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EEG correlates of acquiring race driving skills

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Abstract.
Objective. Race driving is a complex motor task that involves multiple concurrent cognitive processes in different brain regions coordinated to maintain and optimize speed and control. Delineating the neuroplasticity accompanying the acquisition of complex and fine motor skills such as racing is crucial to elucidate how these are gradually encoded in the brain and inform new training regimes. This study aims, first, to identify the neural correlates of learning to drive a racing car using non-invasive electroencephalography (EEG) imaging and longitudinal monitoring. Second, we gather evidence on the potential role of transcranial Direct Current Stimulation (tDCS) in enhancing the training outcome of race drivers. *Approach.* We collected and analyzed multimodal experimental data, including drivers' EEG and telemetry from a driving simulator to identify neuromarkers of race driving proficiency and assess the potential to improve training through anodal tDCS. *Main Results.* Our findings indicate that theta-band EEG rhythms and alpha-band effective functional connectivity between frontocentral and occipital cortical areas are significant neuromarkers for acquiring racing skills. We also observed signs of a potential tDCS effect in accelerating the learning process. *Significance* These results provide a foundation for future research to develop innovative race-driving training protocols using neurotechnology.

Keywords: race driving, electroencephalography, learning, brain plasticity, functional connectivity, neuromarkers, neurotechnology, transcranial Direct Current Stimulation

1. Introduction

Motor skill learning [1] is a fundamental aspect of human development [2], as well as of professional [3] and everyday life function. However, the mechanisms underlying the acquisition of complex motor skills, such as race driving, remain poorly understood. Complex motor learning involves two major aspects: the acquisition of motor skills, substantiated by performance improvements, and their consolidation, as the ability to retain these skills long-term and after long pauses. Recent studies consistently point to the pivotal role played by the cerebellum and the primary motor cortex (M1) in both the acquisition and retention of complex motor capabilities [4, 5]. A great body of neuroimaging literature has nowadays established well that brain plasticity plays a pivotal role in learning [6], influencing everything from the learning of new motor skills to recovery from brain injuries [7, 8]. Gaining a comprehensive understanding of the neuroplasticity mechanisms involved in building up complex motor repertoires can lead to the development of tools and strategies to enhance or accelerate learning in healthy individuals and to aid recovery in patients with central nervous system injuries, thus constituting a goal with significant scientific, translational and technological implications.

One of the main questions related to human brain plasticity revolves around understanding how sensory, motor, and cognitive functions undergo adaptation throughout a longitudinal process of skill acquisition potentially spanning many days, months, or even years [8]. Recently, there has been a surge of interest in identifying the distinct functional and structural characteristics inherent to the brains of athletes. Achieving professional performance in many fields like sports, arts, or music, is tied to the augmentation of sensorimotor and cognitive capacities, and can be investigated to give rise to new training approaches able to push to the very limits of human potential. A particular focus of numerous studies has been to address the question of whether the acquisition of expertise, obtained through adequate, domain-specific training, leaves discernible traces of experience-dependent plasticity within specific, localized neural circuits [8, 9].

Research over the last 30 years has demonstrated that motor skill acquisition is accompanied by plastic changes in the brain which can be revealed and studied, among others, with non-invasive electrophysiological (e.g., EEG) or metabolic (e.g., functional Magnetic Resonance Imaging (fMRI)) neuroimaging techniques. Several works have taken advantage of brain imaging to understand how domain-specific expertise builds up, especially for different sports [10, 11]. A recent study [12] has provided preliminary evidence that neuroimaging can be used to assess proficiency in complex motor skills such as race driving. Specifically, changes in the cerebellum have been identified through fMRI imaging after driving training. Functional differences have also been found between skilled and novice drivers, with many studies focusing on EEG alpha and beta rhythms to link expert performance to changes in neural activity [10, 13]. Research indicates that expert athletes exhibit distinct patterns in these rhythms, with increased alpha activity associated with focused, calm states and stronger beta activity linked to active engagement [14, 13] This "cortical quieting" in skilled individuals reflects reduced cognitive interference, supporting efficient motor and visual processing compared to novices. Identifying these relevant neuromarkers offers the possibility of enhancing motor performance by incorporating neurofeedback training into regular sports training regimens [14], allowing individuals to learn to regulate their EEG activity and potentially accelerate skill acquisition. This understanding supports the application of alpha and beta rhythms as tools for both assessment and intervention, aiming to optimize performance and facilitate the development of skilled motor abilities.

Recently, non-invasive brain stimulation approaches have become popular and have been applied to focally change neuronal activation [15, 16]. One such promising approach involves non-invasive neuromodulation through tDCS, where DC currents are delivered to the brain tissue through electrodes placed on the user's scalp, increasing or suppressing cortical excitability depending on the mode of stimulation (anodal vs cathodal) [15, 16]. A potential role of tDCS in motor learning is reasonable, as it modulates corticospinal excitability leading to the induction of long-term potentiation, a fundamental mechanism underlying learning. The polarity-dependent effects of tDCS play an important role, with the anode electrode over the primary motor cortex (M1) resulting in a relative increase in corticospinal excitability [17, 18, 19]. It is hypothesized that anodal tDCS paired with practice can further enhance motor skill learning. tDCS holds promise as a potential enhancer of motor skill learning in diverse populations, including neurotypical individuals and those with neurological disorders like after stroke [20]. Meta-analysis evidence [21] suggests that individuals who undergo tDCS to the motor cortex during motor skill practice exhibit superior performance compared to those receiving sham tDCS. Studies across various motor tasks support this hypothesis, showing that anodal tDCS to M1 during task practice improves motor performance more significantly than practice with sham tDCS [22, 23]. However, further evidence is required to establish the effects of tDCS, while it remains unclear what type of motor tasks could be positively affected. The identification of neuromarkers associated with complex motor learning, such as race driving, raises the question of whether the underlying mechanisms of brain plasticity can be manipulated to enhance the effectiveness of race driver training through tDCS.

Race driving is a complex motor task which engages multiple cognitive processes in different regions of the human brain to maintain and optimize speed and control throughout the racing track. In particular, racing demands high-level, domain-specific motor skills acquisition to effectively and efficiently command a multi-dimensional vehicle control system (i.e., steering wheel, brakes, throttle and other controls). The functional and structural plasticity promoted by a race driver's rigorous, longitudinal practice begs the question of whether it can be manipulated to give rise to faster and more effective motor training approaches. Highly skilled race drivers, particularly those at the top levels of formula racing car competitions, undergo extensive psychophysical training and face extreme competitive conditions. The need for heightened concentration and precise sensory-motor control places a substantial demand on both their bodies and brains. Many of these drivers have engaged in high-speed activities, such as go-karting or motor racing, from a very young age, a period when brain plasticity is at its peak [12]. Consequently, it is anticipated that visuospatial and motor processing in highly skilled individuals involves significantly more efficient use of brain activity compared to a matched group of untrained naïve drivers.

A few articles [12, 24, 25] have used fMRI to measure brain activity during motor reaction tasks and visuospatial tasks, examining the brain functional correlates associated with extreme training and competitive conditions faced by high-speed car racing drivers. Bernardi et al. [12, 24] conducted a comparison between skilled race drivers and regular car drivers, indicating that racing drivers exhibited more consistent recruitment of brain areas dedicated to motor control and spatial navigation compared to their regular counterparts. This finding suggests a distinct neurological pattern associated with the expertise of race drivers. A similar perspective presented in a different research study [25], hypothesizes that the observed differences in brain activity between racing drivers and regular drivers may be attributed to the task familiarity of the former. This viewpoint suggests that the variance in neural activation could be a result of the specialized cognitive demands and extensive practice associated with racing. Notably, the study in [26] involving a Formula E Champion driving under extreme conditions demonstrated a relation between brain activity in the delta, alpha, and beta frequency bands and hand movements. This article showcases the feasibility of using mobile brain and body imaging even in extreme conditions, such as race car driving, to explore sensory inputs, motor outputs, and brain states characterizing complex human skills.

Only a limited body of literature has been dedicated to the perceptual and cognitive skills of race drivers. According to some published studies [9, 27, 28] a large amount of deliberate, specialized practice is required to obtain professional-level skills in sports. On the contrary, a meta-analysis [29] suggested that practice contributes insignificant improvement to sports performance, emphasizing the need to consider findings from cognitive science, personality psychology, behavioural genetics, and sports sciences to comprehend the determinants of expertise. While many studies have explored the effects of visual stimuli on steering control [30], very few have directly compared the brain activity of experienced racing drivers with that of normal drivers. One study indicated that exceptional driving abilities may involve the acquisition of a specific motor repertoire distinct from that of everyday driving [24]. Another study aimed to highlight the behavioural differences between racing drivers and naïve drivers, revealing superior driving performance in terms of faster lap times and fewer crashes [31].

While various studies have provided insights into how racing drivers can excel in the driving task, making their reactions and decisions vastly different from those of normal road car drivers [31], there remains a gap in understanding how this knowledge can be leveraged to extract even more performance on the track. The ability to measure brain activity using EEG is poised to become the next frontier in performance for race teams, elucidating how a driver's brain reacts to inputs on the track. This avenue holds significant promise for extracting additional performance from drivers. Additionally, exploring the role of tDCS in race training may clarify whether and how electrical stimulation can boost the brain's capacity to learn and consolidate new skills. Notably, there is a lack of studies clearly indicating differences between professional drivers and normal road car users, incorporating both neuromarkers and behavioural analysis during driving and linking with one another. In conclusion, the identification of neuromarkers of race-driving proficiency and the exploration of tDCS to enhance race-driving training demand further research.

This paper aims to explore the neural correlates of learning to drive a racing car with easy-to-deploy EEG signals, and to investigate the potential of tDCS as a tool to enhance race training. To achieve that, we have collected and analyzed multimodal experimental data consisting of drivers' EEG, telemetry from a driving simulator and relevant meta-data. We aspire to lay the foundations for the future design of innovative race-driving protocols exploiting neurotechnology, a perspective that will be discussed in the light of the results extracted here. We found that novice drivers exhibited significant learning effects in lap time, optimal racing line, and steering wheel usage. Professional drivers also showed improvements within a single session, indicating quick adaptation to the simulator. Theta-band EEG rhythms power and alpha-band functional connectivity were identified as significant neuromarkers for acquiring racing skills. Last but not least, although the evidence for tDCS enhancing learning was not definitive, we provide an analysis suggesting that it may have accelerated the learning process of novice users who received active stimulation, compared to those who received sham tDCS.

Figure 1. Main hardware items of the experimental setup.(a) Driving simulator (b) ANT neuro eego EEG system (c) Platoscience Platowork tDCS system.

2. Materials and Methods

2.1. Experimental setup and data synchronization

Each experimental session entailed EEG and electrooculography (EOG) monitoring during driving in a racing simulator with active or sham tDCS taking place before the race driving task. A complete racing simulator provided by GTA Global/Octane Junkies was used for the experiments. The simulator, replicating a Formula E car cockpit, included a Playseat racing seat, Thrustmaster steering wheel and pedals, and a computer monitor, all mounted on a metallic base (Fig. 1a). With regard to software, the rFactor2 racing simulator on Steam was used. The race car model corresponds to that of the e.dams team car of the 2020-21 Formula E season, made available by GTA Global and NISSAN. The EEG (uV units) and EOG (mV) signal was recorded with an ANT Neuro eego 64-channel EEG system (ANT Neuro b.v., Hengelo, Netherlands) extended with two bipolar EOG channels (Fig. 1b) at 512 Hz. An anti-static wrist strap with a ground plug to equalize the body potential to the system ground and prevent electrical interference with the EEG from the simulator was worn by all subjects. The open-source CNBIToolkit Brain-computer Interface (BCI) platform, an implementation of the TOBI common platform [32], was used for acquiring, storing, and annotating biosignal data. A custom rFactor2 plugin exported telemetry and delivered hardware triggers for syncing with the eego amplifier. Neurophysiological and telemetry data were synchronized using a custom USB serial hardware trigger box with an Arduino Micro microcontroller. Brain stimulation was delivered using a PlatoWork tDCS headset (PlatoScience ApS, Copenhagen, Denmark) (Fig. 1c). The PlatoApp and PlatoLab smartphone applications were used to control the active and sham tDCS stimulation, respectively.

The biosignal (EEG, EOG) data were saved in GDF format and telemetry data were saved as a race log text file. The telemetry variables were recorded with a sampling rate of 100 Hz and consisted in: the time elapsed since the previous frame (for sanity check, diagnosing potential lags and delays), the time elapsed since the start of the racing session, the current lap index, the time elapsed since the start of the current lap, the time elapsed since the last car impact (with barriers, etc.), the car's position (x,y,z meters in world coordinates), angular velocity (x,y,z radians/sec in local vehicle coordinates), velocity (x,y,z meters/sec in local vehicle coordinates), acceleration (x,y,z meters/sec^2 in local vehicle coordinates), angular acceleration (x,y,z radians/sec^2 in local vehicle coordinates), speed (meters/sec). We also recorded the current gear (of note, since gear change in Formula E is automatic, this is of little interest), the pushing of the throttle and brake pedals (in [0, +100]% of total range, corresponding to no pedal press and full pedal press, respectively), and the use of the steering wheel (in [-100, +100]% of total range, corresponding to full left turn and full right turn, respectively. Middle steering wheel position corresponds to 0.). The world coordinate system is left-handed with +y pointing up the sky. The local vehicle coordinate system is as follows: +x points out the left side of the car from the driver's perspective, +y points to the sky, and +z points out the rear of the car. Rotations are as follows: +x pitches up, +y yaws to the right, and +z rolls to the right. Date and time stamps ensured that

Table 1. Novice participant information

SubjectID	Age	Gender	Corrected Vision	Handedness	Driving Proficiency	tDCS Group	Sessions	Laps
TE03ES	32	Male	Yes	Right	Naïve	Active	10	195
MA23GI	25	Female	Yes	Right	Naïve	Active	8	159
YA25AI	22	Male	No	Right	Naïve	Sham	10	190
MA16TE	33	Female	Yes	Right	Proficient	Sham	8	170
SA03UR	34	Male	Yes	Right	Naïve	Sham	10	207
EF06HE	33	Male	No	Right	Naïve	Active	10	198
LO30KI	37	Male	Yes	Right	Proficient	Sham	10	193
NI28LD	18	Male	No	Left	Proficient	Active	9	179
JA07NA	30	Male	No	Right	Naïve	Sham	10	200
MA14LY	32	Male	Yes	Right	Proficient	Active	10	200
RE03AN	22	Male	No	Right	Proficient	Active	10	196

the correspondence between the racing log file and the EEG GDF file of each racing run could be established after the experiment.

2.2. rFactor2 racing environment and settings

The racing task is accomplished with the rFactor2 simulator platform. All experimental racing runs were executed with the same settings (including the professional driver sessions) to exclude those as confounding factors. All racing runs were implemented as rFactor2 ”Practice sessions”. There are no opponents on the track, the driver is racing on their own so that no overtaking skills are to be learned and evaluated. Importantly, although all driving aids are disabled (traction control, automatic brake/throttle/steering assistance, etc.), the tyre wear and the car vulnerability were also disabled. Overall, the learning task only involves learning to minimise lap time and impacts by improving the coordinated use of steering, braking and throttling (i.e., no tyre wear management or other skills related to actual racing are evaluated). The demanding 21-turn Diriyah track of the Saudi Arabia Formula E e-Prix was selected for the experiment.

2.3. Experimental protocol

The study comprised two separate legs: a randomized, controlled, and longitudinal training study of novice race drivers, and a uncontrolled, single-session evaluation of professional/experienced race drivers.

In the first leg, each novice participant was asked to undergo 10 experimental race-driving sessions. All participants finished their training sessions within two weeks so that the maximum logistically possible training intensity was achieved. An experimental session comprised, first, 20’ of (active or sham) tDCS stimulation with PlatoWork, followed by approximately 45’ of simulated race driving. 11 novice participants were randomly assigned to one of two tDCS groups (6 active, 5 sham). The active tDCS group received anodal stimulation with PlatoWork’s fixed electrode positioning designed and parameterized to assist learning by increasing neural excitability over prefrontal brain regions associated with learning. The second group received “active sham” stimulation (i.e., stimulation that generates similar feelings without giving rise to cortical excitability). Novice subjects remained blind to their group allocation. Active tDCS was achieved with the PlatoApp of PlatoScience running on an Android smartphone and operating in ”Learning” mode. Sham stimulation was accomplished with the PlatoLab app in the appropriate mode as instructed by our PlatoScience collaborators.

The driving task targeted 20 laps per session. Participants were asked to complete the racing tasks in 5 blocks of 4 laps each. These blocks are defined here as “racing runs”. Each racing run has a race log file and a biosignal GDF file associated with it, as described above. The instructions given to the subjects were simple and focused on three objectives: participants should try, to the best of their ability, to i) minimize lap time (visual feedback on lap time was delivered at the end of each lap by enabling the corresponding rFactor2 setting), ii) minimize the number of crashes (i.e., impact with barriers) and iii) avoid, as much as possible, movements and actions that generate EEG artifacts (speaking, excess blinking, intense neck movements).

In the second leg, three professional race drivers were recruited on two separate days. The two professional drivers of the e.dams Formula E team 2021-22, Sebastian Buemi and Maximilian Günther, executed a single session identical to those of the novice participants (i.e. 5 racing runs of 4 laps each while wearing the eego EEG system). The sessions of the two professional drivers were executed consecutively and included no tDCS. The racing sessions were

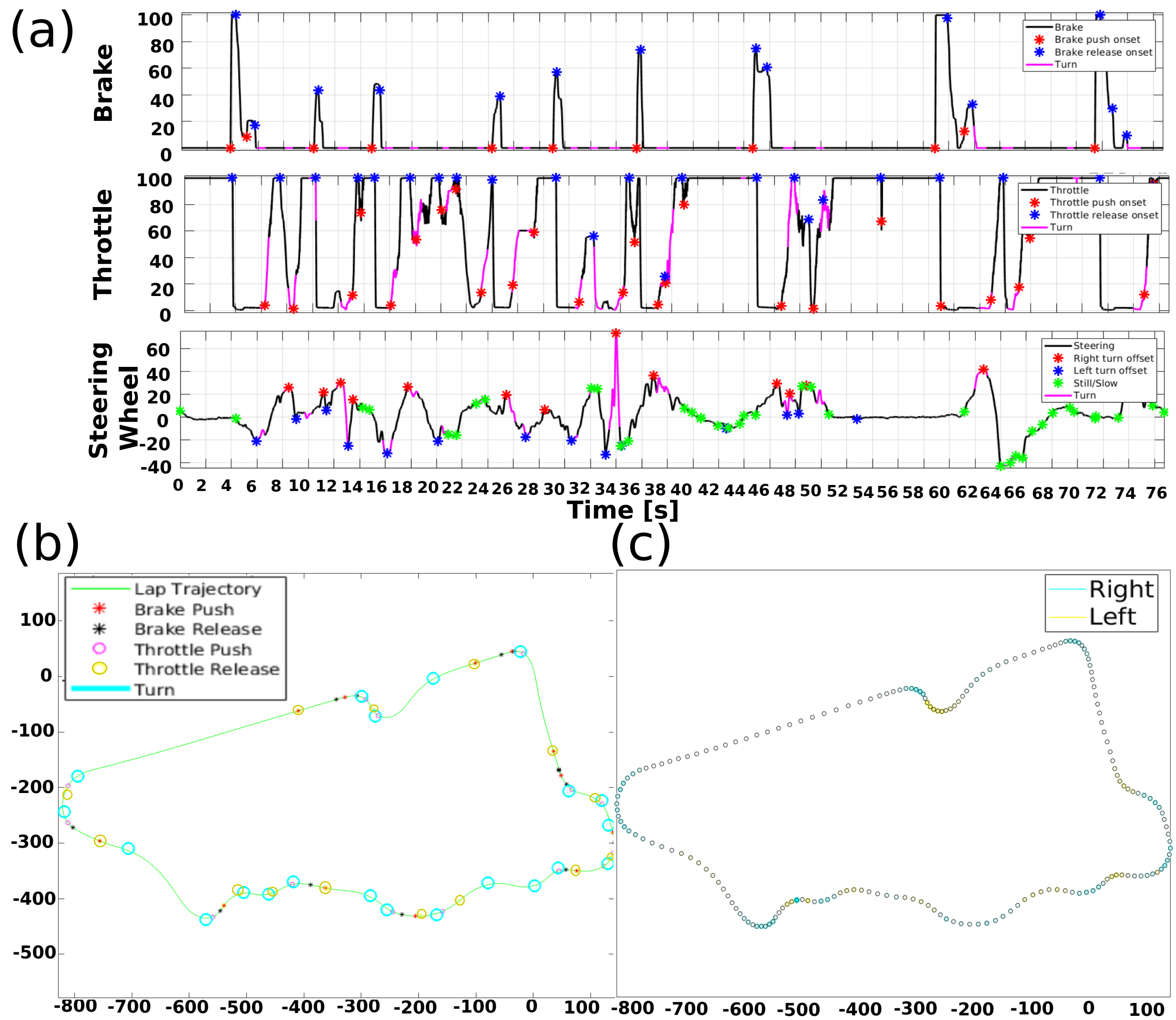

Figure 2. Extraction of brake, throttle and steering wheel events for the best lap of Max Günther. (a) Identification of events in the signal input streams. As colour coded in the legends, the black lines illustrate the corresponding input signal reading from the simulator's telemetry over time (Top: brake, Middle: throttle, Bottom: steering wheel) in % of the respective input's total range ([0, 100]% for brake and throttle, [-100,+100]% for steering wheel). The magenta line shows the time segments where the car went through turning points in the track. From top to bottom, red asterisks denote the timing of detection of brake pedal push, throttle pedal push and right steering wheel turning, respectively, while blue asterisks equivalently visualize brake pedal release, throttle pedal release and left steering wheel turning. Green asterisks in the steering wheel input graph (bottom) indicate the onset of time segments where there is no, or extremely slow, use of the steering wheel. (b) Position of events on the car's trajectory. As shown in the legend, the green line shows the outline of the race track in world coordinates (meters), as the trajectory of Max Günther's car in their best lap. Red and black asterisks denote brake pedal push and release events, respectively. Magenta and yellow circles specify throttle pedal push and release, respectively. Ciel circles visualize the entrances of the 21 turns of the Diriyah race track. (c) Steering events color-coded on the car trajectory. Full right turn (+100 steering wheel input) in ciel, full left turn (-100 steering wheel input) in yellow, and no turning (0 steering wheel input) in white circles. In panels (b) and (c), the two axes represent 2D real-world coordinates in meters.

implemented with the same specifications as for the novice drivers so that the EEG data acquired can be used for comparisons to neurophysiological data. Furthermore, an extra session was done with a 12-year-old male volunteer who has won several junior national karting competitions and was at the time the reigning champion in their category.

2.4. Participants

Eleven (11) participants with no known neurological conditions were recruited. The subject IDs are derived through a standard data anonymization method. Table 1 illustrates the demographics, tDCS group allocation and driving proficiency of all novice drivers recruited. Frane's allocation algorithm [33] was used

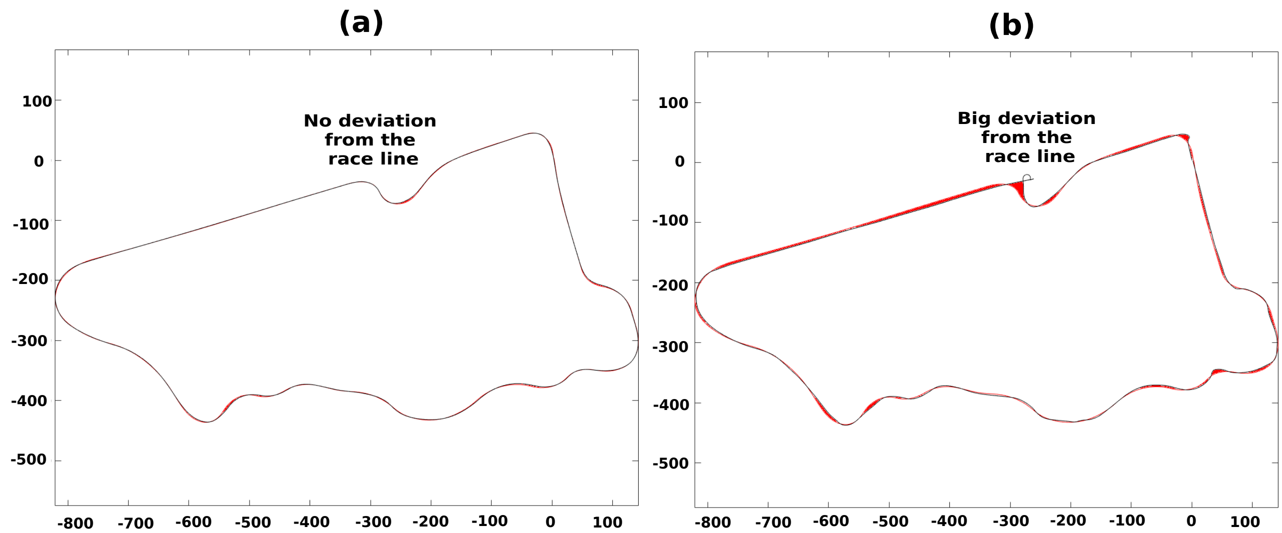

Figure 3. Extraction of racing line deviation. For both panels, the black lines show the trajectory of Max Günther's car in their best lap. The red lines show the trajectory of the car at (a) the first lap lap of Max Günther and (b) the first lap of EF06CH. In both panels, the area between the first-lap and best-lap trajectories is highlighted in red and illustrates the deviation from a near-optimal racing line. The two axes represent 2D real-world coordinates in meters. The most salient turning point where Max Günther consistently follows an optimal path, but novice user EF06CH deviates substantially from it is annotated with text.

to ensure that the two groups were balanced across a number of identified possible confounding factors (age, gender, prior driving proficiency and corrected vision). Of these confounding factors, age and gender were controlled due to their known influence on brain activity in neuroscience, neuroimaging, neuropsychology, and BCI studies. Driving proficiency and visual acuity were also identified as potentially important confounds given the study's focus on learning to race. Prior driving proficiency was assessed taking into account whether a subject had any significant previous driving and, especially, racing experience (karting, sim-race video games etc.). This work considered subjects with a driving license but no recent and regular driving experience as Naïve.

The study was approved by the ethical committee of the University of Essex (UoE) (number ETH2021-1785 and amendment ETH2122-0411 for inclusion of a minor participant). All participants were informed about the tasks to be accomplished prior to the experiments, the protocol, the evaluation methods, the use of their data and any rare potential annoyances (e.g., obtrusive tDCS sensation, itching from EEG placement, headaches). All subjects were explicitly made aware of the possibility to withdraw from the study at any moment without a need to provide a reason. The experimental protocol fully complied with the Declaration of Helsinki.

2.5. Evaluation methods

2.5.1. Data collection: Data collection has approached the maximum of the set targets. As shown in Table 1, 8 out of 11 participants completed all (designated maximum of) 10 sessions. Two subjects completed 8 sessions and one 9. Participants completed on average 187±14 laps (out of the maximum target of 200). The table shows that all subjects almost always completed 20 laps/session, as desired, with a few laps missing in most cases due to wrong counting (4 laps per run were planned).

2.5.2. Balance of confounds: One major goal of the study has been the investigation of any tDCS effects on race-driving learning. It is thus critical to eliminate the influence of any other factors that may affect performance and learning. Elimination is done by balancing suspected confounding factors between the two tDCS groups with Frane's methodology [33] at recruitment. Frane's method is an adaptive minimization method for randomized allocation which monitors the statistical differences of each confounding factor for each possible allocation and selects the one that minimizes the greatest current imbalance across all confounds. The confounding factors considered were: Age, Gender, Driving proficiency/experience and Corrected Vision. It must be noted that all recruits but one (NI28LD) were right-handed. For numerical confounds (e.g. Age) we report averages and standard deviations between the two groups and the p-value of an unpaired, two-sided Wilcoxon Ranksum test. For categorical variables, the p-value of a chi-squared test for proportions is provided.

This investigation further checks whether any of these confounds explain the gains in terms of lap time exhibited by subjects. Lap time is computed as the difference of the average lap time between the first two and the last two sessions. For Age, we correlate the lap time gain to each participant's age and seek for significant correlation. For categorical variables (Gender, Driving Proficiency, Corrected Vision) we calculate the average gain per category (e.g., Male vs Female for Gender) and perform an unpaired, two-sided Wilcoxon ranksum test.

2.5.3. Behavioural driving proficiency metrics: It is critical for the study's goals to identify metrics of race-driving proficiency upon which the concept of "learning to race" can be grounded (as the optimization of these metrics over time). The obvious learning outcome used throughout the study is the lap time (i.e., the time needed to complete one lap). As a secondary measure of proficiency, we also count the number of impacts per lap, since the ability to avoid crashes also reflects driving proficiency and there was explicit instruction to subjects to avoid impacts to the extent possible (even though the car's vulnerability was disabled to avoid large numbers of runs that would have to be restarted because of fatal crashes). This study further defines a "penalized lap time" metric which attempts to combine both aspects of racing (i.e., both fast and "accident-free") by augmenting the actually achieved lap time with 250 ms for each impact. All these metrics are straightforward to compute based on the information stored in the race-log files.

With respect to behavioural metrics, we further analyzed the use of the throttle, brake, and steering wheel, based on the assumption that learning to race could probably lead to the milder, smoother and more precise use of some or all of these inputs. To do so, the number of brake and throttle push/release and turning left/right events per lap must be extracted. This is made possible through suitable processing of the corresponding time-series extracted by the race log files. Specifically, for brake and throttle press/release events, the raw input is first filtered with a Savitzky-Golay smoothing filter [34]. The position and number of major peaks/sinks are then found by thresholding the derivative of the signal and merging events that are too close in time (less than 0.5 s difference) together. The identification of the peaks of these signals is done using the MATLAB function "peakfinder" available in MATLAB Central which finds minima and maxima of an arbitrary signal.

For each event, we computed its slope/derivative as $|S_{min/max} - S_{onset}|/(t_{min/max} - t_{onset})$, where S_{onset} is the signal's value at the onset of the event, $S_{\mathrm{min/max}}$ represents the minimum or maximum signal value after onset, t_{onset} is the time of event onset, and $t_{\mathrm{min/max}}$ is the time at which the minimum or maximum signal value occurs. Therefore, events corresponding to abrupt/clear movements can be distinguished from those that are smoother and less clear to distinguish from the general activity. Finally, left/right turns are identified by using, again, peakfinder to locate the time points with maximum left/right steering wheel turning, signifying the offset of a left/right turn movement. The corresponding onset is found either as the offset of the immediately previous turning movement (e.g., for the cases where a left/right turn succeeds a right/left one, respectively), or, by extracting the offset of the latest period of inactivity (zero-derivative of steering wheel signal), whichever happens last. The slope of steering events is then found in the same manner as for braking/accelerating. We segment and store periods of complete inactivity (with no brake/throttle/steering movements at all) in the lap, to be used as "control" (e.g., for the Motor-related Cortical Potentials (MRCP) analysis). Based on the extraction of braking, accelerating and steering events in this fashion, the amount of extracted events can serve as an index of race driving proficiency as hypothesized. Fig. 2 illustrates this process for the best lap of Max Günther.

Similarly, we assume that proficient racing also prerequisites knowledge and ability to follow the ideal racing line. This aspect is evaluated by computing the deviation of each lap from an optimal trajectory. The best lap of Max Günther (achieved at his $17^{th}/20$ lap), which is also the best lap overall in the study, is taken as a reference. The racing line deviation is then calculated as the area between the curves of a given lap and the optimal lap trajectory. The area between the curve is ideally computed as the integral $|\int_{x_{min}}^{x_{max}} f(x) - g(x)|$, where $f(x), g(x)$ the curves of the optimal and the current lap trajectory. Since the track defines closed trajectories, for any given interval along the horizontal axis the integral is evaluated separately for the upper and lower parts of the trajectory. Furthermore, the integral is not exactly computed, but only approximated by sampling evenly the x-axis with a step of 0.5 m and computing the average of the differences of the two trajectories on each of the N x-points: $\frac{1}{N}\sum_{x_i}|f(x_i) - g(x_i)|$. Fig. 3 illustrates by example this metric (area between the curves highlighted in red). It is clear that the first lap of Max Günther (when he was still getting accustomed to the track and the virtual car) has only marginal deviations from the racing line of his best lap, which is not surprising given his professional racing skills. On the contrary, the deviation of the first lap of subject

EF06CH from the optimal racing line is substantial. This investigation assumes that eventual improvements across time on this metric suggest that part of the learning process entails learning to follow an optimal trajectory (aka, the ideal racing line).

2.5.4. Behavioural results analysis criteria to establish learning effect: Searching for neural correlates of learning and the effects of tDCS on the learning process is pointless if the learning effects themselves are not established first. To quantify and visualize learning in any of the aforementioned behavioural metrics related to race driving, we extract and and report:

- Individual learning curves per lap, with linear and exponential fits (to examine whether a learning curve reaches the consolidation/convergence stage by the training offset)
- Learning curves averaged within sessions either with mean or with median (to attenuate the effects of outliers) for each subject and grand-averaged across all subjects.
- Pre-training vs post-training comparisons with statistical testing (unpaired, two-sided Wilcoxon ranksum tests). For novice users, the first two sessions are compared to the last two. For professional users, the first 6 laps are compared to the last 6.
- Grand averages of lap times within each session with linear fits and Pearson correlation. This is to evaluate learning taking place within each session (20 laps) at the different stages of training.
- For Novice users that underwent active or sham tDCS, we also show the average and standard deviation within each group and overall with statistical significance.

2.5.5. EEG signal pre-processing: Pre-processing operations were applied to the raw EEG signal including linear detrending of each channel, to remove slow signal drifts (as the eego amplifier does not apply any hardware filters) and DC removal. Common Average Reference (CAR) spatial filtering was also applied to remove common noise sources. We further applied, Surface Laplacian (for Power Spectral Density (PSD) and effective connectivity analysis) or anti-Laplacian (for MRCP analysis) spatial filtering. The available four cross neighbours were used. Anti-Laplacian refers to adding, rather than subtracting, the potential average of a channel's neighbours, thus enhancing, rather than removing, the local EEG activity. Artifact removal has been done by using FORCe [35]. For all EEG-based analysis, channels M1, M2 (mastoids) and peripheral channels PO5, PO6 are excluded from the analysis as they are particularly susceptible to noise interference. Depending on the particular analysis domain, we further limit the investigation to specific cortical regions and channels, as specified below.

2.5.6. EEG rhythms: We attempted to identify changes across time in various neurophysiological variables, which could thus suggest (or even subserve) cortical plasticity related to learning to race, as well as to correlate these with the learning outcome (i.e., race-driving performance). A first such candidate regards EEG rhythms. Oscillatory cortical activity has been associated with numerous cognitive processes, especially in the theta and alpha bands, including learning in general, and learning of motor skills, specifically [13, 36, 37]. Hence, we aimed to explore whether any combinations of frequency bands and regions of cortical EEG exhibit such modulation over time and correlation to behavioural outcomes. EEG PSD is extracted for each channel with the Welch method [38] for each lap (i.e., the whole EEG segment corresponding to a lap is fed to the corresponding function). This analysis employs 2 s internal Welch windows with 125 ms overlapping resulting in 0.5 Hz PSD resolution on 59 EEG channels. We then average the lap's PSD within 5 broad bands: delta [1,4] Hz, theta [4,8] Hz, alpha [8,12] Hz, beta [13,30] Hz and (low) gamma [30,40] Hz and 9 Regions of Interest (ROIs): Frontocentral Left (F1, F3, F5, FC1, FC3, FC5, AF3), Frontocentral Medial (Fz, FCz, note that AFz is unavailable as it is the ground channel), Frontocentral Right (F2, F4, F6, FC2, FC4, FC6, AF4), Central Left (C1, C3, C5), Central Medial (Cz), Central Right (C2, C4, C6), Centro-parieto-occipital Left (P1, P3, P5, CP1, CP3, CP5, PO3), Parieto-occipital Medial (Pz, POz, note that CPz is unavailable as it is used as a reference channel) and Centro-parieto-occipital Right (P2, P4, P6, CP2, CP4, CP6, PO4).

Hence, we focus on 5 bands $\times$ 9 ROIs = 45 candidate spatiospectral EEG rhythms that must be investigated for involvement in learning to race. The following criteria are imposed to accept any of these candidates as an index of functional brain plasticity:

(i) The rhythm in question must correlate significantly with lap time.

(ii) It must also correlate significantly with the chronological lap index (i.e., consistently change over time).

(iii) The correlation with the lap index must be negative (i.e., the bandpower must decrease over time, as reported in relevant literature [36, 39]).

(iv) The correlation with lap time must be positive (since decreasing power should be associated with decreasing lap time–better performance thanks to learning).

(v) It must differ significantly when comparing the onset of training (first two sessions) and the learned outcome (last two sessions).

Importantly, given the exploratory (rather than hypothesis-driven) nature of this analysis leading to many comparisons, this investigation employs everywhere strict Bonferroni correction to avoid false positives. Statistical testing for correlations is performed with the Student's corresponding test based on the chi distribution. For pre- vs post-training comparisons, non-parametric, Wilcoxon, unpaired, two-sided tests are used. For novice users, all 10 sessions (i.e., approximately 200 laps) are included in the analysis. For professional users that executed a single session (20 laps), the same criteria apply, but the pre- vs post-training comparison involves the first and the last 2 laps.

2.5.7. Effective functional connectivity: Functional plasticity with respect to brain connectivity has also been implicated with learning [40]. Here, Directed Transfer Function (DTF) effective connectivity is employed, which provides information not only for the strength of the association between two brain regions but also for the direction of this association (i.e., relies on Granger causality). We make use of the DTF algorithm implementation from the eConnectome toolbox [41], with order 10 for the embedded autoregressive model. DTF connectivity is computed for all pairs of channels (in both directions) and for each lap with 1 Hz frequency band resolution and is then averaged within the same bands as for the PSD analysis and within 3 wider regions Frontocentral (F1, F3, F5, F7, FC1, FC3, FC5, Fz, FCz, F2, F4, F6, F8, FC2, FC4, FC6, AF3, AF4, AF7, AF8, FT7, FT8), Central (C1, C3, C5, Cz, C2, C4, C6, T7, T8) and Centro-parieto-occipital (P1, P3, P5, P7, CP1, CP3, CP5, PZ, P2, P4, P6, P8, CP2, CP4, CP6, POz, PO3, PO4, PO7, PO8, O1, O2, Oz, TP7, TP8). There are thus $5\times3\times3 = 45$ candidate connectivity features that are examined in the same manner as the EEG rhythms described above.

2.5.8. Regular and anticipatory Motor-related Cortical Potentials: For regular MRCPs, the Contingent Negative Variation (CNV) signals are time-locked to the onset of the actual execution of driving actions (e.g., braking, turning, etc.) and are analyzed with respect to their amplitude, timing, and slope. In contrast, we define as "anticipatory" MRCPs the CNV signals that are taken to be time-locked to the "ideal" action positions, where the reference of optimality is the best lap in the dataset. These waveforms are meant to reflect the driver's ability to anticipate and align with optimal timing of brake, speeding and steering actions. We aim to determine whether novice drivers' placement of control input actions improves over time, enhancing lap times, and whether these improvements are detectable in the brain through anticipatory MRCPs. This work further hypothesizes that the regular MRCP CNV signals associated with real race-driving actions (braking, accelerating, steering) may also provide information on plastic changes accompanying race-driving learning.

MRCPs are bandpass filtered (Infinite Impulse Response (IIR) filter with pass-band in [0.4, 3] Hz) and spatially filtered with a cross-neighbor anti-Laplacian spatial filter. The interval [-1, 1] s around each brake/throttle push/release and turning left/right event is considered, where $t = 0$ is the event onset. The filtered signals are then averaged separately for each event type within each session to output a final MRCP curve per channel. For regular MRCPs, we investigate whether the amplitude of the negativity peak, its time gap from the movement onset and the slope of the negativity seem to relate to the learning outcomes. For anticipatory MRCPs, we extract the same kind of curves for each participant's lap on the ideal action positions, using Max Günther's best lap as reference. In other words, the existence of MRCPs around the onsets of ideal events is examined, as shown in Fig. 2b.

3. Results

3.1. Balance of confounds

Table 2 shows that all confounding factors were appropriately balanced, as no p-value is significant. It is also shown that none of these confounds seems to explain the learning outcome (in terms of lap time gain). It has to be noted, though, that, as elaborated later in this analysis, the tDCS treatment does not seem to significantly influence the overall lap time gain either. Still, as will be argued, further analysis demonstrates that, in fact, tDCS does seem to have an effect on the learning process, in contrast to any of these other variables.

3.2. Behavioural results on learning to race

Fig. 4, 5, 7 and 8 establish the existence of clear learning effects across the racing proficiency metrics outlined in Section 2.5.4. For novice users and each behavioural metric, an one-way repeated measures ANOVA ($\alpha = 0.05$) is reported with the single factor "session" (time) to substantiate the significance of learning with regard to the variable in question. Furthermore, we perform the corresponding mixed-design ANOVAs with within-subject factor session/time and between-subject factor tDCS, and search for a significant session $\times$ tDCS interaction

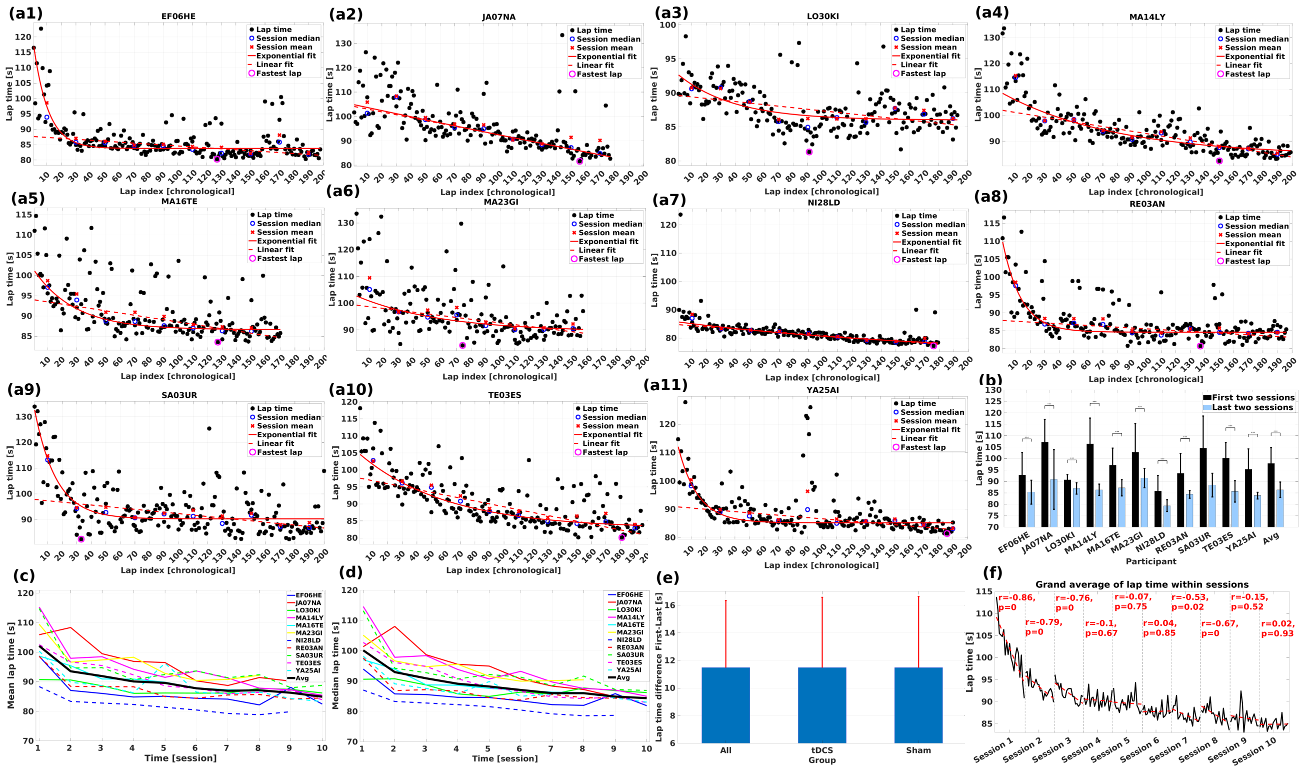

Figure 4. Lap time performance analysis across sessions for novice users. Panels (a1-a11) display individual lap time data for each participant, plotted against the lap index in chronological order. Each subplot includes the lap times (black dots), session medians (blue circles), session means (red 'x'), the exponential fit (solid red line), linear fit (dashed red line), and the fastest lap for each participant (magenta circle). Panel (b) compares the mean and standard deviation of lap times for the first two sessions and the last two sessions across novice participants, highlighting performance improvements over time, with statistically significant differences marked by asterisks (*); * indicates significance with $\alpha = 0.05$, ** with $\alpha = 0.01$ and *** with $\alpha = 0.001$. No asterisk denotes no statistical significance at the 95% confidence interval ($\alpha > 0.05$). Panels (c) and (d) illustrate the mean and median lap time per session, respectively, showing the overall trend of lap time reduction across sessions for all novice participants. Each line represents an individual participant as shown in the legend, the grand average across subjects is shown in thick, black line. Panel (e) shows the average lap time differences across all novice participants and separately for the active tDCS and sham groups, with error bars representing standard deviation. Panel (f) presents the grand average lap time per lap index within each session, emphasizing the consistent improvement in lap times across the ten-session training period. The correlation coefficient between lap time and lap index within each session and its p-value is provided at the top of each session segment, indicating the sessions where intense learning took place.

Table 2. Balance of confounding factors and statistical comparison of their influence on lap time gain. Proportions are presented with respect to Males in Gender, Proficient in Driving Proficiency, and Yes in Corrected Vision.

	Age			Gender (Male/Female)			Driving Proficiency (Proficient/Naïve)			Corrected Vision (Yes/No)		
	Active	Sham	p	Active	Sham	p	Active	Sham	p	Active	Sham	p
Balance	27.0±6.3	31.2±5.7	0.23	5/6	4/5	0.85	3/6	2/5	0.78	3/6	3/5	0.78
	Correlation			Male	Female	p	Proficient	Naïve	p	Yes	No	p
Lap time gain	$r = 0.61$, $p = 0.78$			12.0±5.7	10.1±1.0	0.63	9.9±6.2	12.8±3.4	0.25	12.6±5.6	10.2±3.9	0.54

to test whether the tDCS treatment significantly influences learning. Prior to performing ANOVA analyses, we confirmed the normality of our data for all metrics involved through one-sample Kolmogorov-Smirnov (K-S) tests at the 95% confidence interval ($\alpha = 0.05$).

The final, highest-level goal in racing under the specified conditions is to minimize the lap time. The other, complementary metrics introduced evaluate different, specific facets of the overall racing skill, but the latter is best (necessarily and sufficiently) evaluated overall through lap time. Hence, learning in terms of lap time is of the utmost interest. Fig. 4 and Fig. 5 illustrate the concentrated results for this

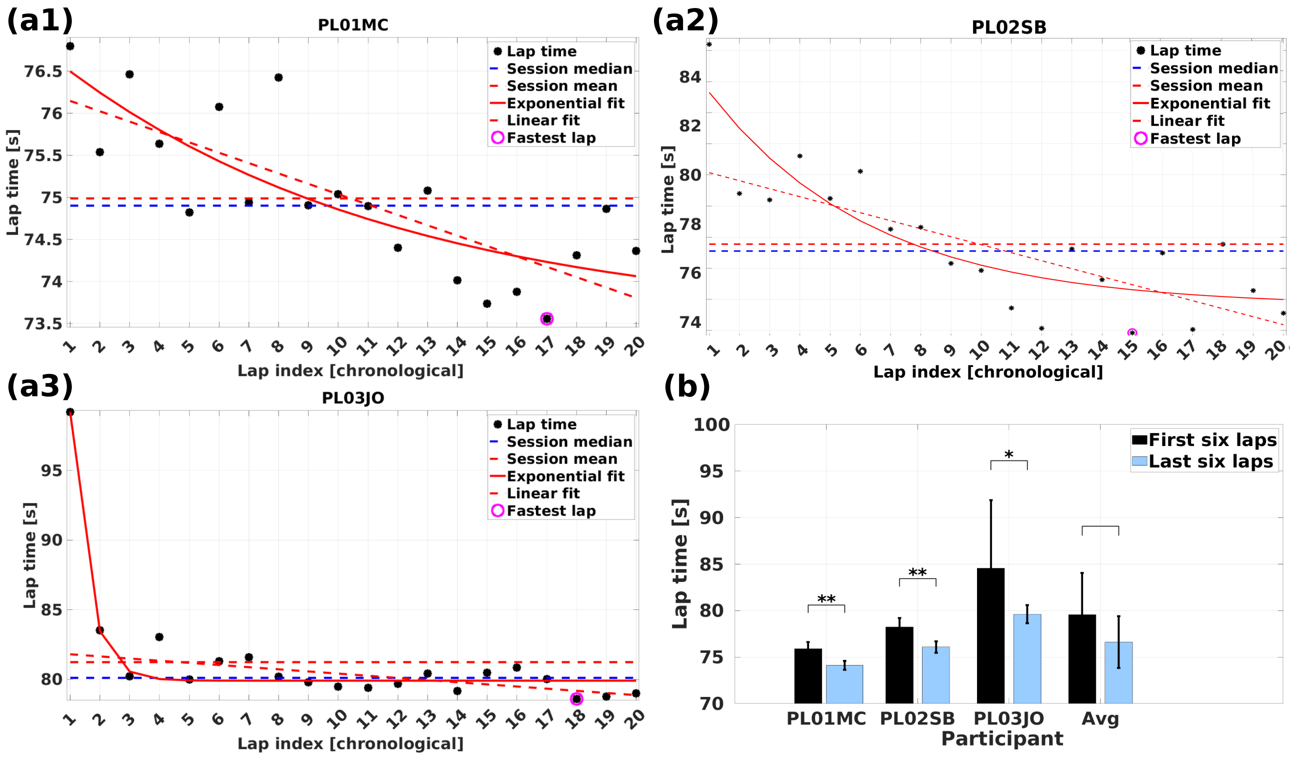

Figure 5. Lap time performance analysis for professional drivers over a single session of 20 laps. Panels (a1-a3) display individual lap time data for each professional driver (PL01MC, PL02SB, and PL03JO), plotted against the chronological lap index. Each subplot includes the lap times (black dots), session medians (dashed blue lines), session means (dashed red lines), the exponential fit (solid red line), the linear fit (dotted red line), and the fastest lap achieved in the session (magenta circle). Panel (b) compares the mean and standard deviation of lap times for the first six laps and the last six laps across professional drivers, highlighting significant improvements over the course of the session, with statistically significant differences marked by asterisks (*). * indicates significance with $\alpha = 0.05$, ** with $\alpha = 0.01$ and *** with $\alpha = 0.001$. No asterisk denotes no statistical significance at the 95% confidence interval ($\alpha > 0.05$).

metric for novice and professional users, respectively.

For Novice users, a significant group learning effect is found through repeated measures ANOVA with single factor time/session ($F = 19.81, p < 10^{-13}$). This is not surprising, as the ability of all subjects to gradually minimise the lap time is ubiquitous. Specifically, it is evident by the individual subject learning curves (Fig. 4a1-a11), the statistically significant (for all subjects) pre- vs post-training lap time comparison (Fig. 4b), the mean and median subject grand averages per session (Fig. 4c-d), the group's distribution of lap time gain (shown also separately for the two tDCS groups, Fig. 4), as well as the respective grand average per lap index within sessions (Fig. 4f).

Professional drivers (including the 12-year-old local champion in this group) also show significant group learning effects within the single session executed, illustrated again by both the individual learning curves (Fig. 5a1-a3) and by the pre- vs post-evaluation comparison (Fig. 5b), although these results should reflect the familiarization process with the simulator, the virtual car and the track, rather than ”learning to race”. Specifically, a repeated measures ANOVA shows a significant effect of time on lap time ($F = 2.4, p = 0.01$).

The comparison between novice and professional users in Fig. 6 shows that pro drivers converged towards 73-75 s best lap time (Fig. 6a), with the 12-year old “professional” driver achieving 78-79 s. Novice drivers converged on average to 81-82 s. Interestingly, one novice subject (NI28LD) performed markedly better than the others, with the fastest lap at 77.2 s and the best session average at 78.9 s, Fig. 6b. This performance is very close to those of the professional drivers, well ahead of the second-best novice driver (EF06CH with 80.3 s fastest lap and best session average of 82.2 s) and also surpasses the achievements of the 12-year-old experienced race driver (fastest lap 78.6 s and session average 81.2 s; of course, it has to be taken into account that the young professional only trained for a single session). Overall, it can be deduced that there is room for further improvement for all novice users, which could potentially benefit from novel

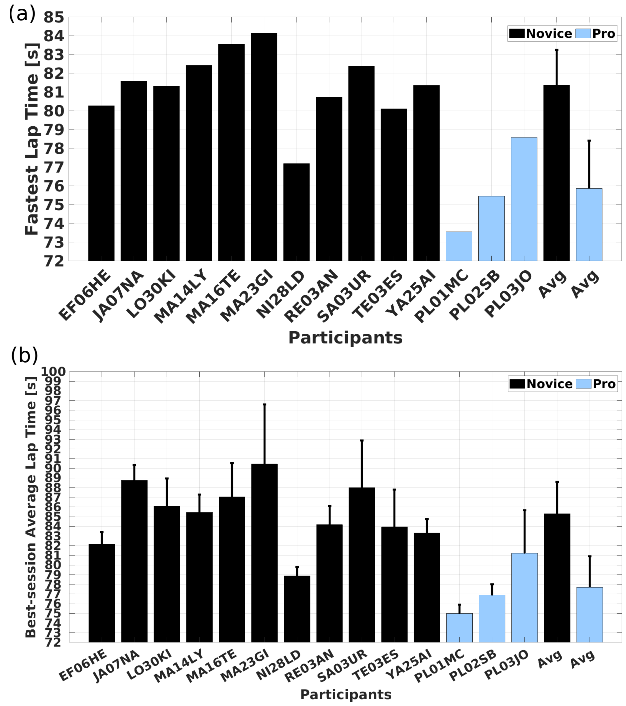

Figure 6. Lap time comparison between novice and professional drivers. (a) Fastest single lap for each user. (b) Best session average of lap time for each user with standard deviation.

training protocols.

Novice users show no group learning effect with regard to the number of impacts (repeated measures ANOVA $F = 1.27, p = 0.27$). This is indicated by mostly flat grand averages in Fig. 7a1-a4 and insignificant pre- vs post-training differences in that respect (Fig. 7a5). In terms of racing line improvement, novice users (Fig. 7b1-b5) do show a significant group learning effect (repeated measures ANOVA $F = 4.37, p = 0.0002$).

We have further assumed that learning to race should also be related to reduced "redundancy" in driving actions (braking, accelerating, turning); in other words, reaching a state where all these actions only happen at specific, optimal positions on the track, with no (or only a few) corrections needed. If this is correct, learning should also show with the reduced number of these events, as described above. However, this assumption is only partially supported by the data. No significant group effect is found when considering the sum of all types of events (ANOVA $F = 0.52, p = 0.85$), although most novice drivers do show significant improvements, evident in pre- vs post-training bar graphs, individual learning curves and grand averages (not shown here). It thus seems that, although not a significant and generic effect, in principle, most subjects tend not to overuse the brake, throttle and steering wheel.

It must be underlined that, as steering events are much higher in number than brake and throttle push/release, the total event metric mostly reflects the steering performance. The brake and throttle use learning curves and pre vs post-tests (not shown here) are erratic and do not really resemble learning curves at all. There exist irregular fluctuations for many users, and pre- vs post-training performance is not consistent across the population. Consequently, the ANOVA result for brake use may be significant (ADD F/p here), but this only shows that session means are not equal, not that they are converging to a consistent learning outcome. This is evident by the corresponding grand averages (not shown here), which are flat, and the individual subject curves which are irregular. The same holds for throttle use, except for the first two sessions where there seems to be a fairly consistent reduction across the sample.

Hence, it turns out that the overall assumption is fully verified only with regard to the use of the steering wheel. As shown in Fig. 7c1-c5, all subjects, but two, reduced their use of steering wheel turning, and most of these significantly; so that, on average, the pre- vs post-training reduction is significant (although the ANOVA main effect is not: $F = 1.45, p = 0.19$). The absence of ANOVA significance at the session level must be attributed to the fact that this effect takes place within the first two sessions only, as shown by the per-session grand average plot (Fig. 7c4). Improved, smoother use of steering is consistent with the racing line improvement found before.

Professional drivers had no significant effect on impact reduction either (ANOVA is degenerate due to too few points, no pre- vs post-training differences found, Fig. 8a). This driver category also improved in terms of racing line consistency, but not significantly (repeated measures ANOVA $F = 1.7, p = 0.13$, no pre- vs post-training significance in Fig. 8b). Reduction trends with no statistical significance are denoted for steering wheel use, too (Fig. 8c). These phenomena should be very likely attributed to a ceiling effect. In other words, professional drivers are already able to almost eliminate the chance of impacts, closely follow the optimal racing line and make the best use of steering at the beginning of the session, so that there is no room for learning in that respect. The insignificant improvements observed in Fig. 8 can be explained through slight optimizations reflecting the acclimatisation of pro drivers to the particular conditions of the experiment (simulator, car settings, etc.).

3.3. tDCS effect on learning

The novice driver study has been designed specifically to investigate the potential role of tDCS in learning to

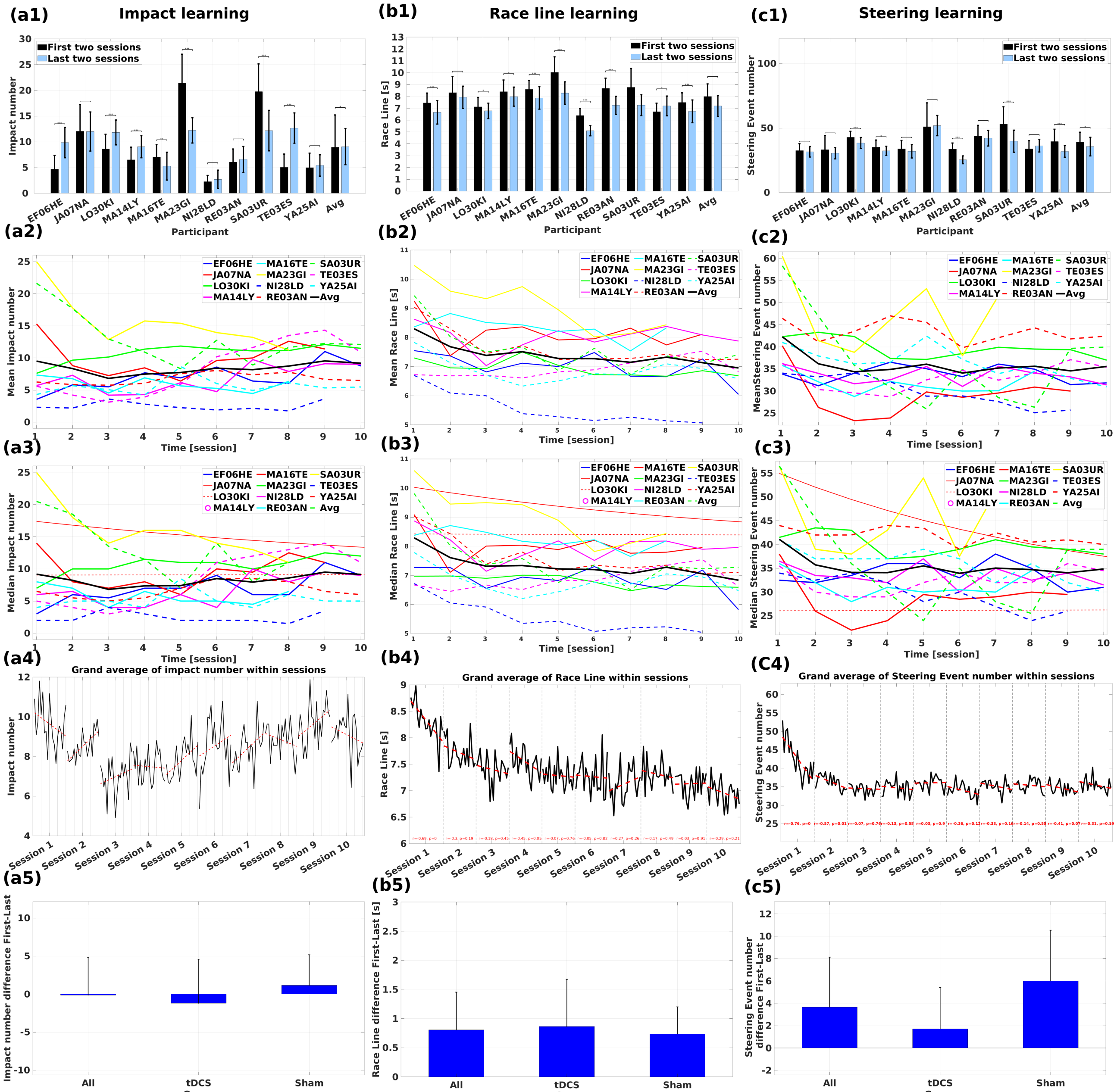

Figure 7. Performance analysis of three facets of driving proficiency across sessions for novice users: number of impacts, racing line deviation, and number of steering events. Panels (a1), (b1), and (c1) display comparisons of average performance for each participant in the first two versus the last two sessions for impact learning, race line learning, and steering learning, respectively, with statistically significant differences marked by asterisks (*); * indicates significance with $\alpha = 0.05$, ** with $\alpha = 0.01$ and *** with $\alpha = 0.001$. No asterisk denotes no statistical significance at the 95% confidence interval ($\alpha > 0.05$). Panels (a2-a3), (b2-b3), and (c2-c3) show the mean and median values across sessions, respectively, for each of these three metrics. Each line represents an individual participant as shown in the legend, the grand average across subjects is shown in thick, black line. Panels (a4), (b4), and (c4) present the grand average impact number, race line, and steering event count, respectively, per lap index within each session, capturing the overall learning trends across the training period. Panels (a5), (b5), and (c5) show the average differences for each learning metric across all novice participants and separately for the active tDCS and sham groups, with error bars representing standard deviation.

race. The first conclusion is that there does not seem to be a strong, clear effect of tDCS on the learning outcome. This has been evaluated by means of mixed-design ANOVAs, where the response variable is the gains on the corresponding behavioural metric (as the average of the last two sessions subtracted from that of the first two sessions), the between-subject factor is the tDCS treatment (with levels active and sham), and

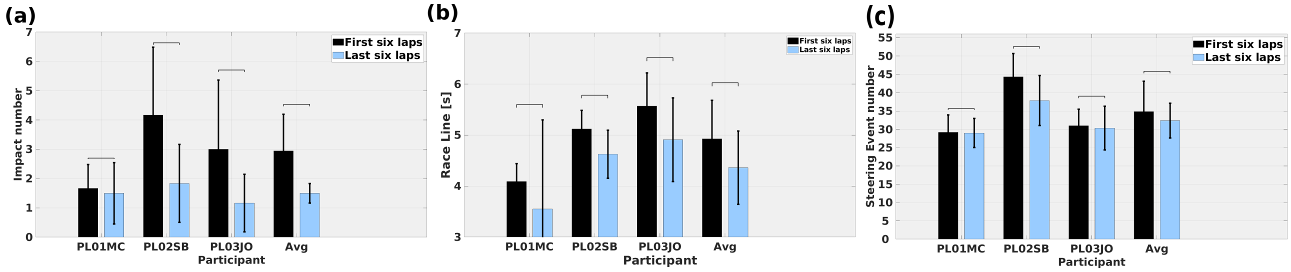

Figure 8. Performance analysis of three facets of driving proficiency in a single session spanning 20 laps for professional drivers: (a) number of impacts, (b) racing line deviation, and (c) number of steering events. All panels display comparisons of average performance for each driver in the first six (black bars) versus the last six laps (blue bars). No asterisk denotes that no statistical significance at the 95% confidence interval has been found for any of these metrics and drivers ($\alpha > 0.05$).

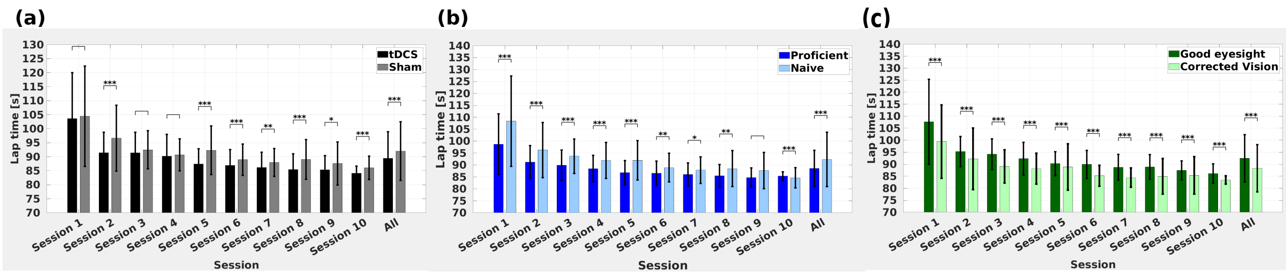

Figure 9. Average and standard deviation of pooled lap time per session compared between two groups across different factors as colour-coded in the legends: (a) tDCS: active vs sham (b) Prior proficiency: Proficient vs Naïve (c) Eyesight (Corrected Vision): Good eyesight vs Corrected Vision, with statistically significant differences marked by asterisks (*). * indicates significance with $\alpha = 0.05$, ** with $\alpha = 0.01$ and *** with $\alpha = 0.001$. No asterisk denotes no statistical significance at the 95% confidence interval ($\alpha > 0.05$).

the within-subject factor is time (in sessions, with 10 levels S1-S10). Our analysis also checks the average, standard deviation and significance with unpaired, two-sided Wilcoxon ranksum tests of the gains in the two groups for each metric.

Almost all ANOVAs for the metrics considered do not result in significant tDCS × session interaction that is the prerequisite for a significant role of tDCS on learning outcomes. Specifically, for each metric, the result is as follows:

- Lap time: $F = 0.63, p = 0.76$
- Penalized lap time: $F = 0.34, p = 0.96$
- Impact number: $F = 1.81, p = 0.09$
- Racing line: $F = 0.65, p = 0.74$
- Total events: $F = 2.25, p = 0.04$
- Brake events: $F = 0.69, p = 0.71$
- Throttle events: $F = 2.22, p = 0.04$
- Steering events: $F = 2.05, p = 0.06$

Therefore, only the throttle and total events show a (marginally) significant interaction, while for steering events the equivalent result is only marginally non-significant at the 95% confidence interval. Even in the significant cases, the trends are either not particularly important in magnitude or even opposite to what was hoped (e.g., active tDCS novice drivers improved far less than sham for throttle, steering and overall events). Hence, a clear, strong and undeniable effect of tDCS on performance gains at the session level cannot be established for any of the behavioural metrics defined to assess driving proficiency.

However, further analysis reveals that pulling all the lap times of all participants in the active tDCS group together and comparing it to the equivalent sham group, allows significantly better performance for the active group to emerge: 89.4±9.5 vs 92.0±10.5, $p < 10^{-17}$, i.e., active tDCS subjects performed on average better than the sham tDCS subjects by almost 3 s throughout the training regime. Fig. 9a shows that the active tDCS group did not perform better than the sham group in the first session, which was anticipated since this study deliberately balanced the prior driving proficiency between the two groups so as to acquire approximately equal performance between them at training onset. The slight, non-significant difference in favour of the active group may be attributed to increased learning effects taking place in this group within the 20 laps of the first session. The difference in favour of active tDCS becomes significant in session 2, and also later on in sessions 5-10 (especially strong in sessions 5 and 8). These intervals largely coincide with the cohort's two main learning breakthroughs (Sessions

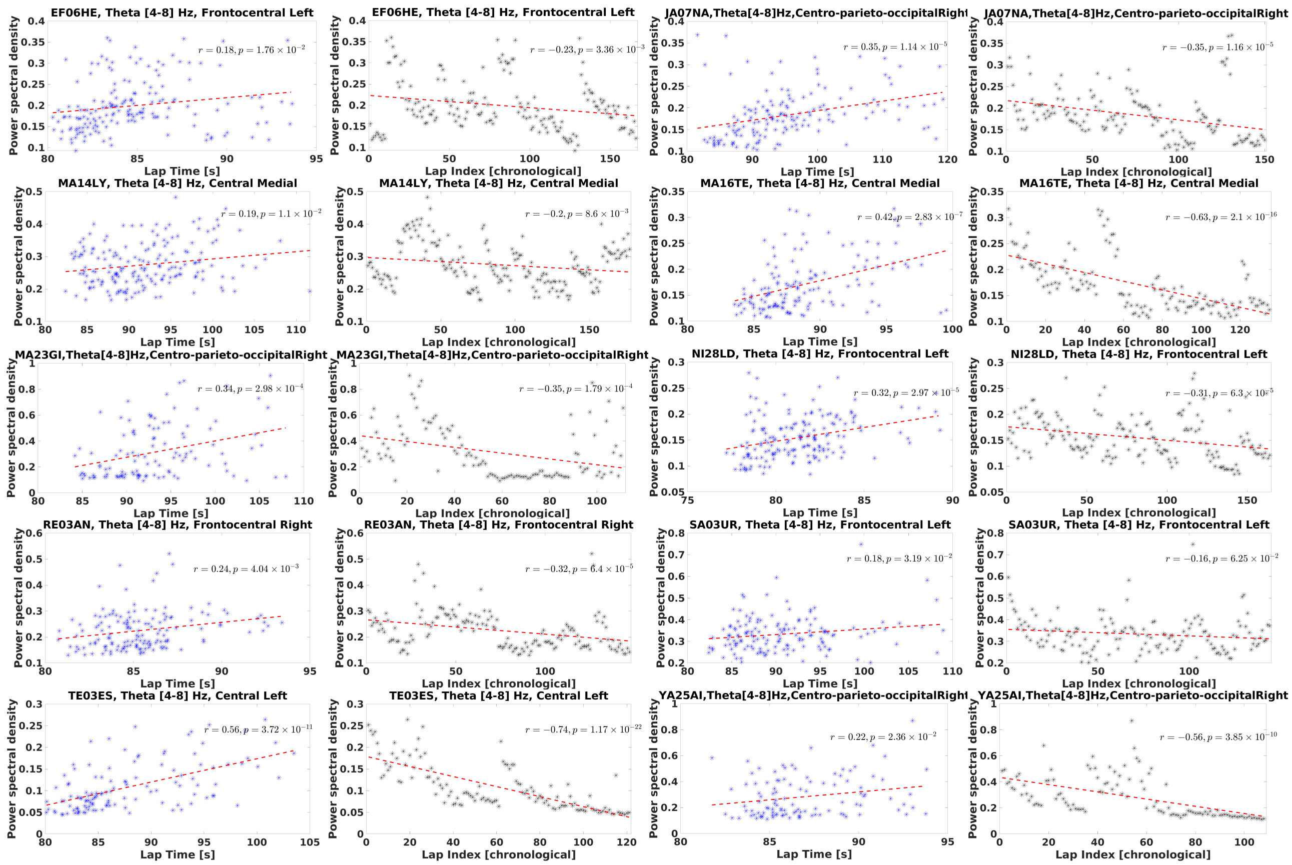

Figure 10. Modulation of the power of EEG theta rhythms by race training for all novice users as indicated by the panel titles. For each participant, the panel on the left shows that theta PSD in the [4-8] Hz frequency band positively correlates with lap time. The respective panel on the right shows that theta-band PSD also negatively correlates with the chronological lap index. The corresponding correlation coefficients and p-values are provided in each panel. The dashed red lines represent the linear fits. Blue (left) and black (right) asterisks illustrate the individual PSD value - lap time/index pairs, respectively. The panel titles state the cortical region where this effect has been located in each case.

1-4 and Sessions 7-8) as seen in the per session grand averages of Fig. 4f).

To contrast with a potential tDCS effect, we examined the respective influence of two other factors considered to be important confounds of lap time performance (and, thus, balanced between the tDCS groups): prior proficiency and eyesight sharpness. Figure 9b presents lap time comparisons across sessions for novice participants with different levels of prior driving proficiency (proficient vs. naïve), while Figure 9c compares lap times for novice participants with good eyesight versus those with corrected vision. It can be seen that subjects with prior proficiency and corrected eyesight maintained a statistically significant advantage. This got smaller as both the respective groups learned, but remained significant throughout the training in both cases. Most importantly, the advantage in these cases has been present at training onset, as it is logical. Conversely, any advantage of the active tDCS group over sham is absent at training onset (further proving the successful balance of confounds as argued above) and only develops gradually during training, weakly implying a potential role of tDCS in learning to race.

3.4. Relation between EEG rhythms and learning to race

Only for the theta EEG band, following the analysis and criteria outlined in Section 2.5.6 there exist ROIs that satisfy all conditions for 7 out of 11 subjects. Relaxing the definition of ROIs this work can also identify single or smaller groups of channels that also satisfy the criteria (always with Bonferroni correction). In more detail, to control for multiple comparisons, a strict Bonferroni correction was applied, setting the significance threshold to $\alpha = \frac{0.05}{59\times5} \approx 0.00017$. This adjustment maintains a family-wise error rate of 0.05 across all 295 comparisons, ensuring that the findings are robust against Type I errors. Effectively, apart from novice driver LO30KI, there exist cortical areas with significantly lower theta

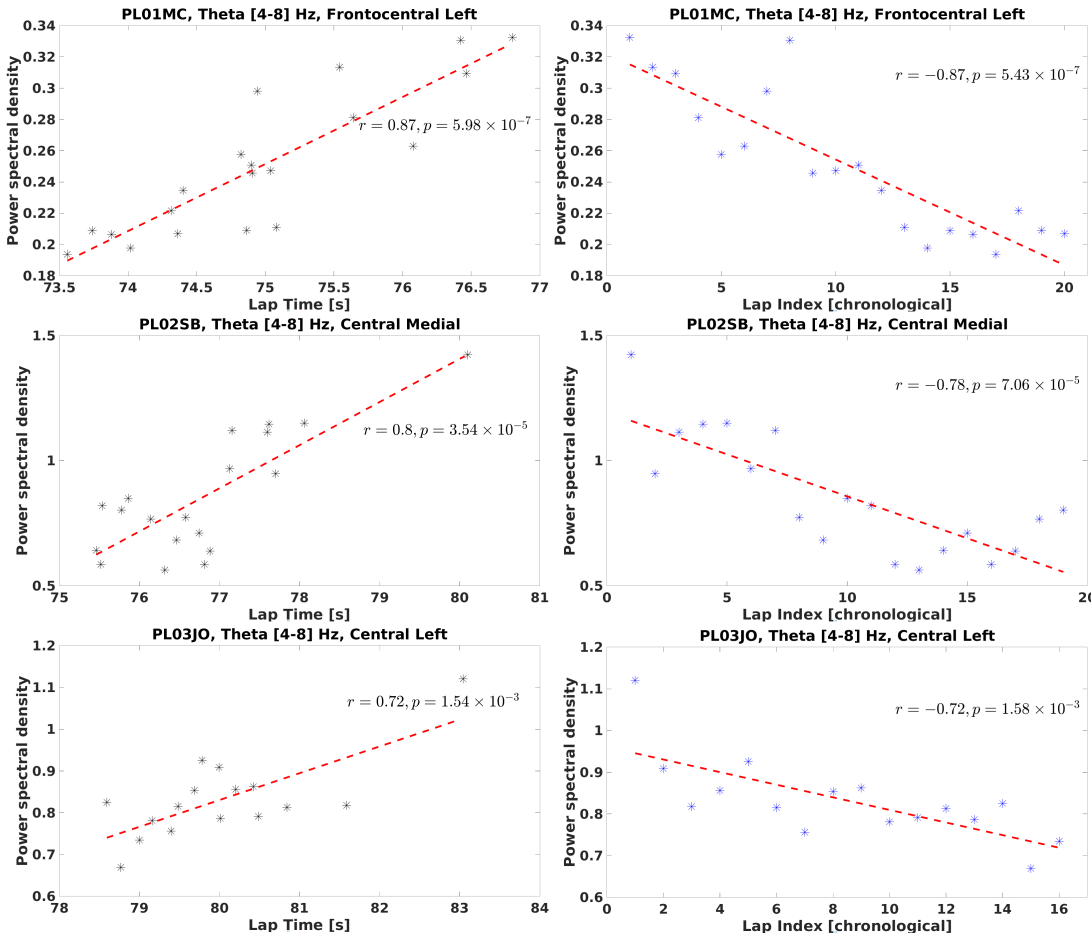

Figure 11. Modulation of the power of EEG theta rhythms during a single training session for all three professional drivers as indicated by the panel titles. For each driver, the panel on the left shows that theta PSD in the [4-8] Hz frequency band positively correlates with lap time. The respective panel on the right shows that theta-band PSD also negatively correlates with the chronological lap index. The corresponding correlation coefficients and p-values are provided in each panel. The dashed red lines represent the linear fits. Blue (right) and black (left) asterisks illustrate the individual PSD value - lap time/index pairs, respectively. The panel titles state the cortical region where this effect has been located in each case.

PSD as training progresses (Fig. 10), which also positively and significantly correlates with lap time. The same holds for the single session of all three experienced drivers (Fig. 11).

3.5. Relation between functional connectivity and learning to race

Similarly to the theta EEG rhythms, this work was able to find significantly increasing DTF effective alpha-band connectivity pre- vs post-training for all but 3 novice drivers (MA16TE, MA23GI, SA03UR) and all professional drivers (Fig. 12). Of note, in this case, connectivity is computed and tested for significance for each channel pair with Bonferroni correction. For novice users, who have a larger dataset, the threshold for significance was adjusted to $\alpha/(59 \times 59 \times 5)$, where 59 represents the number of channels, resulting in a corrected threshold that maintains a family-wise error rate of 0.05. Afterwards, the connectivity of significant channel pairs is selected for each subject and averaged to produce final connectivity index in the broadest region possible for each participant.

Novice drivers displayed notable increases in effective connectivity between frontocentral and occipital regions, as well as in the reverse direction, as their training progressed. These increases in alpha-band connectivity were observed consistently for the majority of novice drivers, indicating a trend toward greater functional coordination between motor planning and visual processing areas as they adapted to the racing task. However, it's important to note that three novice drivers (MA16TE, MA23GI, SA03UR) did not exhibit significant changes in connectivity, which may reflect individual differences in the rate or manner of neural adaptation.

For professional drivers, significant alpha-band connectivity increases were observed within a single

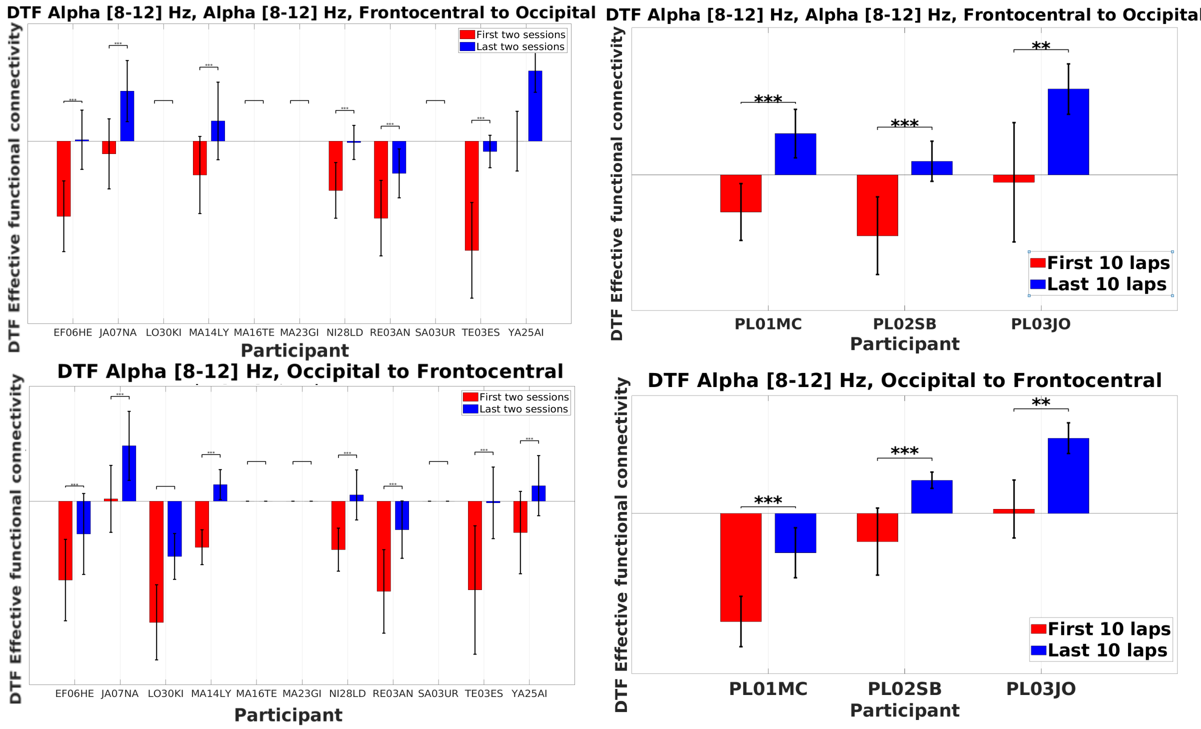

Figure 12. DTF effective connectivity from frontocentral to occipital regions (first row) and vice versa (second row) for novice (first column) and professional (second column) drivers. Red/blue bars illustrate the first/last two sessions for novice participants and the first/last ten laps for professional drivers. Statistically significant differences are marked by asterisks (*); * indicates significance with $\alpha = 0.05$, ** with $\alpha = 0.01$ and *** with $\alpha = 0.001$. No asterisk denotes no statistical significance at the 95% confidence interval ($\alpha > 0.05$).

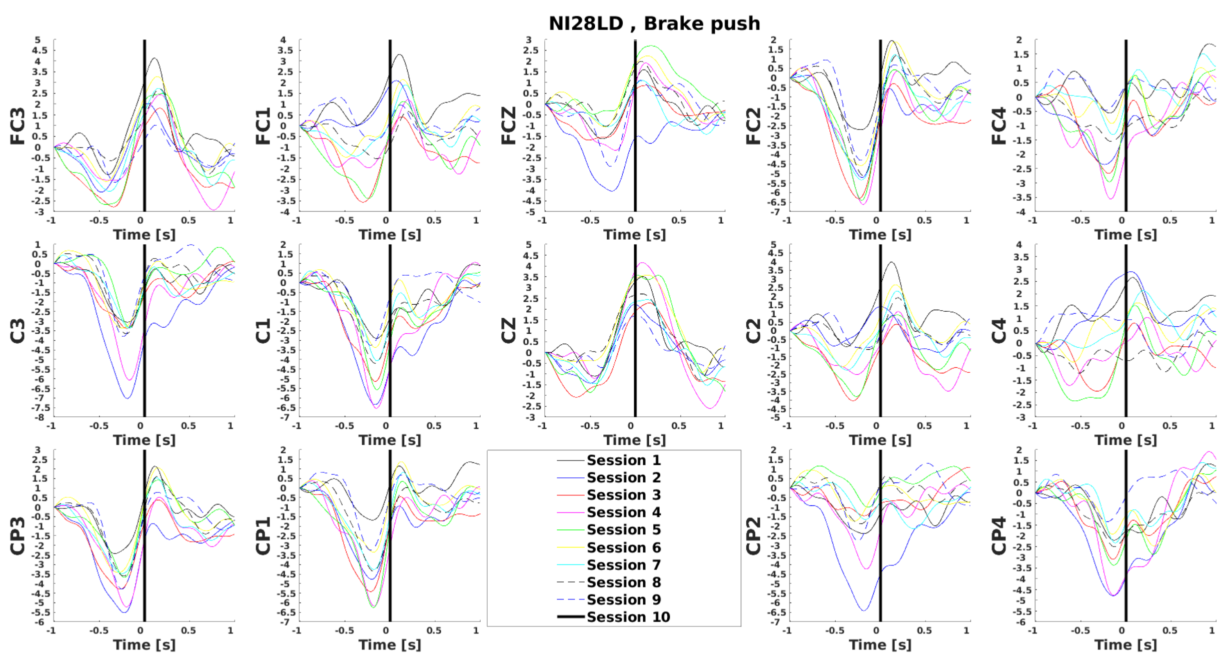

Figure 13. MRCP signals recorded from novice driver NI28LD during the brake push movement across ten sessions. Each line represents the grand average MRCP of an individual session as shown in the legend. Each panel illustrates the MRCPs in a particular EEG channel as indicated by the panel's label. The MRCP waveforms are shown for 1 s before and after the brake push movement onset ($t = 0$).

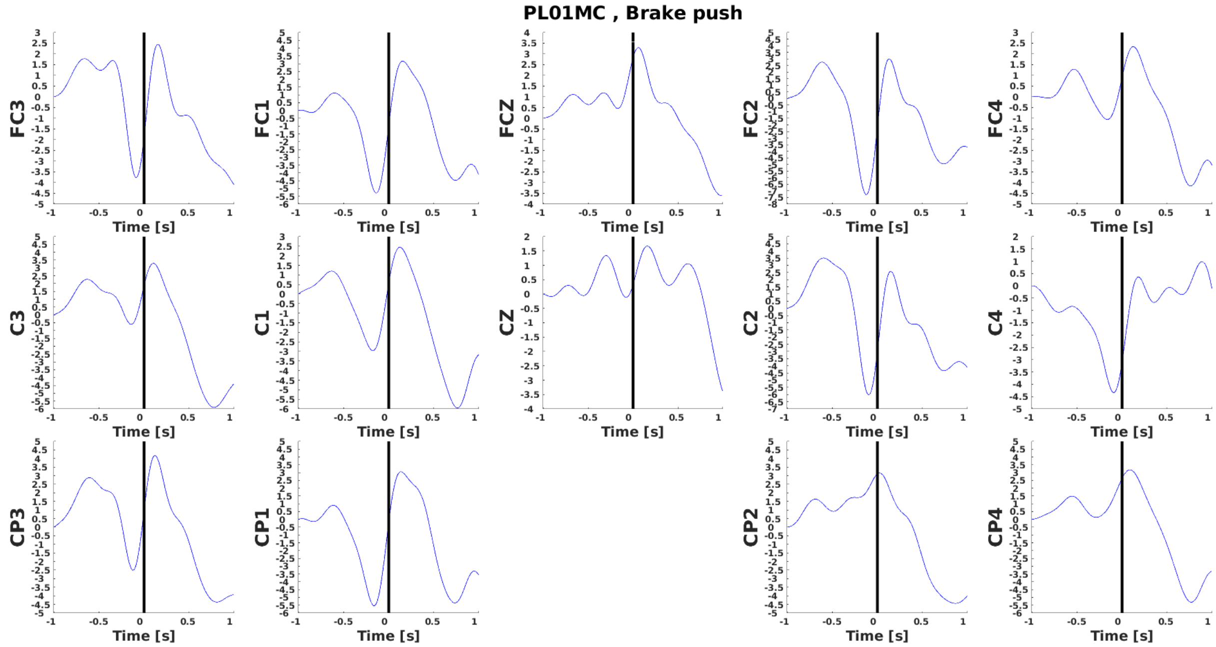

Figure 14. MRCP signals recorded from professional driver Max Günther (PL01MC) during the brake push movement within a single training session. Each panel illustrates the MRCPs in a particular EEG channel as indicated by the panel's label. The MRCP waveforms are shown for 1 s before and after the brake push movement onset ($t = 0$).

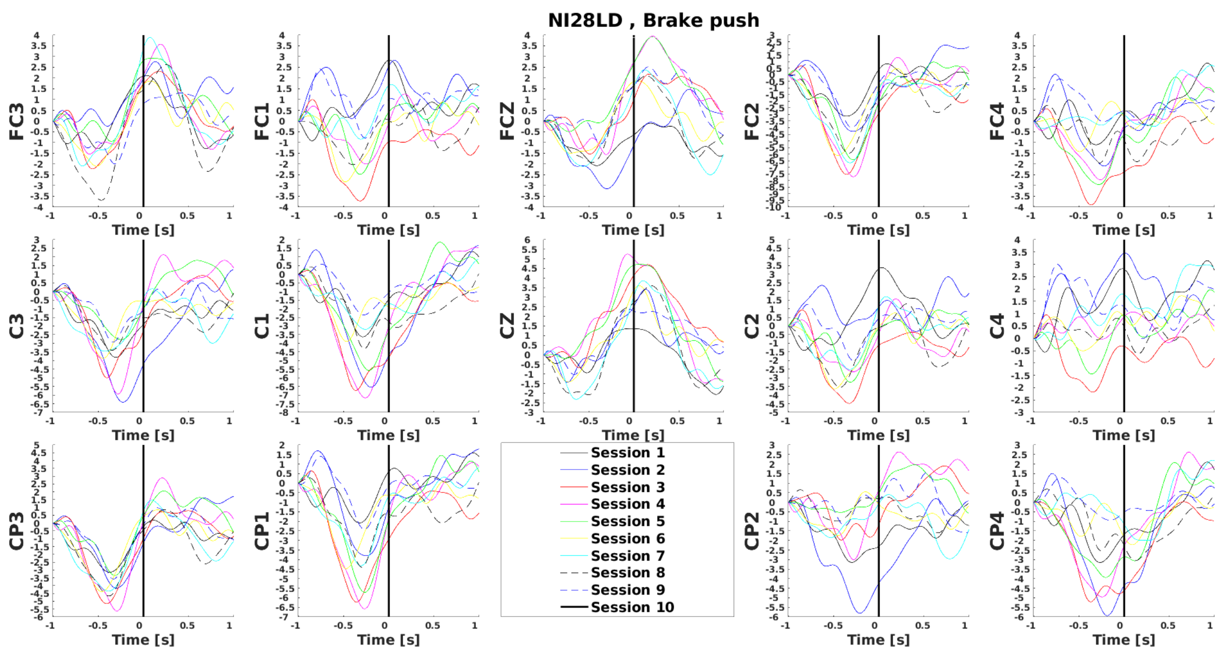

Figure 15. Anticipatory MRCP signals recorded from novice driver NI28LD during the brake push movement across ten sessions. Each line represents the grand average anticipatory MRCP of an individual session as shown in the legend. Each panel illustrates the corresponding MRCPs in a particular EEG channel as indicated by the panel's label. The MRCP waveforms are shown for 1 s before and after the time points corresponding to the track positions where professional driver Max Günther performed brake push movements in his best lap ($t = 0$).

session, specifically when comparing the first 10 laps to the last 10 laps. This pattern suggests that even experienced drivers continue to refine their functional connectivity during task performance, potentially enhancing coordination between frontocentral and occipital areas as they adjust to the specific demands

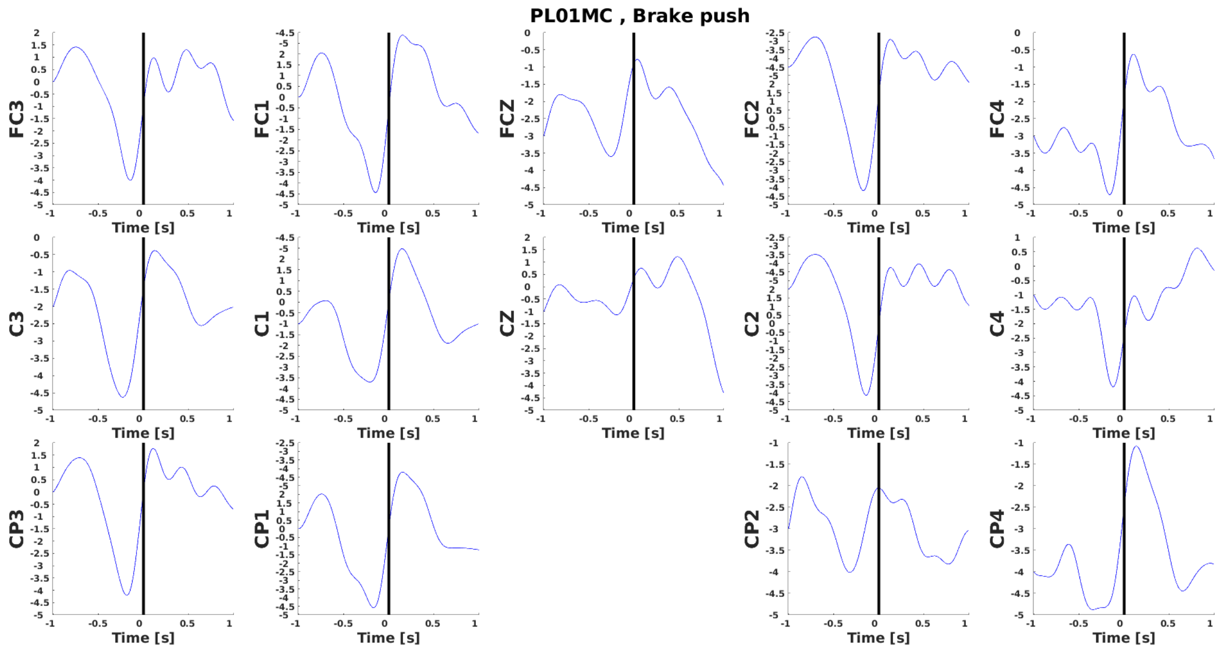

Figure 16. Anticipatory MRCP signals recorded from professional driver Max Günther (PL01MC) during the brake push movement within a single training session. Each panel illustrates the corresponding anticipatory MRCPs in a particular EEG channel as indicated by the panel's label. The MRCP waveforms are shown for 1 s before and after the time points corresponding to the track positions where Max Günther performed brake push movements in his best lap ($t = 0$).

of the session.

The observed connectivity changes in both groups underscore the importance of frontocentral-occipital network dynamics in tasks requiring visuomotor coordination and rapid decision-making. Overall, these results highlight the potential of DTF alpha-band connectivity as an indicator of both learning and familiazation in race driving tasks.

3.6. Regular and anticipatory MRCPs during racing

MRCPs can be identified for both novice and professional drivers (single-subject examples in Fig. 13 and Fig. 14, respectively), but are only prominent for the brake push movement. It is noted that, in most cases, the MRCPs seem to be "smaller" (i.e., with shallower maximum negativity) than what is reported in the literature: The negative peak is around -2.5 to -4 uV, while down to -10 or -15 uV has been previously reported. Every other aspect of the grand average MRCP extracted resembles a textbook case: the shape, the timing of the negativity, the rebound, etc.

The extracted results do not appear to show clear MRCPs for the steering wheel turning and for the throttle push/release actions (no examples are shown here). A possible reason is that these movements are not as "clear-cut" as the brake action (especially the brake push). They are usually smoother and less abrupt, which makes a precise "onset" of these actions hard to define and identify, thus likely having a negative impact on the associated MRCPs. There are still visible CNVs for these movements, but they are not as consistent as those for the brake push action.

Very importantly, even for the clearly identifiable MRCPs of the brake push movements, none of the MRCP waveform's features tested (maximum CNV depth, its latency, and the slope of the linear fit to the CNV signal) significantly correlated to lap time or any other of the facet's of racing proficiency. It seems that regular MRCPs do not constitute a meaningful EEG correlate of learning to race.

Fig. 15 and 16 demonstrate that only the professional drivers and the novice driver NI28LD who achieved near-professional performance exhibit MRCPs at ideal positions (for which we have coined the term "anticipatory" MRCPs), verifying the assumption made in Section 2.5.8. Specifically, for the brake push action, clear anticipatory MRCPs were observed among professional drivers, with distinct negative deflections occurring near the optimal timing point. These MRCPs showed consistent alignment across sessions, indicating precise motor preparation before reaching the ideal brake point on the track. In contrast, novice drivers displayed varying patterns. The novice driver NI28LD, who achieved near-professional performance, demonstrated also well-aligned anticipatory MRCPs for the brake push, similar in form to those seen in professional drivers. Although, MRCPs could be observed in single trials for the remaining novice drivers, these were less consistent in terms of timing with the ideal brake point and thus failed to emerge on grand averages. However, again, the features of anticipatory MRCPs did not correlate with lap time for these 4 participants (3 professional drivers and NI28LD novice user).

4. Discussion

4.1. Behavioural results on learning to race

The study aimed to investigate the neural correlates of learning and the effects of transcranial direct current stimulation (tDCS) on the learning process, contingent upon establishing clear learning effects. Our findings reveal significant learning effects among novice users (Fig. 4). These are apparent both in the individual subject curves and the overall grand averages. All users have significant pre- (first two sessions) vs post-training (last two sessions) improvement, and the difference is also significant at the group level (i.e., comparing the eleven pre-training averages to the equivalent post-training ones). More than 10 s gain in lap time completion is found on average. Most novice users exhibit exponential learning curves (i.e., there is an intense learning period followed by consolidation of the racing skill to a certain level). A few novice drivers seem to have further improvement potential (linear curves). Specifically, 6 out of 11 subjects show significantly smaller root mean square error of residuals of the exponential compared to the linear fit. Within-session learning takes place, especially in Sessions 1-3, followed by another breakthrough around sessions 5-8 (on average), as shown on the per-session grand averages of lap time (with a significant, negative correlation of lap time vs lap index, Fig. 4f). Overall the existence of strong group learning effects in terms of lap time is beyond any doubt; the effect is found for all subjects individually and not only on average.

Professional drivers also demonstrated significant learning effects (Fig. 5). The observed improvements within a single session highlight the professionals' ability to quickly adapt to new conditions. The individual subject curves and grand average corroborate that professional drivers were able to minimize their lap time throughout the session. All professional users exhibit significant pre- (first six laps) vs post-training (last six laps) improvement, the gain in lap time approaching on average 3 s. Individual curves seem to be rather a line, meaning that professional drivers could probably further improve with time, although further gains in this case should be in the range of tens or hundreds of a second. The comparison between novice and professional users (Fig. 6) revealed that professional drivers achieved faster lap times, with novices showing a broader range of performance. Notably, one novice user performed exceptionally well, achieving lap times comparable to those of professional drivers. This outlier underscores the variability in individual learning rates and the potential for novices to reach high levels of performance. Nevertheless, the considerable remaining gap between the average learned outcome of novice participants and the average performance of professional drivers shows that there is room for improvement in quickly training novice drivers to race, which should be the target of future training paradigms.

Interestingly, novice users did not exhibit a significant group learning effect in terms of the number of impacts (Fig. 7a1-a5). Inspecting the individual subject curves and pre- vs post-training comparison, it is noted that there seem to be different/adversary driving styles. Some (about half) users followed the instructions and reduced impacts significantly over time (although even these drivers increased a bit in the end, probably a sign of their effort to further push down lap times). Other users, though, constantly increased their impact throughout. It seems that some subjects, overriding the instructions, ignored impacts by exploiting the invulnerability of the virtual car in order to push the lap times down as much as possible. Here, the fact that there was only end-of-lap feedback on lap time and not on the number of impacts sustained, may have been crucial for "biasing" some users towards this undesired behaviour, although drivers did of course perceive impacts per se through the simulator. Still, inspecting the per session grand averages, there is a significant reduction on average in the first two sessions (significant, large correlation lap index vs impact). It seems that the subjects that do improve, mostly do it in the first two sessions. Of note, given the absence of group learning effects in terms of impacts the composite penalized lap time metric we have come up with is only driven by lap time, and thus has no extra value compared to it.

In terms of racing line improvement, novice users showed significant progress (Fig. 7b1-b5), with the majority of them learning to follow the optimal racing line better over time. The individual subject curves, grand averages and pre- vs post-training comparisons show that all, but one, novice driver learned to better follow the optimal racing line over time, and 9 out of 11 novice drivers significantly so. There exist users with exponential and others with linear learning in this aspect. This indicates that while lap time is a critical metric, adherence to the racing line also plays a vital role in the overall skill development of novice drivers.

The study shows that parsimonious use of brake, throttle and steering (Fig. 7c1-c5) is essential; however, it seems that novice users follow different driving styles, so, it is not always the case that frequent use improves more parsimonious one during training, as we have initially hypothesized. On the contrary, comparing for example the average braking events between novice and professional drivers and the individual pre- vs post-training bars, it looks like many novice drivers started with very low use of brakes and converged closer to the optimal number of brake push/release. These are the subjects that initially did not use the brake at all, and tried to decelerate by merely releasing the throttle. Hence, it must be noted that a different metric reflecting better the fitness of using brake/throttle (e.g, deviation from the optimal number, which could be taken from the fastest lap of a professional user, similar to the racing line metric) may have shown clearer signs of learning. Such metrics can be attempted in future analysis. The absence of significant learning effects in terms of impacts and other driving actions for professional drivers (Fig. 8) is likely attributable to a ceiling effect. These drivers already exhibited high-performance levels at the training onset, leaving little room for further improvement in these specific aspects. It is somewhat surprising that professional drivers did show some improvement in following racing lines, however, this improvement was less pronounced compared to novice drivers. Clearly, professional drivers already possess the skill of following the correct racing line and only need to quickly adapt to and memorize the specific track.

4.2. tDCS effect on learning

Although a mixed-design ANOVA showed no significant effect of tDCS on lap time gain ($F = 0.63, p = 0.76$), session-wise lap time comparisons (Fig. 9a) between the two groups suggest that tDCS may indeed influence learning to race. On average, subjects receiving active tDCS performed significantly better in the final session, improving by almost 3 seconds compared to the sham group. While performance was balanced in the first session, the advantage for the active tDCS group became more pronounced over subsequent sessions and was statistically significant from session 2 through sessions 5-10. Of course, this does not necessarily imply a role of tDCS on learning; this difference could be attributed to inherently better, more "talented" drivers and/or better learners recruited by chance in the active tDCS group. However, it motivates the analysis to examine this comparison per session, as well as with other variables that are reasonable to assume may be implicated with racing performance, but for which the analysis has no reason to believe that is associated with learning: prior proficiency and eyesight.

In sessions 3 and 4, there is no significant difference and the two groups are also very close to each other. In other words, it seems that the active tDCS group demonstrates better outcomes only during and after the training stages where intense learning takes place, while in the beginning, the two groups are balanced, as desired. On the contrary, both of the other two factors examined, the prior proficiency and the eyesight sharpness, although both seem to affect performance, do so in a uniform manner that seems irrelevant to learning. Specifically, prior driving and/or racing experience indeed affects the initial performance (this is precisely why we balanced this factor across the two tDCS groups) where, predictably, experienced drivers do better than naïve ones. The effect persists throughout the training sessions, although it diminishes with time (which is also reasonable: poorly-performing drivers at onset tend to "catch up" as time goes by, since their margin of improvement through training is probably larger). Regarding the two groups with respect to eyesight (people with/without lenses or glasses), we observe that novice drivers with corrected vision did significantly better throughout; the conclusion that can be drawn from this is not, of course, that glasses help one to race faster, but, rather, that this factor did not affect learning and performance in any way: it simply happened that better drivers in this study were, on average, those with the need of corrected vision (since prior proficiency was balanced for the tDCS factor, not for the corrected vision factor). Hence, tDCS seems to be the only factor that is balanced at training onset and seems to gives an advantage to the active group progressively during training. It can thus be claimed that tDCS may have had a positive effect on race driving learning, but not so strong as to appear also in the per session ANOVA analysis, or at least not with the limited sample of 11 users available in our study.

Therefore, the observed group difference is likely attributable to the tDCS effect, making it a strong candidate for further exploration. It is reasonable to assume that a larger sample size might have provided sufficient power to reliably establish the role of tDCS at the level of the mixed-design ANOVA. The positive trends observed in session-wise comparisons underscore the need for further investigation.

4.3. Relation between EEG rhythms and learning to race

Our study, as all investigations conducted with low-resolution EEG imaging, cannot possibly offer insights into the neural mechanisms subserving skill acquisition at the cellular level. We have thus focused on the macroscopic "systems" level, studying potential connections of the brain networks' connectivity and ensemble oscillatory activity with the evolution of racing proficiency. In that respect, we have established a relation between theta-band EEG rhythms and alpha-band connectivity offering intriguing insights into the neural mechanisms underpinning race-driving learning. In addition to this, we have searched for supporting evidence from the literature [26, 42, 43, 44] linking the same phenomena to the acquisition of other complex skills. Put together, the general mechanistic principle giving rise to these correlations seems to regard functional plasticity processes that enable more efficient cognitive processing and visuomotor coordination during driving.

The findings from the analysis of the theta EEG band provide significant insights into the neural mechanisms underlying the learning process. Distributed cortical PSD in the theta band was notably correlated with improvements in performance, as evidenced by the reduction in lap times. This decrease in theta rhythms may suggest a shift towards more efficient cognitive processing as drivers learn to perform the task, potentially reflecting the diminishing need for high-level cognitive control as skills become more automated. This pattern was observed consistently across both novice and experienced drivers, highlighting a potential neural marker for learning and performance enhancement. Decreasing theta power, observed in a majority of subjects, aligns with existing literature [26, 42, 44] that associates theta rhythms with cognitive and motor task learning. In the context of motor learning, lower theta activity is associated with efficient neural resource use and cognitive engagement in well-practiced tasks [42]. This theta-band neuromarker could become the target of neurofeedback training protocols aiming at faster learning and/or adaptation to a new track by race drivers.

4.4. Relation between functional connectivity and learning to race

The relation between functional connectivity and learning to race further elucidates the neural adaptations associated with skill acquisition. This study identified a significant increase in DTF effective alpha-band connectivity occurring between the initial and final training periods for most novice and all professional drivers. The increase in alpha-band connectivity was observed across multiple channel pairs, with significance tested and corrected for multiple comparisons. Consistent with our findings, increased functional connectivity in the alpha band has previously been associated with motor learning [43]. Furthermore, enhanced alpha connectivity is often linked to improved neural communication and coordination [43], which are crucial for acquiring and refining motor skills. Similarly to the aforementioned EEG rhythms plasticity, these results imply that alpha-band connectivity could also serve as a neural marker of the learning progress, as well as the modulation target of neurofeedback training towards improved racing performance.

4.5. MRCP and anticipatory MRCP associated with racing proficiency

Regular MRCP, where “time t=0” with respect to which the anticipatory behaviour is examined is taken to be the behavioural onset of a movement (e.g., an abrupt brake pedal push as extracted by telemetry), are studied to investigate whether any feature of the CNV (peak amplitude, latency, slope) is affected by learning. The study identified MRCPs in both novice and professional drivers, particularly during brake push movements. As reported in Section 3.6 of the Results, regular MRCP were found to be barely identifiable for all movements other than brake push. The MRCP exhibited smaller negative peaks compared to the relevant literature [45]. A first reasonable explanation for the swallow depth is that the realistic scenario followed here creates greater misalignment, imposes great cognitive workload and, importantly, creates overlapping MRCPs due to movements happening too close in time to one another, resulting in lower average depths (which, anyway are not far off the -5uV amplitude reported elsewhere [45] for break push movements in a less realistic protocol). In addition to this, the MRCPs extracted here are filtered in the band [0.4 3 Hz] instead of the ideal [0.01 1] or [0.1 1]Hz pass-band, in order to avoid instability (given the comparatively low sampling rate used here). Rejecting the high-energy 0-0.4 Hz band may explain the small depths of the MRCPs. Lastly, it must be underlined that in certain cases (e.g., novice driver JA07NA) the MRCP depth reaches the range of -10 uV.

Despite successfully extracting MRCP signals, it has not been possible to relate features of these like their depth, or the timing of the negative peak to the learning and performance metrics at the session level. There are no significant correlations with the lap time or with the lap index (i.e., there is no chronological improvement), neither for the depth nor for the time gap to the movement onset. A per-lap analysis, as done here for the PSD and connectivity results, may reveal significant associations to learning; however, the quality of lap-wise MRCP averages may be compromised because, within a lap, one only gets a small amount of each MRCP type. Furthermore, no correlation between other facets of driving proficiency and the peak amplitude, timing or slope of the MRCP could be established for this type of movement. Effectively, it seems that the hypothesis that MRCP features reflect driving proficiency must be rejected.

Anticipatory MRCPs are defined here for the brake push actions by taking t=0 to be the time points in a lap where a driver passes from the exact same points where professional driver M. Günther pushed the brake pedal in his best lap. The research question asked here is whether subjects show the expected anticipatory behaviour to produce well-timed braking in order to optimize their lap time. Our results in Section 3.6 show that the professional drivers exhibit clear anticipatory MRCPs, as also the best-performing driver NI28LD (not surprisingly, the only one that significantly approached the professional driver performances). Other novice users did not show clear anticipatory MRCPs, which is logically related to the fact that their braking actions were not well aligned with the optimal braking timing. The implications of these results are, first, that anticipatory MRCPs are a good index of reaching peak racing performance, as they emerge only when the use of the brake pedal is optimized both in terms of braking style and timing. While it can be argued that the same type of information can be retrieved by analysis of the car telemetry alone, an EEG metric provides a useful alternative. Similarly, this index may have some use in a closed-loop training protocol, where the CNV negativity is used to assess on-the-fly whether drivers will be able to proceed with the next needed action in a timely fashion. Furthermore, anticipatory MRCPs have unique characteristics that open revolutionary future avenues of pilot-car confluence. For example, as the CNV appears around 0.5 s earlier than the actual brake onset (as proven by our own results, too, see Fig. 15 and Fig. 16, future "collaborative racing" could involve the car sensing the driver's intention to brake through their EEG and implementing it semi-autonomously in an optimal way.

4.6. Embedding neurofeedback protocols into race training

The findings of this study could be leveraged to promote the integration of neurofeedback protocols into race training by employing real-time EEG monitoring to extract the key neuromarkers identified here (e.g., central theta-band rhythms, frontocentral-to-occipital alpha-band connectivity) while participants drive. Real-time feedback on these markers could be projected onto the dashboard, allowing drivers to actively modulate their brain activity on-the-fly. For instance, participants could be trained to optimize specific EEG frequency bands linked to optimal learning using visual cues akin to the brake and throttle indicators on their dashboard. This kind of feedback aims to enhance the neural states conducive to learning. Future implementations could incorporate wearable devices, such as the Google Glass, to deliver visual feedback directly within the participant's field of view. This approach would be especially useful for unobtrusive, continuous feedback during simulated or real-world driving tasks, supporting neural state modulation. Training could occur in both simulated and real driving environments, providing neurofeedback to help participants refine the neural states associated with peak performance. Ultimately, this approach aims to accelerate skill acquisition by fostering optimal neural modulation during race training.

The primary mode of technology transfer of our findings into race training regimes, as envisioned at this stage, is the embedding of neurofeedback into simulated or real driving. Additionally, we find that the identified metrics, particularly the anticipatory MRCPs, can also be used to evaluate learning proficiency, either as standalone measures or in conjunction with traditional metrics, offering an additional dimension. Lastly, although currently beyond the regulations and standards of professional racing, our results pave the way for deeper integration between humans and machines, where semi-autonomous racing cars interface with the driver's brain to accomplish the driving task optimally.

While these findings present exciting possibilities for race training and human-machine integration, it is important to acknowledge the limitations of the study that may have influenced the results and their broader applicability. The main limitation of this study is the small sample size (N=11 novice participants and N=3 professional drivers). The limited number of subjects may have impacted the observed effects or concealed their actual magnitude, including the ability of tDCS to support race-driving learning. It must be highlighted that, due to the study's longitudinal nature, the implemented recruitment yielded a very high total amount of sessions executed (109 sessions, with 4 sessions discarded due to technical issues). Logistical constraints limited our ability to proceed with additional recruitment. In the inherent trade-off between the size of the study and the length of training, we prioritized the latter to better capture the dynamics of race-driving learning over time. Hence, while we did consider recruiting more participants with fewer sessions, this approach was turned down because it would have hindered our ability to thoroughly investigate the full scale of the long-term learning effects of race driving, which was the primary objective of this study. The limitations imposed by the small sample size extend to the reliability of findings regarding the neural correlates of learning to race, particularly given the presence of exceptions (participants that deviated from the identified trends) in both EEG rhythms and effective connectivity. Thus, validation through larger-scale future studies is necessary to confirm these results.

Another limitation that will be addressed in future work regards the collection of questionnaires to assess motivation, anxiety, mental workload and other psychometric variables that could have also confounded our results. Nevertheless, we believe that the highly engaging, competitive and entertaining sim-racing task in this study, together with subject compensation for participation (not dependent on performance) and the experimental design that prevented fatigue have adequately ensured that these factors have probably not affected our findings and conclusions. Last but not least, although substantial effort has been devoted to including behavioural metrics that evaluate and quantify the main aspects of driving proficiency, we acknowledge that additional and/or improved metrics may need to be employed in future work to fully capture the racing task's great complexity.

5. Conclusion

This work assessed the neurobehavioural signatures and brain plasticity effects during learning to race. At the same time, we proceeded with a first assessment of the potential role of tDCS in enhancing this learning process. The results show clear changes in the power of theta-band EEG rhythms of broad central networks that correlated with lap time for both professional and novice participants. Alpha-band, frontocentral-to-occipital functional connectivity also seems to be a neuromarker of learning to race. We further conclude that tDCS may be able to support faster learning of race driving by novice users, although the effect was not strong and would require replication in future studies. Future work will seek to delineate and confirm these effects in experimentation with larger populations.

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