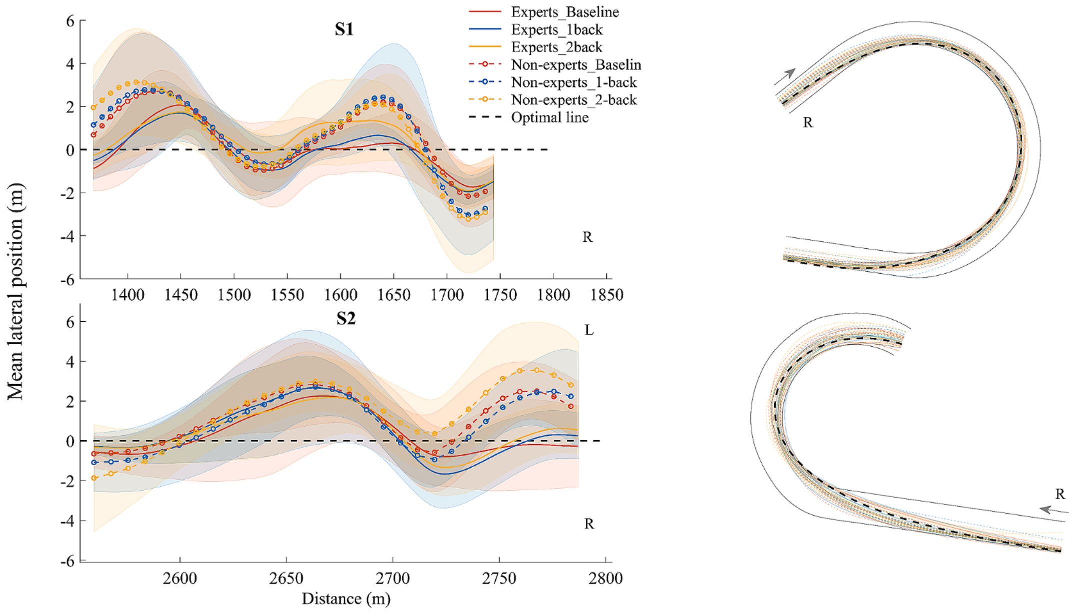

Fig. 5. The mean lateral position of expert and non-expert drivers for H1 and H2 curvesNote. L = left racetrack border, R = right racetrack border. Right panels show the individual trajectories, while the graphs display the mean lateral position with respect to the optimal line.

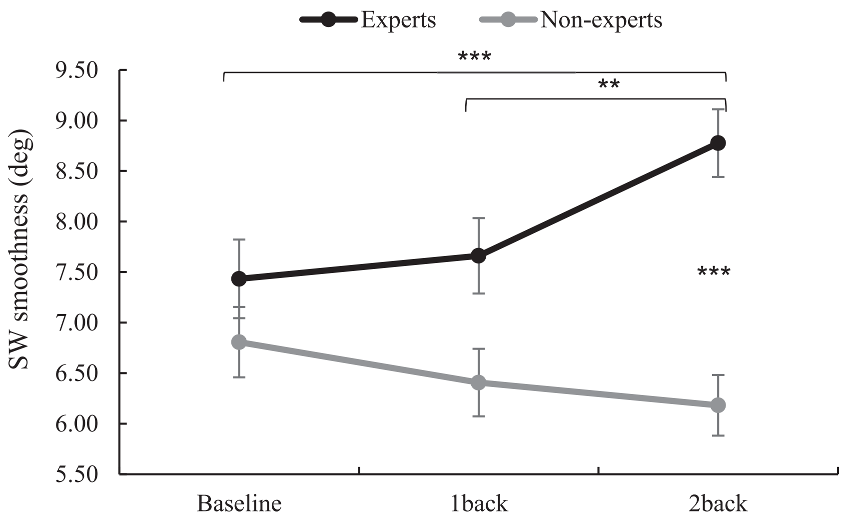

Fig. 6. The Expertise x CL interaction effect on steering smoothness (error bars = SE)** = p < 0.01, *** = p < 0.001.

3.2. Compound curves

3.2.1. Longitudinal performance

In the case of max speed, only a significant main effect of Expertise ($F(1,16) = 11.16$, $p = 0.004$, $\eta_p^2 = 0.41$) was obtained, indicating higher max speed in the case of expert drivers ($M_E = 101.15$, $SE = 2.13$; $M_{NE} = 91.61$, $SE = 1.90$). Similarly, mixed model ANOVA run for average speed resulted in a significant main effect of Expertise ($F(1,16) = 16.79$, $p < 0.001$, $\eta_p^2 = 0.64$), showing that experts' average speed was significantly higher ($M = 75.14$, $SE = 2.81$) than the average speed of non-experts ($M = 68.13$, $SE = 2.78$).

3.2.2. Lateral performance

For the RMSE and steering smoothness, no significant main or interaction effects were found, while for the SWRRs only the main effect of CL ($F(2,32) = 3.45$, $p = 0.04$, $\eta_p^2 = 0.18$) was found significant (Fig. 8). The simple effect analysis revealed that the number of small steering corrections decreased in the 2-back condition when compared to the baseline ($p = 0.05$), but not when compared to the 1-back condition ($p = 0.43$).

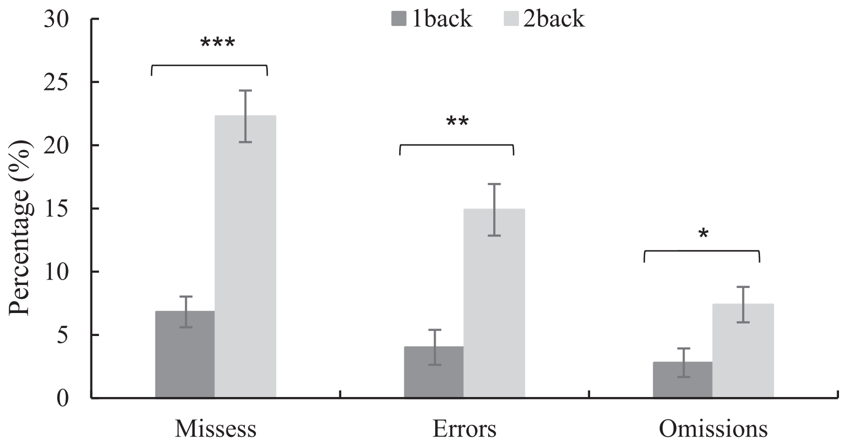

Fig. 7. The main effects of CL on Misses, Errors, and Omissions (error bars = SE)Note. * = p < 0.05, ** = p < 0.01, *** = p < 0.001.

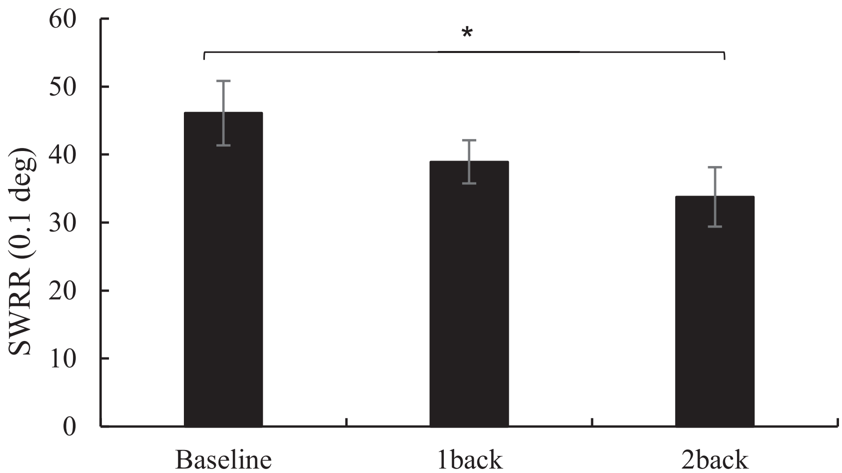

Fig. 8. The main effect of CL on SWRR (error bars = SE)Note. * = p < 0.05.

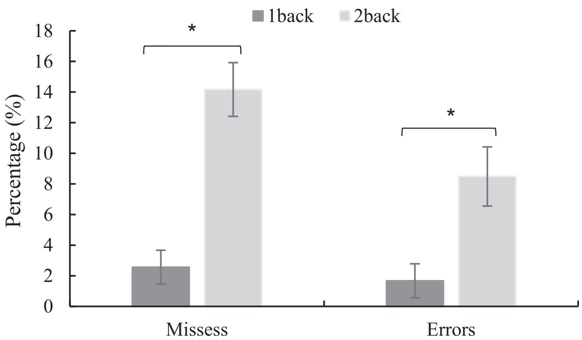

Fig. 9. The main effect of CL on Misses and Errors (error bars = SE)Note. * = p < 0.05.

3.2.3. Secondary task performance

Three separate mixed-model ANOVAs run for the three secondary task performance indicators showed significant main effects of CL on misses ($F(1,16) = 6.35, p = 0.02, \eta_p^2 = 0.39$) and errors ($F(1,16) = 4.34, p = 0.05, \eta_p^2 = 0.22$), with both indicators increasing from 1- to 2-back condition (Fig. 9). No differences between experts and non-experts were found.

3.3. Reverse curves

3.3.1. Longitudinal performance

When mixed-model ANOVAs were run on max- and average speed, in both cases only the main effect of Expertise was obtained ($F_{max}(1,16) = 10.92$, $p = 0.004$, $\eta_p^2 = 0.41$; $F_{avg}(1,16) = 20.33$, $p < 0.001$, $\eta_p^2 = 0.72$), indicating that experts ($M = 130.42$, $SE = 2.58$) reached significantly higher max speed than non-expert drivers ($M = 118.98$, $SE = 2.30$) and that experts ($M = 98.81$, $SE = 2.67$) had higher average speed than non-experts ($M = 88.29$, $SE = 2.45$).

3.3.2. Lateral performance

A significant main effect of CL ($F(2,32) = 10.08$, $p = 0.002$, $\eta_p^2 = 0.39$) on RMSE was obtained, indicating a decrease in deviations from the optimal line as the CL increased (Fig. 10). While 1-back – 2-back comparison was not found significant, RMSE values decreased significantly from baseline to 1-back ($p = 0.002$) and baseline to 2-back condition ($p = 0.04$). Mean lateral position in different CL conditions for the three reverse curves is displayed in Fig. 11. The main effect of Expertise was found only for steering smoothness ($F(1,16) = 10.68$, $p = 0.005$, $\eta_p^2 = 0.40$), showing significantly higher values for experts ($M = 11.05$, $SE = 0.37$) compared to non-expert ($M = 9.41$, $SE = 0.33$) drivers. No significant differences in SWRRs were found between the two groups or different CL conditions.

3.3.3. Secondary task performance

Mixed-model ANOVAs run for the misses, errors, and omissions, only showed a significant main effect of CL on errors ($F(1,16) = 5.75$, $p = 0.03$, $\eta_p^2 = 0.32$). The percentage of errors was higher in 2-back than in 1-back condition (Fig. 12). Differences between expert and non-expert drivers were not obtained.

4. Discussion

This study investigated the effects of CL on experts' and non-experts' driving performance in hairpin, compound, and reverse curves. According to the cognitive control hypothesis (Engström et al., 2017), expert racing drivers were expected to be less vulnerable to task interruptions from CL when compared to non-expert drivers, as their driving skills are believed to be more automatized and, therefore, less susceptible to the effects of CL.

As expected, expert drivers drove significantly faster and reached higher maximum speeds than non-experts, on hairpin, compound, and reverse curves. This is in line with previous studies which showed that more experienced, professional drivers (Lyu et al., 2017), and racing drivers (van Leeuwen et al., 2017) drove faster than their less experienced counterparts. Moreover, for all curves, expert drivers managed to drive faster and reach higher maximum speeds while performing the secondary tasks as equally well as non-experts. While, to the best of our knowledge, there are no studies that report expertise-related differences in n-back task performance, several studies have shown that there are no differences between less experienced and experienced or even professional drivers for the performance of different cognitive-motor (Bernardi et al., 2013; van Leeuwen et al., 2017) or auditory-verbal tasks (Kerruish et al., 2022). Contrary to earlier studies (e.g., Meule, 2017) the percentage of errors appeared to be the most sensitive secondary task performance indicator, showing differences for all three curve types. However, for all curve types, at least one indicator showed a decrease in performance of the 2-back task compared to the 1-back task, although driving-related compensatory actions were detected only for hairpin curves. Namely, in hairpin curves in the 2-back condition, both experts and non-experts compensated for the increased task demands by reducing their maximum speed compared to baseline. In this study, drivers were instructed to do the best lap they could which might have rather been perceived as a speed instruction suggesting driving at unnaturally high speeds, even for expert racing drivers who were not familiar with the racetrack. Going in line with the cognitive control hypothesis (Engström et al., 2017; Lewis-Evans et al., 2011), it can be speculated that, when the more complex concurrent activity was introduced, drivers decreased the driving task demand by resorting to their preferred/optimal speed that could be controlled automatically or at least to the one they felt more comfortable at given the nature of the task. The same as for baseline – 1-back comparison, differences in maximum speed between 1-back and 2-back conditions were not found, which together with the increase in the percentage of misses, errors, and omissions in the 2-back condition, indicated that drivers prioritized the driving task over the secondary task performance. The prioritization of the driving task was also shown by non-significant differences in maximum or mean speed between different CL conditions in reverse and compound curves, although secondary task performance indicated an increase in misses (compound curves) and errors (compound and reverse curves). While one explanation might be that drivers managed to drive at their optimal speed in CL conditions (Engström et al., 2017), due to, for instance, better visibility which allowed them to predict the optimal speed more accurately, it seems that these two curve types, compared to hairpin curves, were less challenging. Namely, Onate-Vega and colleagues (2020) found that road geometry, compared to visual and cognitive distraction, had a greater impact on driving performance and that observed speed reductions were the result of a subconscious perception of certain geometries as more demanding.

Regarding lateral performance, experts had lower steering smoothness than non-experts in reverse curves, irrespective of CL level, however, contrary to our expectations, there were no differences in trajectory deviations or small steering corrections between these two groups when negotiating hairpin, compound, or reverse curves without secondary tasks. This is not fully consistent with previous findings showing that non-experts drove closer to the centreline although curve cutting tendencies could still be observed (van Leeuwen et al., 2017). Different forms of curve cutting behaviours were confirmed in several earlier studies (Spacek, 2005; Yu et al., 2021; Xu et al., 2018) and especially while driving on sharp curves (Spacek, 2005; Xu et al., 2018) and at high speed (Xu et al., 2018). While curve cutting is often seen as a riskier behaviour and compensation for excessive curve approach and entry speed (Boer, 1996;

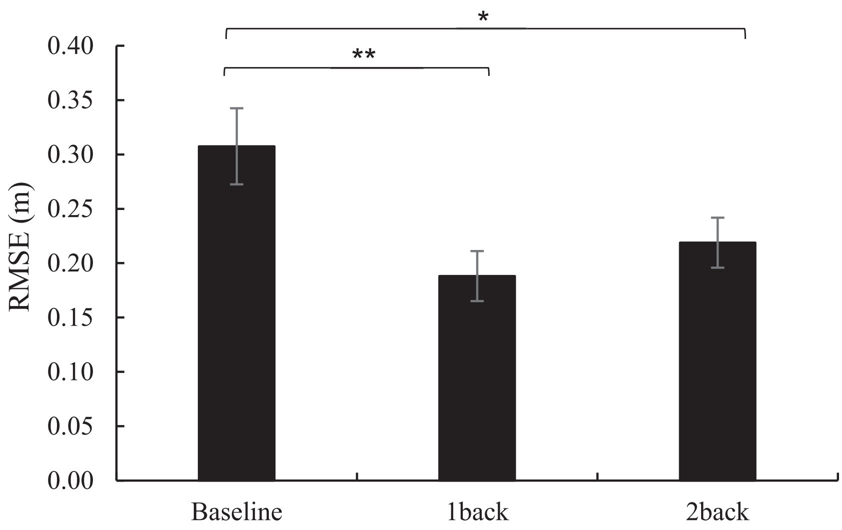

Fig. 10. The main effect of CL on RMSE (error bars = SE)Note. * = p < 0.05, ** = p < 0.01.

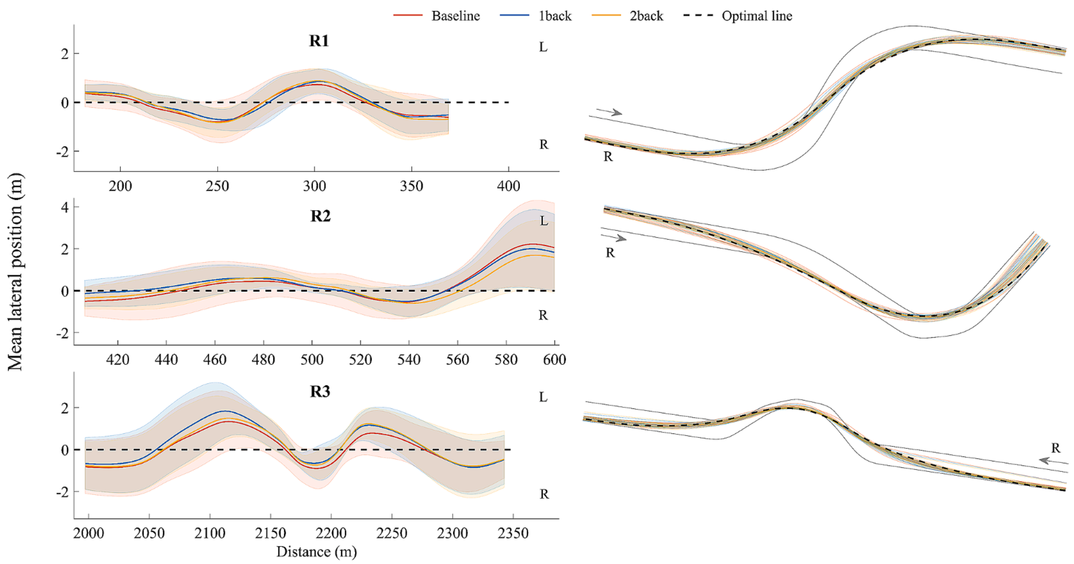

Fig. 11. The mean lateral position with respect to the optimal line for R1, R2, and R3 curves Note. L = left racetrack border, R = right racetrack border. Right panels show the individual trajectories, while the graphs display the mean lateral position with respect to the optimal line.

Crundall et al., 2012; Yu et al., 2021), this study confirmed that expert and non-expert drivers naturally cut curves. Therefore, more curve cutting might mean better performance and skill rather than greater error, as it was commonly argued. Supporting this notion, Yuan-Yuan and colleagues (2012) have shown that cutting trajectory is one of the safest trajectories through curves as it ensures longer sight distance as well as best steering stability. This might also explain why differences in steering corrections between experts and non-experts were not observed in the baseline condition, for any curve type. Moreover, changes in steering corrections were not obtained for hairpin or s-shape curves even when CL was exceeding drivers' resources. This might be explained by looking at trajectory deviations under CL. Namely, in s-shape curves, drivers decreased their trajectory deviations during both the 1- and 2-back conditions. As they moved closer to the optimal line, steering performance without significant corrections was seen under CL. Similarly, when drivers managed to drive close to the optimal line in all CL conditions, such as in compound curves, more demanding secondary task even reduced steering corrections. It might be that a reduction in steering corrections with CL happened because demanding concurrent task removed drivers' attention from steering and, as stated by Medeiros-Ward and colleagues (2013), highly automated tasks, such as steering, are improved once attention is shifted away. On the other hand, for hairpin curves, non-experts' deviations increased and experts' decreased in the 2-back condition, but this effect was not mirrored by any changes in steering corrections. In line with theoretical models (Engström et al., 2017; Yuan-Yuan et al., 2012), this extreme curve cutting behaviour, might have been a non-automatized activity for non-experts and, as such, required cognitive resources which in combination with the 2-back task led to

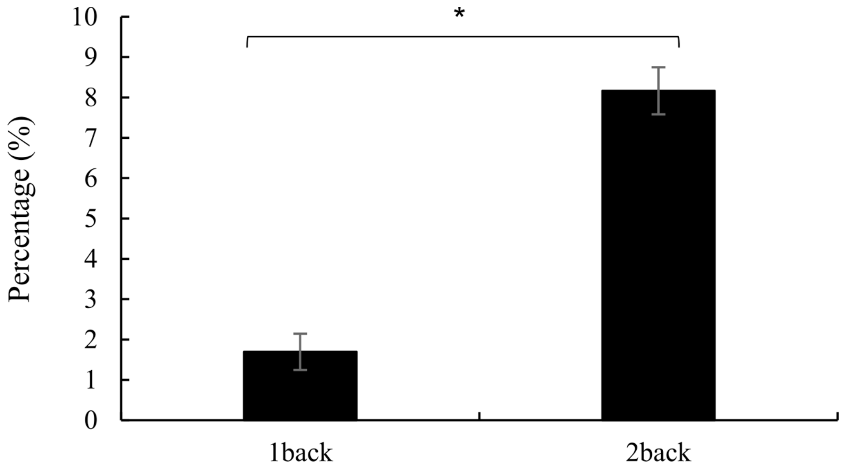

Fig. 12. The main effect of CL on Errors (error bars = SE)Note. * = $p < 0.05$.

increased deviations from the optimal line. Since previous studies have shown that CL leads to gaze concentration towards the road centre and consequent guidance of steering movements (e.g., Kountouriotis & Merat, 2016; Li et al., 2018; Wang et al., 2014), it seems plausible to conclude that changes in gaze patterns under CL in hairpin curves were not the same for expert and non-expert drivers. However, although experts decreased and non-experts increased their lateral deviations while cognitively loaded, they were still driving close to the track edge. This near-road information, as shown by several earlier studies (e.g., Kountouriotis et al., 2012; Land & Horwood, 1995; Wilkie et al., 2008), was most likely enough for them to steer accurately, i.e., without significant corrections. Unlike near-road information, which benefits steering accuracy, far-road information, according to previous studies (Macadam, 2003; Salvucci & Gray, 2004; Wilkie et al., 2008), is necessary for trajectory planning and steering smoothness. Since research has shown that skilled drivers rely more on the far road information (Lappi et al., 2017; Lehtonen et al., 2014), CL-induced decrease in lead time and distance of look-ahead gaze fixations (Lehtonen et al., 2011) might have more detrimental effects on expert drivers' performance and might explain why only expert drivers' steering smoothness decreased in the 2-back condition. As demonstrated by Tuhkanen and colleagues (2021), both gaze and steering are influenced by anticipation of the future path, in line with the use of an internal model. Another plausible explanation, therefore, is that utilizing such internal models demands cognitive resources. Given that only expert drivers were likely to possess an internal model of the driving environment, any failure to activate or apply this model in secondary task conditions may have resulted in reduced steering smoothness.

While differences between expert and non-expert drivers, as well as CL-related changes in driving performance, were most visible in hairpin curves, not being able to directly compare performance across the different types of curves is a limitation of this study. Although this study allowed us to exhibit drivers' natural behaviour with all the complexity of high-speed driving in real curves, different curve characteristics could not be controlled, making it difficult to single out one element that might have affected the results. A study in which different curve elements can be varied is, therefore, needed to understand which aspects of a curve's geometry and length are more demanding and, when coupled with the demands of a secondary task, lead to significant performance decrements even in the case of expert drivers. To increase the ecological validity of the findings, more realistic secondary activities might be employed in future studies. However, the n-back task is often used as a substitute for hands-free conversations as it is considered to engage similar cognitive resources (Mehler et al., 2011), while being more controllable and easier to quantify alternative (e.g., Fotios et al., 2021), leading to medium to large effect sizes (von Janczewski et al., 2021). Another notable limitation is the sample of this study. Although the relatively small sample size undermined the statistical power of the results and possibly impacted between group differences, it is important to note that this sample is still larger than those employed in other studies, especially given the difficulty in recruiting expert racing drivers. However, the selected sample constrains the generalizability of the findings, as the results may not be representative of the broader population of expert drivers, further limiting the applicability of the conclusions across different contexts or demographic groups. Namely, racing drivers may develop a unique motor repertoire that differs from ordinary driving, and that type of expertise may not be the one that aids safety on public roads. Consequently, it might be valuable to investigate whether changes in performance observed in this study are also seen in urban driving scenarios with more realistic secondary activities, where safety, rather than speed or lap time, is more likely to be a priority. The inclusion of other expert drivers, for instance, emergency service drivers who not only drive regularly during their duty times but also undergo specific driving training, would surely help us understand whether and to what extent expertise is a protective element against distraction-related accidents. Such knowledge would help develop training programs and systems that monitor drivers' states and aid their perceptual and motor performance limits when cognitively loaded.

5. Conclusion

While the idea that the performance of less skilled drivers would suffer more under CL has a firm footing in theory, there has not been much research comparing the effects of CL on highly skilled versus less skilled drivers' performance. Even though experts outperformed non-experts in terms of speed in normal conditions, this was hardly the case with lateral or secondary task performance. This study, therefore, supports the current consensus that the main differences between expert and non-expert drivers are task-specific and that there are no significant differences in the performance of cognitive tasks. In general, this study showed that distracted driving in complex road environments can be challenging for both expert and non-expert drivers and can lead to compensatory actions, such as maximum speed reduction, or even corrective behaviors, such as increased steering corrections. Although the effects of curve geometry were not directly assessed in this study, CL-induced changes in performance appeared to be different for hairpin, compound, and reverse curves, suggesting sharp hairpin curves as the most demanding ones. To better understand the differences between experts and non-experts in lateral performance, in order to form adequate safety-related guidelines, gaze data should be taken into account and considered as an area that can lead future studies.

CRediT authorship contribution statement

M. Celic: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **S. Arefnezhad:** Validation, Software. **S. Vrazic:** Supervision, Funding acquisition, Conceptualization. **J. Billington:** Writing – review & editing, Supervision, Project administration. **N. Merat:** Writing – review & editing, Supervision, Project administration.

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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Appendix A

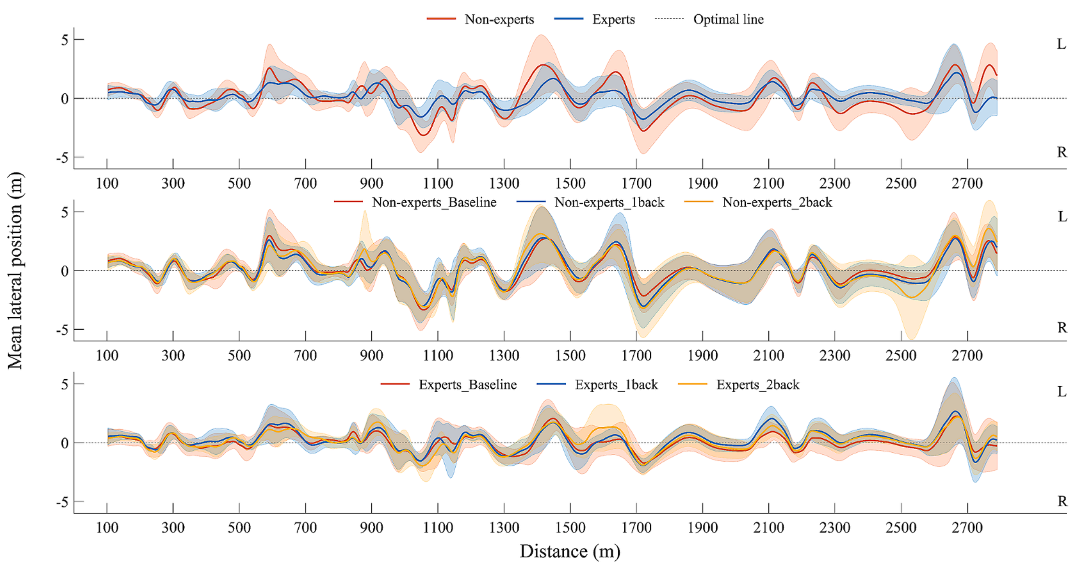

Fig. 13. Mean lateral position with respect to the optimal line for expert and non-expert drivers and for different CL conditions *Note.* L = left racetrack border, R = right racetrack border.

Appendix B

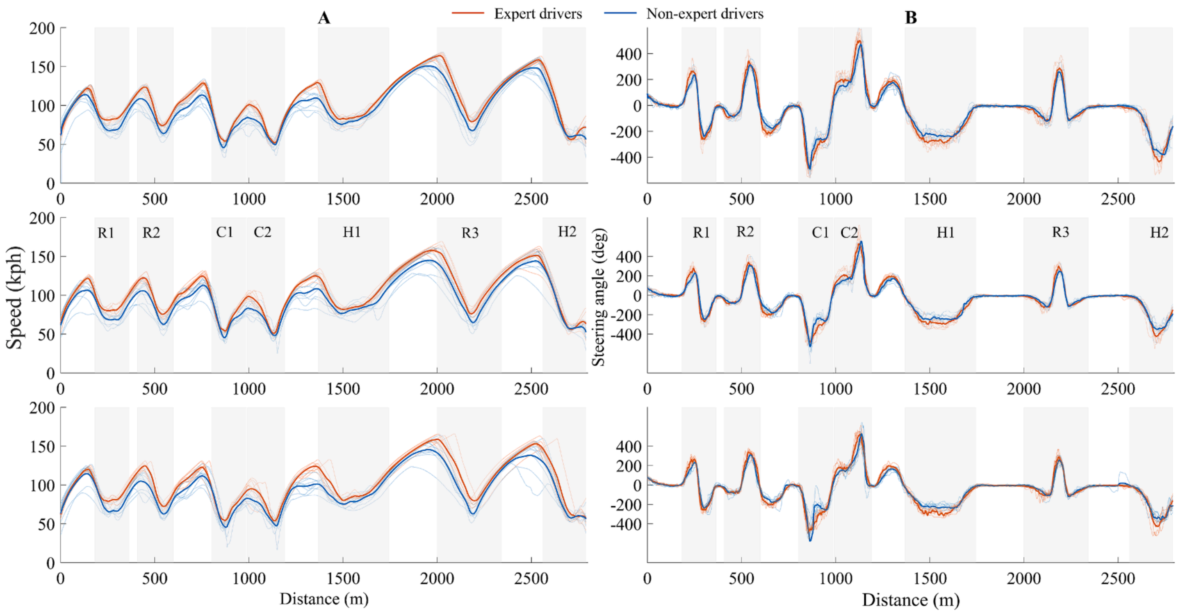

Fig. 14. Speed (A) and steering (B) data for expert and non-expert drivers and for different CL conditions

Note. The left panel (A) displays individual and average speed data for experts and non-experts across the baseline, 1-back, and 2-back conditions (from top to bottom). The right panel (B) displays individual and average steering angle for experts and non-experts across the baseline, 1-back, and 2-back conditions (from top to bottom). Grey areas indicate the seven corners.

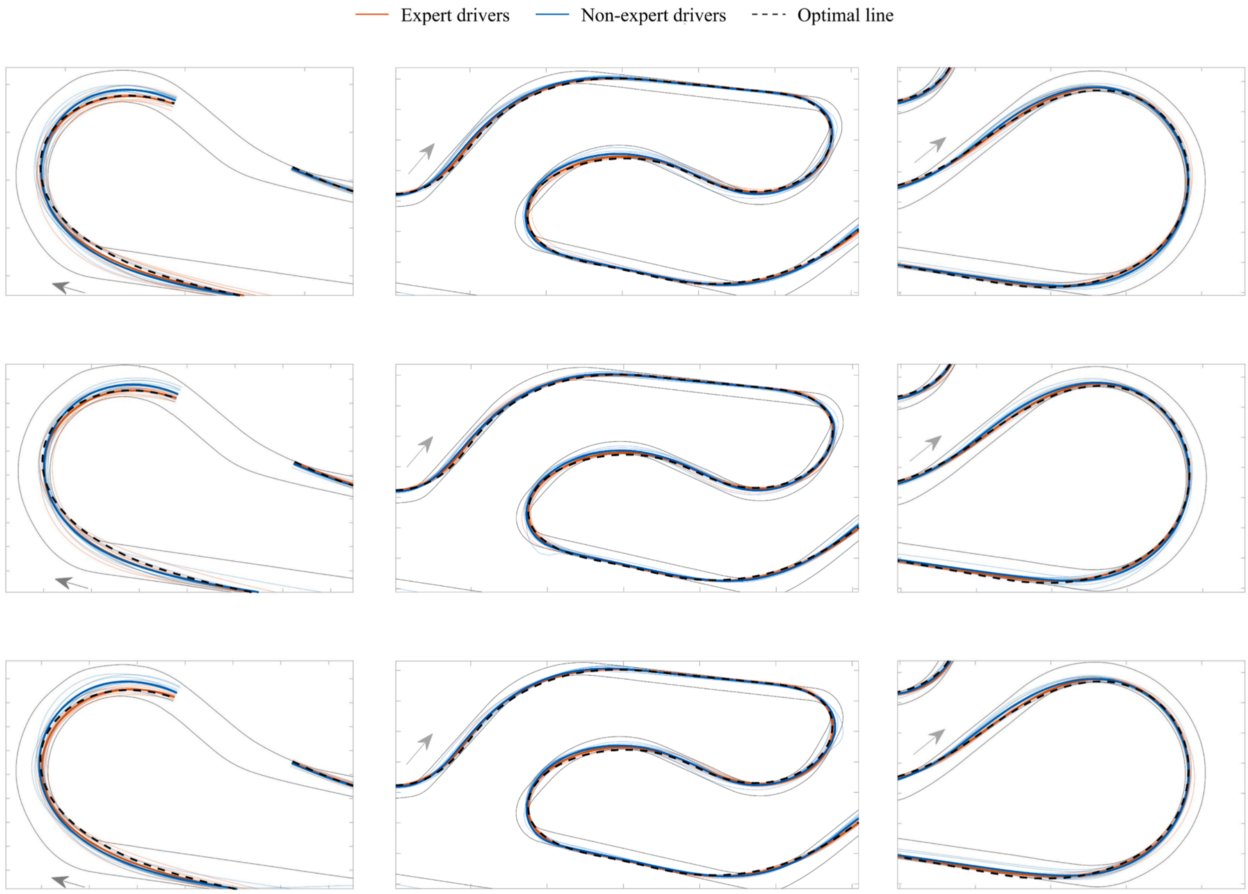

Fig. 15. Vehicle trajectories for expert and non-expert drivers and for baseline (a), 1-back (b), and 2-back (c) conditions Note. The tick blue trajectory indicates the mean trajectory of non-expert drivers, while the tick orange trajectory indicates the mean trajectory of expert drivers.

Appendix C

Table 1
Mixed-model ANOVA results for longitudinal and lateral performance for hairpin-, compound-, and reverse curves.

	Hairpin curves	Compound curves	Reverse curves									
	Mean speed											
	F (df)	*p*	η^2	π	*F (df)*	*p*	η^2	π	*F (df)*	*p*	η^2	π
Expertise	8.08 (1,16)	**0.01**	**0.37**	**0.76**	16.79 (1,16)	**0<.001**	**0.64**	**0.91**	20.33 (1,16)	**0<.001**	**0.72**	**0.93**
CL	0.34 (2,32)	0.71	0.01	0.07	0.84 (2,32)	0.44	0.06	0.10	1.75 (2,32)	0.19	0.11	0.32
Expertise x CL	0.61 (2,32)	0.55	0.07	0.10	0.03 (2,32)	0.97	0.01	0.06	0.05 (2,32)	0.96	0.01	0.06
	Max speed											
Expertise	8.86 (1,16)	**0.009**	**0.36**	**0.80**	11.16 (1,16)	**0.004**	**0.41**	**0.88**	10.92 (1,16)	**0.004**	**0.41**	**0.87**
CL	4.43 (2,32)	**0.02**	0.22	0.72	0.17 (2,32)	0.84	0.01	0.08	2.20 (2,32)	0.13	0.13	0.42
Expertise x CL	0.95 (2,32)	0.40	0.06	0.20	0.20 (2,32)	0.66	0.01	0.08	0.07 (2,32)	0.93	0.01	0.06
	RMSE											
Expertise	11.31 (1,16)	**0.004**	**0.41**	**0.88**	3.68 (1,16)	0.07	0.19	0.44	0.22 (1,16)	0.64	0.01	0.07
CL	0.89 (2,32)	0.41	0.05	0.19	0.96 (2,32)	0.39	0.06	0.20	10.08 (1.41,22.54)	**0.002**	**0.39**	**0.93**
Expertise x CL	3.98 (2,32)	**0.05**	**0.14**	**0.52**	0.17 (2,32)	0.85	0.01	0.07	0.31 (1.41,22.54)	0.66	0.02	0.09
	SWRR											
Expertise	0.10 (1,16)	0.76	0.01	0.06	0.68 (1,16)	0.42	0.04	0.12	0.51 (1,16)	0.49	0.03	0.10
CL	2.01 (2,32)	0.15	0.11	0.38	3.45 (2,32)	**0.04**	**0.18**	**0.60**	0.12 (2,32)	0.89	0.01	0.07
Expertise x CL	1.90 (2,32)	0.17	0.11	0.37	1.80 (2,32)	0.20	0.10	0.24	1.96 (2,32)	0.16	0.11	0.38
	Steering smoothness											
Expertise	11.72 (1,16)	**0.003**	**0.42**	**0.90**	0.48 (1,16)	0.50	0.03	0.10	10.68 (1,16)	**0.005**	**0.40**	**0.87**
CL	5.52 (1.45,23.26)	**0.02**	**0.26**	**0.72**	0.98 (1.41,22.49)	0.36	0.06	0.18	2.75 (2,32)	0.07	0.15	0.50
Expertise x CL	9.65 (1.45,23.26)	**0.002**	**0.38**	**0.92**	0.12 (1.41,22.49)	0.82	0.01	0.06	0.41 (2,32)	0.67	0.03	0.11
Note. η^2 = partial eta square, π = statistical power.												

Table 2
Mixed-model ANOVA results for secondary task performance for hairpin-, compound-, and reverse curves.

	Hairpin curves	Compound curves	Reverse curves									
	Misses											
	F (df)	*p*	η^2	π	*F (df)*	*p*	η^2	π	*F (df)*	*p*	η^2	π
Expertise	0.64 (1,16)	0.44	0.06	0.17	0.12 (1,16)	0.73	0.02	0.07	1.34 (1,16)	0.26	0.11	0.16
CL	15.42 (1,16)	**0.001**	**0.85**	**0.92**	6.35 (1,16)	**0.02**	**0.39**	**0.73**	2.57 (1,16)	0.13	0.17	0.27
Expertise x CL	0.24 (1,16)	0.63	0.02	0.08	0.001 (1,16)	0.94	0.01	0.06	0.21 (1,16)	0.65	0.03	0.11
	Errors											
Expertise	2.92 (1,16)	0.11	0.17	0.44	0.41 (1,16)	0.53	0.04	0.07	2.34 (1,16)	0.15	0.11	0.36
CL	8.84 (1,16)	**0.009**	**0.62**	**0.81**	4.34 (1,16)	**0.05**	**0.22**	**0.53**	5.75 (0.75,12)	**0.03**	**0.32**	**0.71**
Expertise x CL	0.07 (1,16)	0.79	0.02	0.07	0.45 (1,16)	0.51	0.06	0.12	2.01 (0.75,12)	0.18	0.13	0.24
	Omissions											

(*continued on next page*)

Table 2 (*continued*)

	Hairpin curves	Compound curves	Reverse curves									
Expertise	0.46 (1,16)	0.51	0.07	0.22	0.06 (1,16)	0.81	0.01	0.06	0.15 (1,16)	0.71	0.02	0.1
CL	7.29 (1,16)	**0.02**	**0.35**	**0.73**	2.22 (0.75,12)	0.16	0.09	0.34	0.06 (1,16)	0.81	0.01	0.09
Expertise x CL	3.16 (1,16)	0.09	0.18	0.47	0.70 (0.75,12)	0.42	0.07	0.19	0.35 (1,16)	0.56	0.03	0.06

Note. η^2 = partial eta square, π = statistical power.

Appendix D

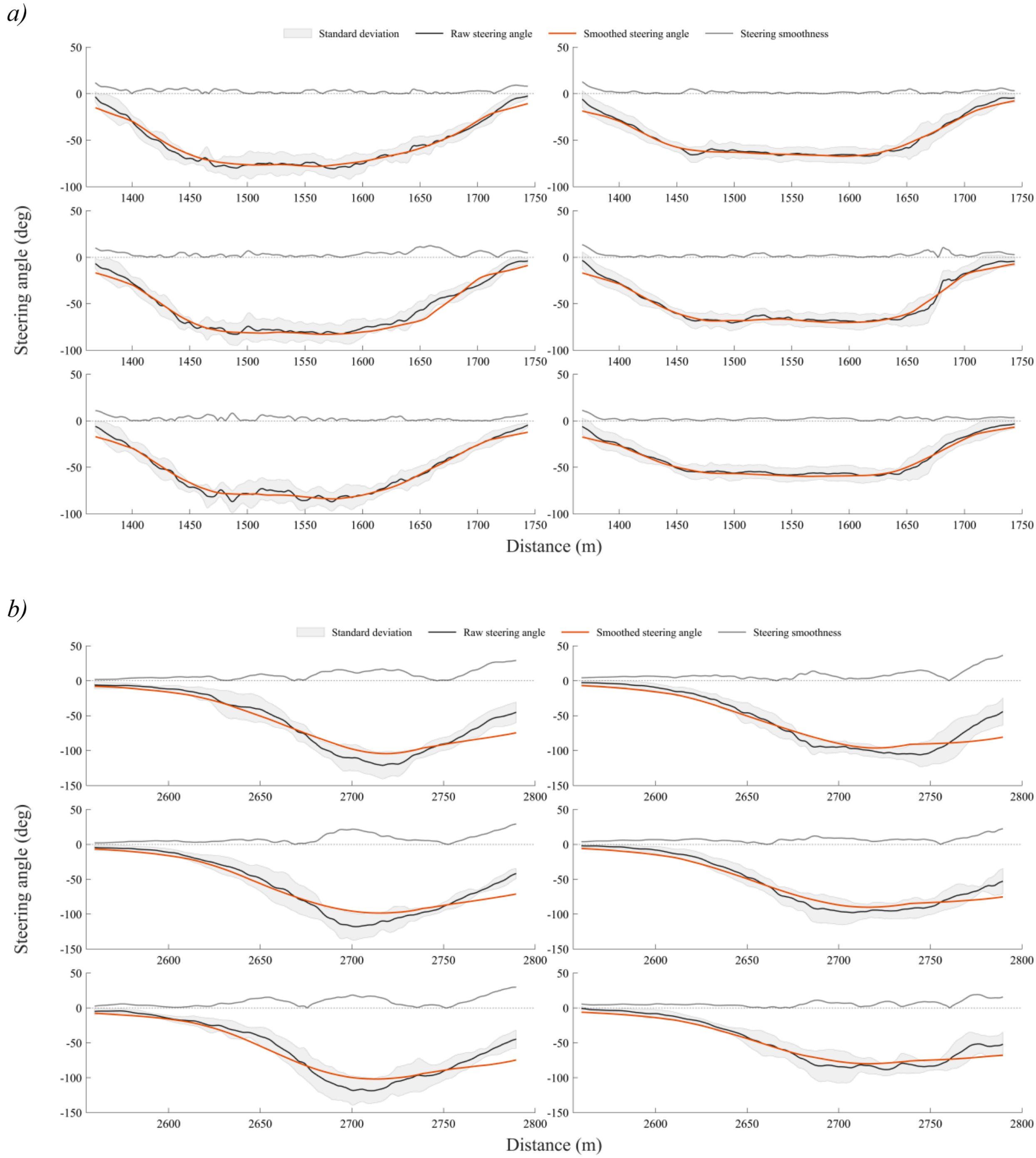

Fig. 16. Raw steering angle, smoothed steering angle, and the difference between the two signals for H1 (a) and H2 (b) curves

Note. Left panel displays unprocessed and processed steering angle signal for expert drivers (from top to bottom: baseline, 1-back, and 2-back conditions), while right panel displays steering angle signals for non-experts (from top to bottom: baseline, 1-back, and 2-back conditions). Negative values indicate that the steering wheel is turned to the right (clockwise), while positive values indicate that the steering wheel is turned to the left (counterclockwise).

Appendix E

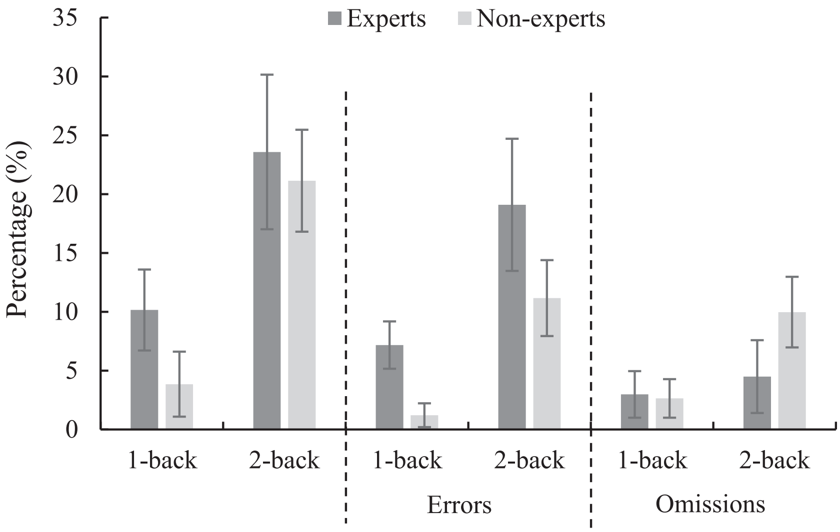

Fig. 17. The CL x Expertise interaction effect on Misses, Errors, and Omissions for hairpin curves

Data availability

The authors do not have permission to share data.

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