Psychological Research (2025) 89:59
https://doi.org/10.1007/s00426-025-02091-7

RESEARCH

Cognitive, Neurophysiological, and Behavioral Adaptations in Golf Putting Motor Learning: A Holistic Approach

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Received: 21 July 2024 / Accepted: 13 February 2025 / Published online: 1 March 2025

Abstract

Objectives Research indicates that the development of cognitive structures significantly influences motor learning. However, this perspective overlooks the broader nature of motor learning, which encompasses not only cognitive changes but also neurophysiological and behavioral factors. This study aims to simultaneously examine the intricate motor learning process through cognitive, neurophysiological, and behavioral lenses to achieve a more comprehensive understanding.

Methods Thirty participants were randomly assigned to either a practice group ($n = 15$) or a control group ($n = 15$) and tested at pre-, post-, and retention tests. The practice group underwent an acquisition phase involving three practice days (3×100 trials of a golf putting task), while the control group did not participate.

Results A hierarchical cluster analysis was conducted to group the basic action concepts into a coherent hierarchical structure, represented as a dendrogram. This dendrogram illustrated the relationships between basic action concepts. Analysis of mean group dendrograms revealed a significant increase in the organization of the cognitive structure within the practice group. EEG results indicated that the practice group's low and high alpha power increased significantly in frontal, central, and parietal areas ($p < .05$). Repeated measures ANOVA revealed that the practice group's motor performance errors decreased significantly ($p < .05$), while no changes were observed in the control group.

Conclusions Our findings suggest that motor learning involves simultaneous cognitive, neurophysiological, and behavioral adaptations. It appears that the motor learning process involves gradually constructing these structures over time, providing an extensive understanding of the motor learning process.

Introduction

Understanding the fundamental mechanisms of the motor learning process and the factors that influence it is essential for developing effective educational and training methods. This understanding helps to minimize disabilities, enhance capabilities, and maximize human potential.

In this regard, researchers have proposed various perspectives on how motor learning occurs. Cognitive scientists argue that motor learning happens through the development of the motor program (Adams, 1971; Anderson, 1982; Fitts & Posner, 1967; Lebiere et al., 1993; Proctor & Dutta, 1995; Schmidt, 1975). The cognitive views on developing a motor program are based on a closed-loop and top-down perspective (Anderson, 1983; Fitts & Posner, 1967; Lebiere et al., 1993; Proctor & Dutta, 1995). According to *the open-loop control theory* (Keele & Posner, 1968), during the execution of movements (motor control), the central nervous system generates movements based on internal representations or motor commands (Edwards, 2010). Over time, these motor commands are stored in the central nervous system during motor learning. When necessary, the brain instructs lower areas; once motor commands are initiated, they enable movements to be executed without relying on sensory feedback (James, 1892; Keele & Posner, 1968; Lashley, 1917; Woodworth, 1899). However, critics of this theory believe that motor commands cannot be the only factor determining the execution of actions, as the same motor command sometimes results in different movements (Bernstein, 1967). Additionally, without feedback, the elegance and beauty of movements are lost. Furthermore, the nervous system is different from a programmed computer (Williams et al., 2005).

Adams proposed *the closed-loop control theory* after considering criticisms. He believed that motor learning occurs through strengthening a motor program that consists of two separate neural pathways (memory trace and perceptual trace) in the cortex (Adams, 1971). However, the closed-loop theory couldn't explain how to control movements

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Extended author information available on the last page of the article in open-loop processes and address the issues of novelty, storage, and variability of practice (Schmidt et al., 2018). Schmidt (1975) introduced *schema theory* as a solution to the problems of motor programs. His concept of a generalized motor program (GMP) was at the core of schema theory (Schmidt, 1975; Schmidt & White, 1972). According to Schmidt, two types of memory or schema are developed during the learning process to control movements. The recall schema generates the motor program before the movement starts so that the movement can be performed without feedback intervention, and the recognition schema evaluates the movement (Schmidt, 1975). According to *schema theory*, a group of movements can be controlled by a single GMP, instead of controlling specific movements (Schmidt et al., 2018). Although *schema theory* solves some of the problems of the motor program, it fails to explain how the motor program is created when the GMP is not yet formed; it also could not explain how to create and use rules related to sensory parameters and consequences, or how to generate movements when there is no schema (Schmidt et al., 2018). In sum, the cognitive approach believes that motor learning occurs due to the development of a motor program (Adams, 1971; Anderson, 1983; Fitts & Posner, 1967; Lebiere et al. 1993; Proctor & Dutta, 1995). However, it has not convincingly explained motor control and learning, therefore, the ecological approach was suggested.

The ecological approach to understanding motor control and learning emphasizes the importance of the relationship between the environment and the body's systems (Gibson, 1979). According to this perspective, organisms do not need mental representations to perceive their surroundings or to perform actions (Gibson, 1979; Turvey, 1991). The environment provides meaningful information and opportunities for action (i.e. affordances) which directly controls behavior (Edwards, 2010; Gibson, 1979; Turvey, 1991; Williams et al., 2005). With practice and experience, individuals become more skilled at perceiving and using the information in the environment to guide their actions; as a result, motor learning is the growth of perception–action coupling and coordination with affordances (McMorris, 2014). However, the ecological approach does not fully explain the fundamental mechanisms of motor control and learning (Williams et al., 2005). For instance, it does not clarify how learners identify opportunities for action in their environment and decide which affordances and actions are appropriate for specific situations (McMorris, 2014).

The emphasis of perceptual approaches on the environment and reducing the importance of the individual in controlling and learning actions on the one hand and reducing the importance of the environment in cognitive approaches led to the emergence of *the perceptual-cognitive approach* or *action-driven views* which are derived from *Ideomotor theory* (James, 1890). For example, *the common coding theory* (Prinz, 1997), *the anticipative behavioral control* (ABC; Hoffmann, 1993; Hoffmann et al., 2004), *motor simulation theory* (MST; Jeannerod, 2001), *the theory of event coding* (TEC; Hommel, 2009; Hommel & Wiers, 2017; Hommel et al., 2001), and *the Cognitive Action Architecture—Approach* (CAA-A, Schack, 2004). To explain how control and learning occur, the perceptual-cognitive approach emphasizes both the interconnected relationship between the learner and the environment and cognition or cognitive structures (Schack, 2004). The action-driven or effect-based views believe in a common representational system of perception and action (Prinz, 1997). They share the idea that actions are planned and guided by cognitively represented perceptual effects (e.g., Hoffmann, 1993; Hommel et al., 2001; Jeannerod, 2001; Knuf et al., 2001; Kunde, 2001; Prinz, 1997; Schack, 2004; Frank et al., 2024), and a link between an action and its effects is established during learning (*ideomotor theory*: James, 1890; Hommel & Elsner, 2009; Wulf & Prinz, 2001). Hence they highlight the goal-directed nature of actions, the importance of anticipated perceptual effects, and the crucial role of mental representations in controlling actions (Prinz, 1984, 1997; Prinz et al., 1987).

The cognitive action architecture approach (Schack, 2004), derived from theories such as *the ideomotor theory* (James, 1890) and *Bernstein's approach* (1967), posits that individuals may possess simple and rudimentary cognitive structures at the onset of motor learning (Schack & Frank, 2021). Though not fully developed, these initial cognitive representations and references serve as a foundation for subsequent learning. As motor learning progresses, these structures evolve from simple and general versions in structure and function into more organized and complex versions (Schack, 2004). Research across various sports—such as volleyball (Velentzas et al., 2011), tennis serve (Schack & Mechsner, 2006), windsurfing (Schack & Hackfort, 2007), judo (Weigelt et al., 2011), golf putting task (Frank et al., 2013; Land et al., 2014), climbing (Bläsing et al., 2014), soccer (Lex et al., 2015), basketball free throw (England et al., 2019), and throwing movement (Gromeier et al., 2022)—further supports the idea that cognitive structures specific to the task domain become increasingly organized and complex throughout the learning process. These representations in skilled individuals are structured hierarchically, aligning closely with the functional and biomechanical demands of the tasks, suggesting that while some cognitive frameworks may be general, they are refined and tailored to the demands of the specific task at hand (Schack & Frank, 2021).

In exploring motor control and learning theories, it is clear that they provide different perspectives. Altogether, motor learning is an intricate process that requires further investigation. Our study specifically focuses on examining certain aspects of this process. We propose that motor learning involves creating and constructing knowledge and/or structures through continuous interaction with the environment. In this regard, one of our study's objectives is to measure cognitive structures in the context of a golf putting task, utilizing the Structure Dimensional Analysis—Motorics (SDA-M) software. The rationale for adopting this approach is based on the limitations of traditional methods used in previous research, such as questionnaires, interviews, and paper-and-pencil tests, which have been employed to investigate mental representations (French et al., 1987; McPherson & Kernodle, 2003). These conventional approaches often face challenges related to objectivity and reliability (Schack, 2004; Thomas & Thomas, 1994). Additionally, such studies generally focus on explicit knowledge and lack an empirical foundation, raising doubts about whether the knowledge reported by practitioners accurately reflects the knowledge needed for their actual performance (Schack, 2004). In contrast, our approach utilizes structural dimensional analysis of mental representations, an empirical method that captures more implicit knowledge than traditional methods can provide (Schack, 2012). This transition not only improves the objectivity and reliability of our findings but also offers a deeper understanding of the cognitive processes involved in motor learning. We aim to broaden the understanding of motor learning and its underlying mechanisms by analyzing how these cognitive structures develop and influence motor performance.

While our goal is to analyze learners' cognitive structures, we recognize that this examination may not be sufficient as we believe that changes occurring during the motor learning process extend beyond mere cognitive changes. For example, in the study of the neurophysiological mechanisms involved in controlling and executing movements and actions, it's been found that brain activity changes when learning a specific task or skill (Haufler et al., 2000; Parr et al., 2019; Taliep & John, 2014). Research reveals that the power of brain waves decreases in certain regions of the brain associated with cognitive control and attention processes, like the anterior cingulate cortex (Seo et al., 2012) and the frontal cortex (Petrini et al., 2011). Skilled marksmen display a decrease in the left-temporal alpha power compared to novices (Haufler et al., 2000; Janelle et al., 2000). Additionally, experienced tennis players compared to less experienced tennis players, exhibit less power in mu and beta frequency bands while observing actions (Denis et al., 2017; Fox et al., 2016). Skilled marksmen show reduced brain activity in the left hemisphere in comparison to the right hemisphere (Hatfield et al., 1984). Elite golfers compared to amateur golfers display lower alpha power at Pz and T8, Fz and T8, and lower mu power before putting (Wang et al., 2020). Moreover, in expert golfers, alpha (8–12 Hz) and beta (13–30 Hz) rhythms decrease in the frontal midline and the arm and hand areas of the right primary sensorimotor cortex (Babiloni et al., 2008). Furthermore, when learning a motor skill, alpha and theta wave power in the central regions and temporal cortex decreases (Ghasemian et al., 2017). The connection between the frontal areas and the left hemisphere decreases (Cheng et al., 2015; Gallicchio et al., 2016; Parr et al., 2021), and expert archers exhibit less alpha in the left temporal-frontal connection (Deeny et al., 2003).

Contrary to some research indicating wave power in various brain regions decreases due to learning, other studies suggest that learning leads to increases in theta power, alpha power, mu rhythm, and sensorimotor rhythm (Abdoli et al., 2024; Baumeister et al., 2008; Doppelmayr et al., 2008; Haufler et al., 2000; Parr et al., 2019, 2021). For instance, novice archers showed increased alpha power in the left temporal region during the learning process (Landers et al., 1994); while theta power increased in the middle frontal region and alpha power increased in the parietal and occipital regions after practicing a computer game (Smith et al., 1999). Skilled shooters exhibited increased alpha wave power in the left hemisphere before shooting, with no significant difference in the right hemisphere (Haufler et al., 2000). Additionally, skilled golfers showed increased theta power in the frontal and central regions before putting (Baumeister et al., 2008). During shooting, skilled shooters experienced increased alpha wave power in the left temporal region (T3/T7), while no change was observed in the central region (Kerick et al., 2001). Similarly, Doppelmayr et al. (2008) and Baumeister et al. (2008) reported that experienced athletes display increased theta activity in frontal regions during anticipatory phases of tasks compared to novices. This suggests that heightened theta may be linked to improved attention and focus, crucial for performance success. Another study found increased neural activity in elite and skilled archers compared to novices in various brain regions, including the superior frontal, middle frontal cortex, temporoparietal, supplementary motor area, and cerebellum (Kim et al., 2014). Skilled individuals exhibited higher alpha power in the left temporal region (Taliep & John, 2014) or all brain areas (Parr et al., 2019) compared to novices; also expert golfers showed higher power of the mu rhythm in the central area or motor cortex (Abdoli et al., 2024).

According to *the psychomotor efficiency hypothesis*, an increase or decrease in brain wave power during the learning process is due to the efficiency of information processing (Hatfield & Hillman, 2001). Researchers propose that at the initial of learning when people learn a new skill, their cognitive and mental processes are highly involved (Fitts & Posner, 1967). As they become skilled, the level of involvement of these processes decreases, along with decreased brain activity (Haufler et al., 2000), indicating more efficient use of specific neural circuits related to the task (Kelly & Garavan, 2005). This increased efficiency leads to better performance and requires less conscious effort (Deeny et al., 2003). As individuals learn a task and become more skilled, the cognitive effort related to the task (Haufler et al., 2000) and self-talk decreases (Deeny et al., 2003), and irrelevant cognitive processes are suppressed, leading to improved motor performance (Hatfield, 2018; Hatfield & Hillman, 2001). Hence, in the advanced stages of learning, some cognitive analyses are likely inappropriate, and additional inputs from the cognitive areas of the brain, such as the left temporal cortex, to the motor planning areas, like the posterior frontal cortex, may lead to interference, resulting in decreased motor performance quality (Deeny et al., 2003). Therefore, the different brain activity in novices and skilled individuals likely reflects the refinement and improvement of cognitive-motor functions as skills improve (Kim et al., 2014). As a result of such efficient processing, unrelated cognitive processes are inhibited, while task-related cognitive processes are enhanced (Hatfield, 2018; Hatfield & Hillman, 2001). That is, with increasing skill levels and motor learning, unused neural connections and networks decrease or are lost while those related to task execution increase, and new connections are formed (Hedrick et al., 2024), a fundamental process of neuronal circuit refinement in learning and memory (Morizawa et al., 2022) known as "*synaptic pruning*" (Greenough et al., 1987; Hedrick et al., 2024). In essence, elite and expert individuals have more advanced and refined cognitive-motor processes, associated with minimal energy consumption (Deeny et al., 2003, 2009). Hence, skilled individuals' cerebral cortex processes more efficiently, leading to higher quality and consistent motor performance (Deeny et al., 2003).

Building on previous research, this study hypothesizes that motor learning encompasses simultaneous neurophysiological changes alongside cognitive and behavioral adaptations. To investigate this hypothesis and deepen our understanding of the motor learning process, we aimed to simultaneously assess brain function, cognitive structures, and motor performance. Our research focused specifically on measuring alpha wave power in three key brain regions; the frontal region (F3, Fz, F4) associated with motor planning processes (Haufler et al., 2000), the central region (C3, Cz, C4) linked to motor execution (Schinke et al., 2016), and the parietal region (P3, Pz, P4) involved in integrating sensorimotor information (Medendorp & Heed, 2019) for planning (Ferri et al., 2015) and executing motor actions (Medendorp & Heed, 2019).

While we acknowledge the relevance of other EEG frequency bands, in our study, we focus specifically on alpha rhythm, which is particularly important for athletic performance, as supported by a wealth of literature (Babiloni et al., 2008; Baumeister et al., 2008; Deeny et al., 2003; Doppelmayr et al., 2008; Haufler et al., 2000; Janelle et al., 2000; Kerick et al., 2001; Kim et al., 2014; Landers et al., 1994; Parr et al., 2019, 2021; Smith et al., 1999; Taliep & John, 2014; Wang et al., 2020). Previous research indicates that alpha activity is critically linked to motor performance. There is a notable divide in the existing literature regarding changes in alpha power; some studies report increases, while others indicate decreases following motor learning. Therefore, we anticipate the following hypotheses in our study: (a) we hypothesize that physical practice will enhance cognitive structures relevant to task performance, potentially leading to improved skill execution; (b) we hypothesize that physical practice will increase low alpha power (8–10 Hz) and high alpha power (10–12 Hz) in the brain's frontal, central, and parietal regions, which are associated with successful motor execution; (c) we hypothesize that physical practice will reduce performance errors, including inaccuracies, biases, and inconsistencies; (d) we hypothesize that motor learning involves simultaneous cognitive, neurophysiological, and behavioral adaptations, which will increase with practice.

Methods

Participants

We used G*Power 3.1 software (Faul et al., 2009) to determine the sample size for the study, focusing on golf putting accuracy as the primary variable. Our plan involved creating two groups and conducting three tests. For the repeated measures ANOVA, the input parameters were as follows: alpha = 0.05, power = 0.90, effect size = 0.3, and actual power = 0.91. Based on these parameters, we recruited thirty university students (12 females, 18 males; M_{age}: 25.6 ± 2.1 years), divided equally into a control group (n = 15) and a practice group (n = 15). All participants had normal vision and no known psychological, cognitive, or neurological disorders. They were all right-handed (Oldfield, 1971) and had no previous experience with golf putting tasks, remaining unaware of the specific purpose of the experiment. Before the experiment, participants were asked to avoid consuming caffeine, alcohol, or drugs that could affect brain function for at least one day. Informed consent was obtained from all participants through a consent form.

Measures

Tasks and procedures

In this research, we employed two primary tasks: a golf putting task and a splitting task. The golf putting task was conducted in a controlled laboratory environment on an artificial turf green. This task involved a 91 cm golf club, a standard-sized golf hole with a diameter of 10.8 cm, and standard white golf balls with a diameter of 4.27 cm.

The splitting task, which involved analyzing the golf putting skill, was performed using a computer system and the

Structure Dimensional Analysis—Motorics (SDA-M) software (for further details on the SDA-M analysis, please refer to Schack, 2012). We used the splitting task to measure the structural dimensions of the participants' mental representations or cognitive structures.

The study consisted of three test days (pre-test, post-test, and retention test) and an acquisition phase (as shown in Table 1). These tests included cognitive, neurophysiological, and behavioral measurements.

Pre-test

Cognitive procedure: To ensure that participants were well-acquainted with the golf putting task, they first observed a video of an expert golfer executing it thrice. After the participants observed a video of an expert golfer's performance, they needed to understand the sixteen basic action concepts (BACs) related to the golf putting skill before proceeding with the splitting task. These sixteen concepts were identified in previous research (Frank et al., 2013; Land et al., 2014). To facilitate this understanding, we utilized the SDA-M software to introduce BACs to participants (Schack, 2012). This approach helped introduce the key concepts of skill execution, after which we conducted the splitting task to analyze the participants' mental representations.

As shown in Fig. 1, the golf putting task can be split into five phases, each encompassing specific BACs. These phases are: (1) *Preparation phase*: shoulders parallel to target line (BAC 1), align club face square to target line (BAC 2), grip check (BAC 3), and look to the hole (BAC 4). (2) *Backswing phase*: rotate shoulders away from the ball (BAC 5), keep arm-shoulder triangle (BAC 6), and transition smoothly (BAC 7). (3) *Forward swing phase*: rotate shoulders toward the ball (BAC 8) and accelerate the club (BAC 9). (4) *Impact phase*: impact with the ball (BAC 10), club face square to target line at impact (BAC 11), follow-through (BAC 12) and rotate shoulder through the ball (BAC 13). (5) *Attenuation phase*: decelerate the club (BAC 14), direct the clubhead to planned position (BAC 15), and observe the outcome (BAC 16).

After introducing the BACs to the participants, they completed the splitting task using the SDA-M software to examine the structural dimensions of their mental representations (Frank et al., 2013; Land et al., 2014). During the

Table 1 The design of the study includes three test days and an acquisition phase

	Pre-test	Acquisition			Post-test	Retention-test
	Day 1	Day 1	Day 2	Day 3	Day 4	Day 5
Practice group	SDA-M* EEG Putting task	Putting practice			SDA-M EEG Putting task	Putting task
Control group	SDA-M EEG Putting task	–	–	–	SDA-M EEG Putting task	Putting task

SDA-M: structural dimensional analysis of cognitive structure; putting task: 20 trials, putting practice: 10 (trials) × 10 (blocks) each day

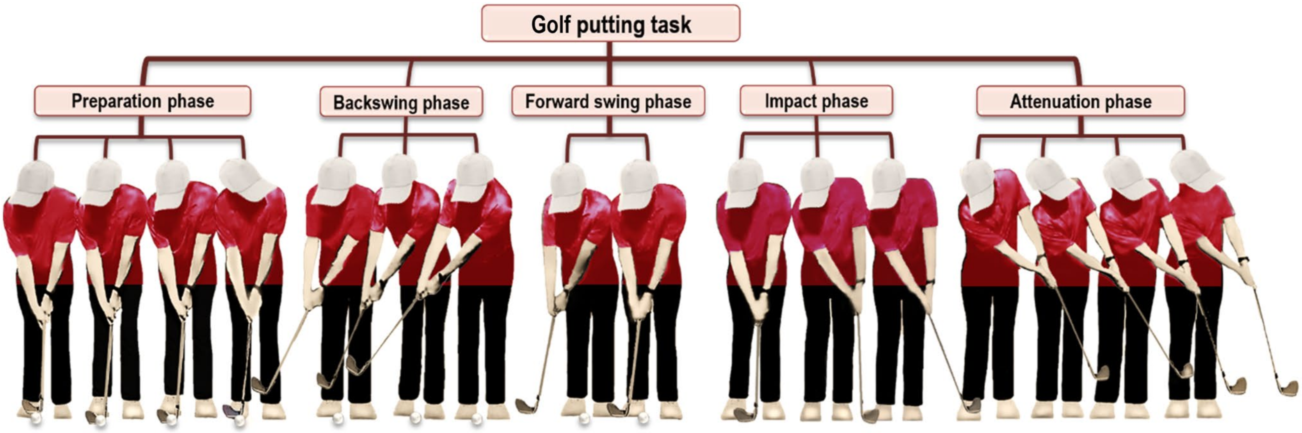

Fig. 1 The golf putting task is divided into five distinct phases: preparation phase (BACs 1–4), backswing phase (BACs 5–7), forward swing phase (BACs 8–9), impact phase (BACs 10–12), and attenuation phase (BACs 13–16). These five phases encompass a total of 16 basic action concepts (BACs)

pre-test, each participant sat in front of a computer screen displaying one of the sixteen BACs as the anchor concept on the left side, while the remaining fifteen concepts appeared randomly on the right side. During the splitting task, participants were required to compare each concept with an anchor randomly displayed on the screen. They assessed whether a functional relationship existed between the displayed concept and the anchor. If they identified a relationship, they pressed the right key; if not, they pressed the left key. Figure 2 shows a view of the SDA-M software that the participants used for the splitting task. The splitting task continued until each of the sixteen concepts had served as the anchor in a series of comparisons, resulting in a total of 240 judgments (16 anchors × 15 comparisons) to facilitate the analysis of their mental representations (Frank et al., 2013). Following the cognitive assessment, participants took a brief break before individually engaging in neurophysiological and behavioral evaluations.

EEG recording: We utilized a set of twenty-one Ag/AgCl electrodes, which were securely placed on the participants' scalps using neoprene caps. These electrodes were positioned according to the international 10–20 standard system (Jasper, 1958). The ground electrode for recording was positioned at the FCz site, and the recording references were on the left (A1) and right (A2) mastoids (Jasper, 1958). We used a Mitsar 202 EEG amplifier (Mitsar company) and "WinEEG" data acquisition software to amplify, quantify, record, and store all EEG data. To maintain impedance below five kiloohms, we adjusted electrode positions, ensured the participants' scalp and hair were clean, and applied an adequate amount of electrolyte gel (Kao et al., 2014). Before recording, we reviewed the waves received from all channels using WinEEG software to ensure that there were no bad electrodes or sites, resulting in the absence of recorded artifacts. Additionally, we instructed participants to minimize blinking, head and eye movements, and teeth clenching during recording to reduce interference with brain wave data. EEG signals were collected while participants performed the golf putting task, with recordings amplified and filtered within the range of 0.1–70 Hz and a digital notch filter at 50 Hz, using a sampling rate of 250 Hz. Since the EEG data were recorded continuously over an extended period, we precisely marked the timing of each trial (event) within the continuous EEG signal by pressing a designated key and entering a code in the WinEEG software simultaneously with the moment the putter made contact with the ball, without the participants' awareness. This approach allowed

Are these two actions directly associated during task execution?

Fig. 2 This figure depicts the SDA-M software used by participants during the splitting task. The software displays one of the sixteen basic action concepts (BACs) as the anchor concept on the left side of the screen, while the remaining fifteen concepts are shown randomly on the right side. Participants compared each displayed concept on the right with the anchor to assess any functional relationships during the golf putting task us to isolate relevant brain activity from unrelated signals, enhancing the data's clarity and validity.

Behavioral procedure: Since the participants were inexperienced in the golf putting task, we provided them with instructions before the pre-test phase. They stood 300 cm away from the hole and were guided to position their feet shoulder-width apart and parallel to the target line to establish a stable stance. Participants were asked to lean forward slightly from their hips and to concentrate on the target. They were encouraged to grip the putter comfortably but firmly, initiating a smooth backward movement while keeping the putter head low to the ground. They were instructed to swing the putter back and through along the target line, ensuring a fluid motion to enhance accuracy and consistency. After the instructional phase, participants completed three warm-up trials to familiarize themselves with the task before proceeding to the pre-test. During the pre-test, all participants executed the golf putting task consisting of 20 trials from a distance of 300 cm. During the pre-test, they received no instructions or augmented feedback on technical issues and how to perform the task.

We recorded the coordinates of the ball's stopping positions in two dimensions (X and Y axes) to measure three key performance metrics: accuracy, bias, and consistency. Accuracy was defined as how close participants' putts landed to the target hole, measured by the mean radial error (MRE). A lower MRE indicated that the balls rested nearer to the hole, reflecting greater accuracy in putting performance. Bias referred to a systematic deviation from the target, capturing the tendency of participants' putts to consistently overshoot or undershoot the hole, quantified by the subject-centroid radial error (SRE). This metric helped identify patterns in errors that suggested a consistent inclination in the direction of the errors across trials. Finally, consistency assessed the reliability of participants' performances by evaluating the variation in the stopping positions of their putts across multiple trials, measured using the bivariate variable error (BVE). A lower BVE score indicated more consistent putt placements, suggesting that participants could reliably replicate their performance over the trials.

Acquisition phase

After the pre-test, the practice group participated in the acquisition phase, which lasted three days. They performed the golf putting task in 10 blocks of 10 trials (i.e., 100 trials) with a short break between every block each day. They did not receive any instructions or augmented feedback on technical issues and how to perform the task. The only feedback available was the visible outcome (inherent feedback, Schmidt et al., 2018, p. 448). The practice group did 300 trials (3 days × 100 trials) during the acquisition phase (Frank et al., 2013). The control group participated in all tests but did not participate in the acquisition phase.

Post-test and retention-test

After 24 h (day four), both practice and control groups participated in the post-test. In the post-test, the participants' cognitive structures were measured again to specify the effect of physical practice on them. After the cognitive measure, the participants did a 20-trial block while their brain waves were recorded. After 48 h of non-practice (day five), all participants participated in the retention test and did a 20-trial block (see Table 1).

Data analysis

Cognitive analysis

The Qsplit SDA-M software was used to conduct structural dimensional analysis of cognitive structures or representations, specifically the structural-dimensional relationships of BACs. For further details on the SDA-M analysis, please refer to Schack (2012). This analysis consisted of four steps:

The first step involved analyzing the proximity of BACs, which provided information on the distances between BACs: After the participants performed the splitting task, in the first step of the analysis, the number of positive and/or negative decisions for each particular reference concept (i.e., anchor) was collected and was formed into separate subsets so that obtained the euclidean distance scaling between the BACs of the golf putting task. Then, the subsets were transformed into z values for standardization and eventually combined into a z-matrix; this z-matrix formed the starting point for all subsequent analyses.

The second step involved measuring a constructed dendrogram as a result of linked BACs: In this step, a hierarchical cluster analysis was used to transform the set of BACs into a dendrogram (i.e., a hierarchical structure). For hierarchical cluster analysis, the average-linkage method was used to transform the z-matrix into a euclidean distance matrix. This leads to the construction of cluster solutions (i.e., relationships between the BACs) which themselves form a dendrogram (i.e., a hierarchical structure). Each cluster solution is constructed by determining a critical euclidean distance (d_{Crit}). The d_{Crit} is used as a criterion to determine the significance level of each cluster. For cluster analysis, the significance level used in this study was < 0.05, which resulted in a critical value $d_{Crit} = 3.41$ (horizontal red line in Figs. 3 and 4). The cluster solutions that were placed below the horizontal line (critical value) were considered statistically significant, and the cluster solutions that were above this critical line were considered statistically insignificant or irrelevant.

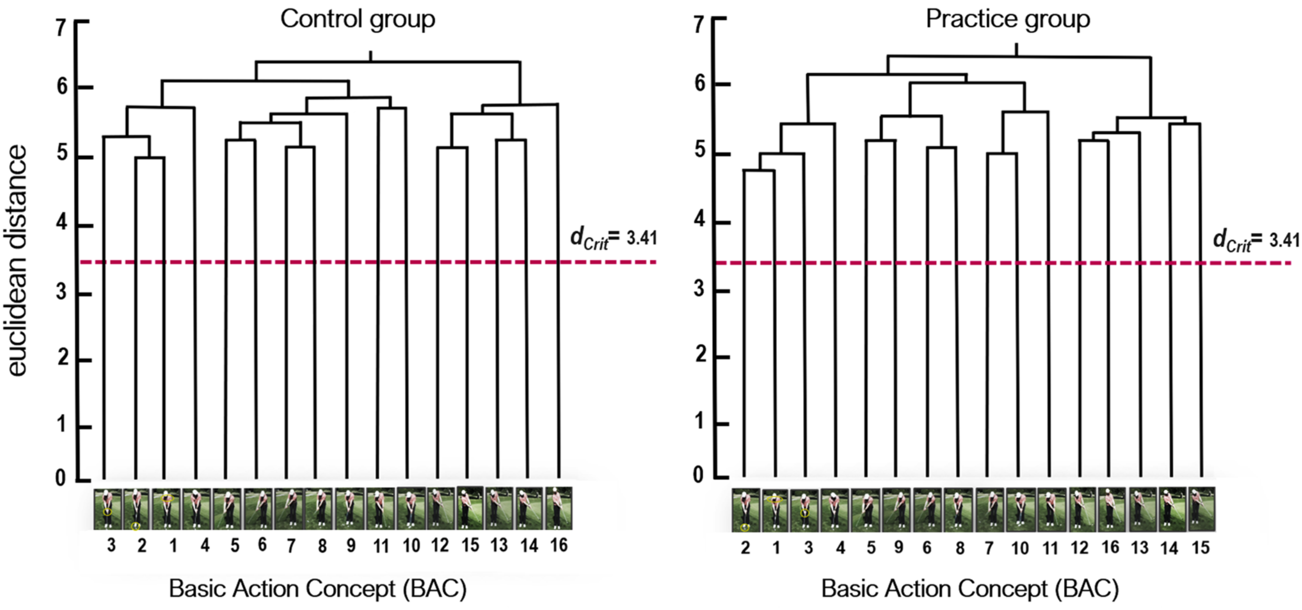

Fig. 3 The results of the hierarchical cluster analysis of the SDA-M demonstrate the mean group dendrograms for the practice group (n = 15) and the control group (n = 15) at the pre-test ($\alpha = 0.05$; $d_{crit} = 3.41$). The value for dcrit is represented by a red bar that splits the scale of Euclidean distances, distinguishing relevant structural links from less relevant ones (above d_{crit}) for a given probability. The values on the y-axis represent Euclidean distances, while the x-axis corresponds to the Basic Action Concepts (BACs) related to the golf putt. As shown, no significant clusters are evident in the cognitive structures of either the practice or control groups (color figure online)

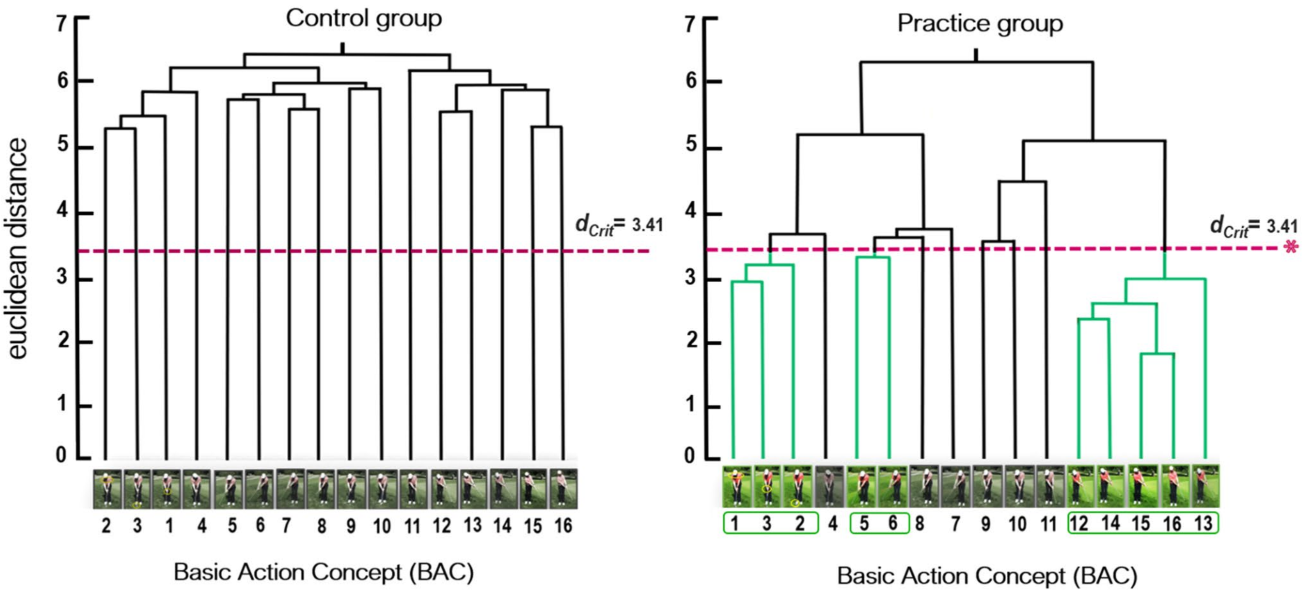

Fig. 4 In the post-test, the results of the hierarchical cluster analysis show connections that fall below the critical value (indicated by the horizontal red line) which are statistically considered as connections. In contrast, connections above this line are regarded as distinct clusters. As illustrated, three distinct functional clusters have formed within the practice group, corresponding to different phases of the action: the preparation phase, the backswing phase, and the impact and attenuation phases. However, no significant clusters are observed within the control group (color figure online)

The third step involved determining the feature dimensions of the cluster solutions (i.e., the linked BACs): In this step, the z-matrix is converted into a correlation matrix, and then by using a factor analysis linked to a specific cluster-oriented rotation process, the dimensions of the cluster solutions or linked BACs are revealed. Factor analysis presents the characteristics (factors) and their weights (factor loadings) based on which cluster formation (structure) is done in each individual case. Factor loadings can range from -1 to 1 and show how much a factor contributes to a given cluster. The random value for factor loadings d_{Crit} is defined by z-matrix correlations and the number of factors, the high d_{Crit} factor loadings are the most relevant for the given cluster (Schack, 2012).

The final step involved determining the invariance of the cluster solutions: In this step, the homogeneous created cluster solutions were evaluated for (structural) invariance inter and between-individual and groups (Schack, 2012). To compare the difference between cluster solutions via a critical λ, an invariant analysis was used to show the significance of the differences. The invariance criterion is determined by the number of concepts in the cluster solution, pairwise cluster solutions, and the average number of clusters. The invariance value of the cluster solution (λ) can range from 0 to 1, where 0 indicates the least identical structure of the two cluster solutions, and 1 indicates the most identical structure of the two cluster solutions. To determine the significant difference between the two groups, λ value was set to $I = 0.68$, when $\lambda \leq 0.68$, two cluster solutions were considered different, and when $\lambda \geq 0.68$, the two cluster solutions were considered similar and did not differ significantly (for more information about the SDA-M method please see Schack, 2012).

EEG data analysis

After identifying the exact timing of the trials within the EEG signal, we established the moment of ball contact as the reference point (time 0 ms). The EEG data were then segmented into epochs based on this timing, covering a period from 2000 ms before to 2000 ms after the impact. Subsequently, we extracted the data from 2000 ms before and 2000 ms following the impact (i.e., the total duration of each trial) based on the reference point. By analyzing the EEG data over this 4000 ms window, our goal was to investigate the neural activities associated with motor planning, preparation for action, and the execution of the action.

After the EEG signal preprocessing, the EEG data were analyzed using the EEGLAB toolbox. We then applied independent component analysis (ICA) within the EEGLAB toolbox to remove non-neural components, such as artifacts from muscle activation, eye movements, and heart activity (Delorme & Makeig, 2004). We calculated alpha power in regions of interest (ROIs), including the frontal (F3, Fz, F4), central (C3, Cz, C4), and parietal (P3, Pz, P4) regions. To evaluate alpha wave activity, we employed the Welch method, utilizing a Hanning window function (Welch, 1967). For the analysis, we applied a two-second time window with 50% overlap and a frequency resolution of 0.5 Hz (Wang et al., 2020). This approach enables us to estimate the power of low alpha (8–10 Hz) and high alpha (10–12 Hz) waves, providing valuable insights into the neural mechanisms underlying motor control and learning during the golf putting task.

Behavioral data analysis

In our study, we sought to assess the effect of physical practice on golf putting task by measuring accuracy (MRE), bias (SRE), and consistency (BVE). To measure MRE, SRE, and BVE, the coordinates of the ball stop position were recorded in two dimensions (X and Y axes), and then the obtained points were placed in the radial error (RE) formula to obtain performance accuracy. MRE represents the average deviation of the ball from the hole, with lower scores indicating more accurate movement. The formula for MRE is as follows: $\mathrm{MRE} = \overline{\mathrm{RE}} = \left(\frac{1}{\mathrm{m}}\right) \sum_{\mathrm{i}=1}^{\mathrm{m}} \left(\mathrm{x}^2 + \mathrm{y}^2\right)^{\frac{1}{2}}$, where “RE” is the radial error, “m” is the number of trials, and “i” is the specific trial. In addition, bias or subject-centroid radial error (SRE), which provides information about the direction and magnitude of bias error in two dimensions, was calculated using the formula: $\left(x_c, y_c\right) = \left(\overline{x}, \overline{y}\right) = \left[\left(\frac{1}{m}\right) \sum_{i-1}^{m} x_I, \left(\frac{1}{m}\right) \sum_{i=1}^{m} y_i\right]$; $\mathrm{SRE} = (\mathrm{x}_\mathrm{c}^2 + \mathrm{y}_\mathrm{c}^2)^{\frac{1}{2}}$, where "m" is the number of trials "x_C" is the mean constant error on the X-axis, and "y_C" is the mean constant error on the Y-axis. Lastly, bivariate variable error (BVE), a measure of performance consistency in two dimensions, was determined as the square root of the mean squared distance of a subject's k shots from their centroids in centimeters. The BVE was calculated using this formula: $\mathrm{BVE} = \left\{\left(\frac{1}{\mathrm{k}}\right) \sum_{\mathrm{i}=1}^{\mathrm{k}} \left[(\mathrm{x}_\mathrm{i} - \mathrm{x}_\mathrm{c})^2 + (\mathrm{y}_\mathrm{i} - \mathrm{y}_\mathrm{c})^2\right]\right\}^{\frac{1}{2}}$, where "k" is the number of trials and "i" is the specific trial (for further details, refer to Hancock et al., 1995).

Statistical analysis

A 2×2×3 mixed-factorial ANOVA was conducted separately for low and high alpha power, with factors including Group (practice, control), Time of measurement (pre-test, post-test), and Region (frontal, central, parietal). To evaluate the performance of the practice group during the acquisition phase, a within-subjects ANOVA was performed for each dependent variable (MRE, SRE, BVE), considering factors Day (3 levels) and Block (10 levels). For the comparison between groups, a 2×3×3 mixed ANOVA (factors: group, time of measurement, and variable: MRE, SRE, BVE) was conducted, with Group as a between-subjects (BS) factor and Time of measurement as a within-subjects (WS) factor. Assumptions of ANOVA were checked, including normality, equality of covariances, and error variances. Shapiro–Wilk and Levene's tests assessed normality and homoscedasticity, respectively. Wilks' lambda was used when the assumption of covariance homogeneity was not met, and the Greenhouse–Geisser correction was applied when sphericity was violated. A significance level of $p \leq 0.05$ was set for all analyses, and the effect size was calculated as partial eta-squared (ηp2).

Results

Cognitive results

Pre-test

We measured cognitive structures by calculating mean group dendrograms via cluster analysis. As seen in Fig. 3, control and practice groups' constructed dendrograms as a result of hierarchical cluster structural dimensional analysis, do not show any significant clustering of the linked BACs so that all the links of the dendrograms are higher than the critical value ($d_{crit} = 3.41$, the horizontal red line; a = 0.05). This result reveals that the cognitive structures of both groups are not significantly different at the pre-test phase.

Post-test

The results of the analysis of structural dimensional indicate links of the dendrogram of the control group are all higher than the critical value ($d_{crit} = 3.41$) whereas due to physical practice, the cognitive structure of the practice group (the mean dendrograms) changed after the acquisition phase and became significantly more complex so that three distinct functional clusters related to different phases of the action have formed at the post-test compared to the pre-test.

The first significant cluster related to the preparation phase consists of BACs 1 to 3. This cluster is comprised of shoulders parallel to target line (BAC 1), align club face square to target line (BAC 2), and grip check (BAC 3). The second significant cluster is related to the backswing phase of the golf putting task, comprising rotate shoulders away from the ball (BAC 5), and keep arms-shoulder triangle (BAC 6). The third significant cluster encompasses BACs associated with the impact and follow-through phases. This cluster consists of follow-through (BAC 12), rotating the shoulders through the ball (BAC 13), decelerate club (BAC 14), direct clubhead to the planned position (BAC 15), and look at the outcome (BAC 16). These five BACs are illustrated in Fig. 4, where only those below the horizontal red line are identified as significant concepts.

Furthermore, although three significant clusters were identified in the cognitive structure of the practice group (mean dendrograms) following the acquisition phase, the cognitive results indicated six basic concepts that did not achieve significance in the post-test. Specifically, as shown in Fig. 4, the following concepts were not significant: From the preparation phase, look to the hole (BAC 4); from the backswing phase, transition smoothly (BAC 7); from the forward swing phase, both rotate shoulders toward the ball (BAC 8) and accelerate the club (BAC 9); from the impact phase, two out of three concepts, impact with the ball (BAC 10) and club face square to target line at impact (BAC 11), were not significant.

In addition to examining group dendrograms to analyze structural dimensions, the homogeneous created cluster solutions were evaluated for (structural) invariance within-group and between groups. The results of statistical analyses of within-group invariance to compare the cognitive structure revealed no significant difference between the cluster solutions of the control group in the post-test compared to the pre-test phase ($\lambda > \lambda_{crit} = 0.68$); in contrast, inter-group invariance analysis showed that the cognitive structure of practice groups in the post-test is significantly different from the pre-test ($\lambda = 0.45 < \lambda_{crit} = 0.68$). Moreover, the between-groups invariance analysis of cluster solutions revealed that the cognitive structure of the two practice and control groups were significantly different ($\lambda = 0.39 < \lambda_{crit} = 0.68$) at post-test so that, the cognitive structure of the practice group have become more organized and complex (see Fig. 4).

EEG results

Low-alpha Power

A mixed-factorial ANOVA with one between-subjects factor (Group) and two within-subjects factors (Time and ROI) revealed a significant main effect for Group, $F(1,28) = 4.719$, $p = 0.009$, ηp2 = 0.353, and power = 0.846. Additionally, there was a significant main effect for Time, indicating that low alpha power increased from the pre-test to the post-test, $F(1,28) = 13.315$, $p < 0.001$, ηp2 = 0.606, and power = 0.999. A significant Group × Time interaction was also observed, F(1,28) = 7.732, p = 0.001, ηp2 = 0.471, and power = 0.974.

Further analysis using a within-subjects ANOVA revealed that the time of measurement significantly affected low alpha power across different regions of interest (ROI); frontal region, $F(1,28) = 13.960$, $p = 0.001$, ηp2 = 0.328, and power = 0.946; central region, $F(1,28) = 37.333$, $p < 0.001$, ηp2 = 0.571, and power = 1; and parietal region, $F(1,28) = 12.862$, $p = 0.001$, ηp2 = 0.315, and power = 0.933. These results indicate that the practice group's low alpha power significantly increased in all three ROIs (see Fig. 5). A significant interaction effect of Group × Time was found in the frontal region, $F(1,28) = 9.076$, $p = 0.005$, ηp2 = 0.245, and power = 0.828; central region, $F(1,28) = 21.805$,

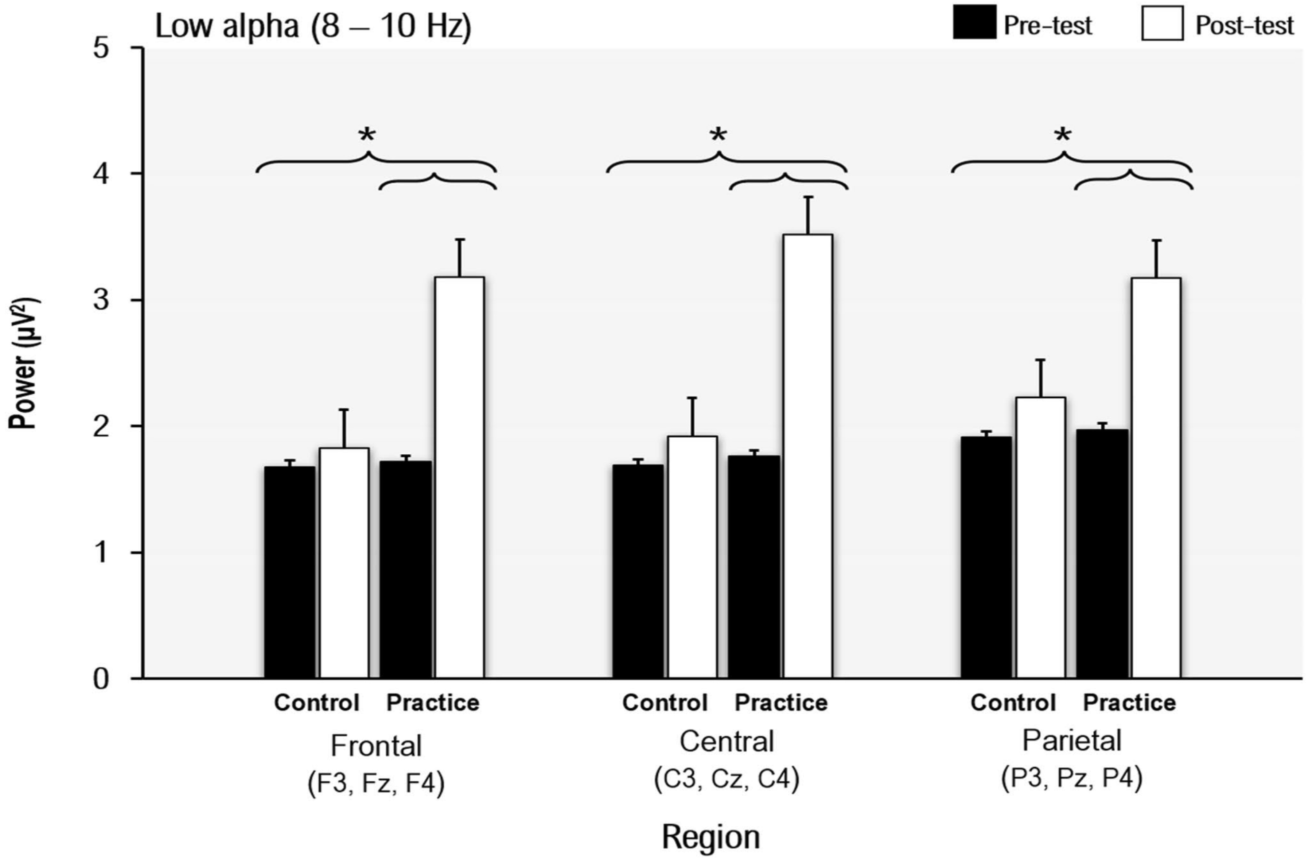

Fig. 5 Results of the low alpha power (8–10 Hz) at frontal, central, and parietal regions of the brain

$p < 0.001$, ηp2 = 0.438, and power = 1; and parietal region, $F(1,28) = 5.837$, $p = 0.022$, ηp2 = 0.172, and power = 0.645.

Additionally, a between-subjects ANOVA indicated that the group factor significantly affected alpha power in the central region, $F(1,28) = 8.182$, $p = 0.008$, ηp2 = 0.226, and power = 0.778; and parietal region, $F(1,28) = 3.958$, $p = 0.05$, ηp2 = 0.124, and power = 0.485. These results demonstrate a significant difference between the practice and control groups. However, no significant effect was observed in the frontal region, $F(1,28) = 2.964$, $p = 0.09$, ηp2 = 0.096, and power = 0.383. As shown in Fig. 5, the practice group's low alpha power significantly increased in the central and parietal regions from the pre-test to the post-test, while no significant increase was noted in the control group.

High-alpha power

A mixed-factorial ANOVA revealed a significant main effect for Time, indicating that high alpha power increased from the pre-test to the post-test, $F(1,28) = 12.315$, $p < 0.001$, ηp2 = 0.587, and power = 999. However, no significant main effect for Group was found, $F(1,28) = 2.473$, $p > 0.05$, ηp2 = 0.222, and power = 0.547. A significant Group × Time interaction was also seen, F(1,28) = 12.921, p < 0.001, ηp2 = 0.599, and power = 999.

Within-subjects ANOVA indicates that the time factor has a significant effect on high alpha power in the frontal region, $F(1,28) = 9.947$, $p = 0.004$, ηp2 = 0.262, and power = 0.861; central region, $F(1,28) = 35.679$, $p < 0.001$, ηp2 = 0.560, and power = 1; and parietal region, $F(1,28) = 5.877$, $p = 0.022$, ηp2 = 0.173 and, power = 0.648. This indicates that high alpha power in the practice group significantly increased compared to the control group during the post-test phase relative to the pre-test phase (see Fig. 6). A significant interaction effect of Group × Time was seen in the frontal region, $F(1,28) = 10.148$, $p = 0.004$, ηp2 = 0.266 and, power = 0.867; central region, $F(1,28) = 35.909$, $p < 0.001$, ηp2 = 0.562, and power = 1; and parietal regions, $F(1,28) = 4.298$, $p = 0.047$, ηp2 = 0.133, and power = 0.517.

Between-subjects ANOVA showed a significant difference between groups in the central region, $F(1,28) = 5.188$, $p = 0.031$, ηp2 = 0.156, and power = 0.595; however, no significant differences were observed in the frontal region $F(1,28) = 1.029$, $p > 0.05$, ηp2 = 0.035, and power = 0.165; and parietal region $F(1,28) = 2.509$, $p > 0.05$, ηp2 = 0.082, and power = 0.334. As illustrated in Fig. 6, high alpha power

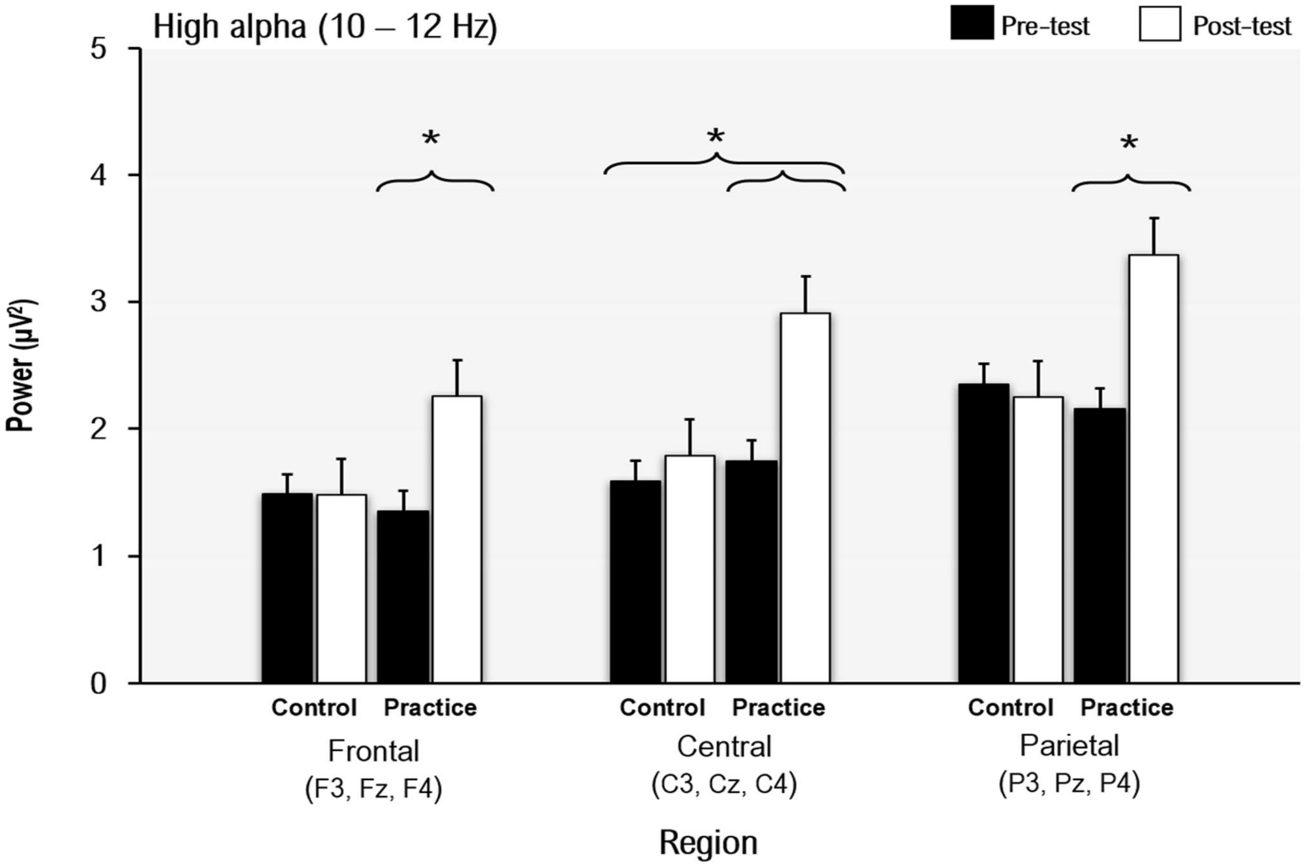

Fig. 6 Results of the high alpha power (10–12 Hz) at frontal, central, and parietal regions of the brain

significantly increased in the practice group during the post-test, while no increase was observed in the control group.

Behavioral results

Acquisition phase

A 3 (day) × 10 (block) within-subjects ANOVA over MRE revealed a significant main effect of day, $F(2,28) = 17.121$, $p < 0.001$, ηp2 = 0.550, and power = 991, as well as a significant main effect of block, $F(9,126) = 3.443$, $p = 0.001$, ηp2 = 0.197, and power = 0.973. The day by block interaction, $F(18,252) = 0.771$, $p > 0.05$, was not significant. For bias, a 3 × 10 within-subjects ANOVA on SRE indicated a significant main effect of day, $F(2,28) = 6.926$, $p = 0.004$, ηp2 = 0.331, and power = 0.894. A significant main effect of block, $F(9,126) = 2.117$, $p = 0.033$, ηp2 = 0.131, and power = 0.859, as well as the day by block interaction, $F(18,252) = 0.382$, $p > 0.05$, was not significant. For consistency, a 3 × 10 within-subjects ANOVA on BVE indicated a significant main effect of day, $F(2,28) = 5.680$, $p = 0.009$, ηp2 = 0.289, and power = 0.823, as well as a significant main effect of the block, $F(9,126) = 3.235$, $p = 0.001$, ηp2 = 0.188, and power = 0.976. The day × block interaction, $F(18,252) = 0.365$, $p > 0.05$, was not significant. Therefore, for the three dependent MRE, SRE, and BVE variables, performance improved during the acquisition phase (see Fig. 7).

Pre-, post-, and retention-test

A 2 (Group) × 3 (Time) × 3 (MRE, SRE, BVE) three-way repeated measure ANOVA revealed a main effect for group, $F(1,28) = 3.424$, $p = 0.032$, ηp2 = 0.283, and power = 0.702; and a main effect for time of measurement $F(2,56) = 5.303$, $p = 0.001$, ηp2 = 0.580, and power = 0.976. Repeated measure ANOVA showed no significant interaction effects between group and time ($p > 0.05$). Within-subjects ANOVA on MRE, $F(2,56) = 15.416$, $p < 0.001$, ηp2 = 0.335, and power = 1, SRE, $F(2,56) = 9.554$, $p = 0.001$, ηp2 = 0.254, and power = 0.975, and BVE, $F(2,56) = 6.753$, $p = 0.002$, ηp2 = 0.194, and power = 0.903 revealed a significant main effect of time. According to the pairwise comparison although from the pre-test to the post-test phase time is a significant factor on MRE, SRE, and BVE, no significant difference was observed from the post-test to the retention phase ($p > 0.05$). Figure 8 presents means of groups at pre,

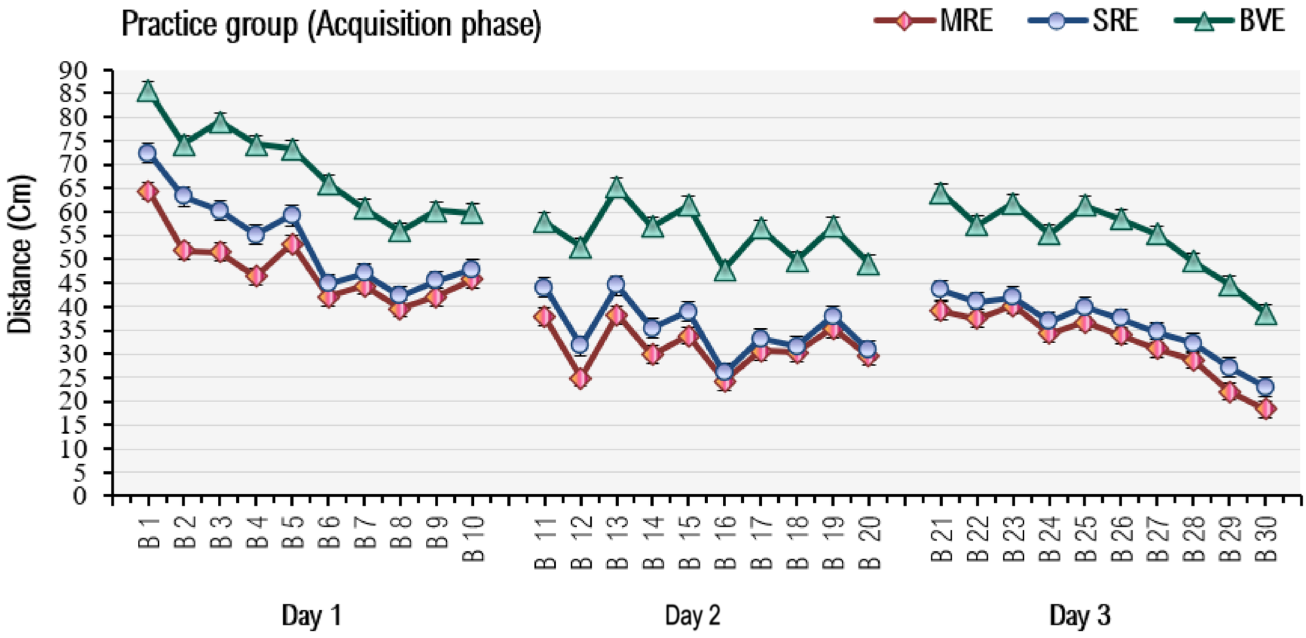

Fig. 7 The figure illustrates the practice group's average scores for accuracy (MRE), bias (SRE), and consistency (BVE). As indicated, the practice group's average scores for MRE, SRE, and BVE decreased significantly during the acquisition phase

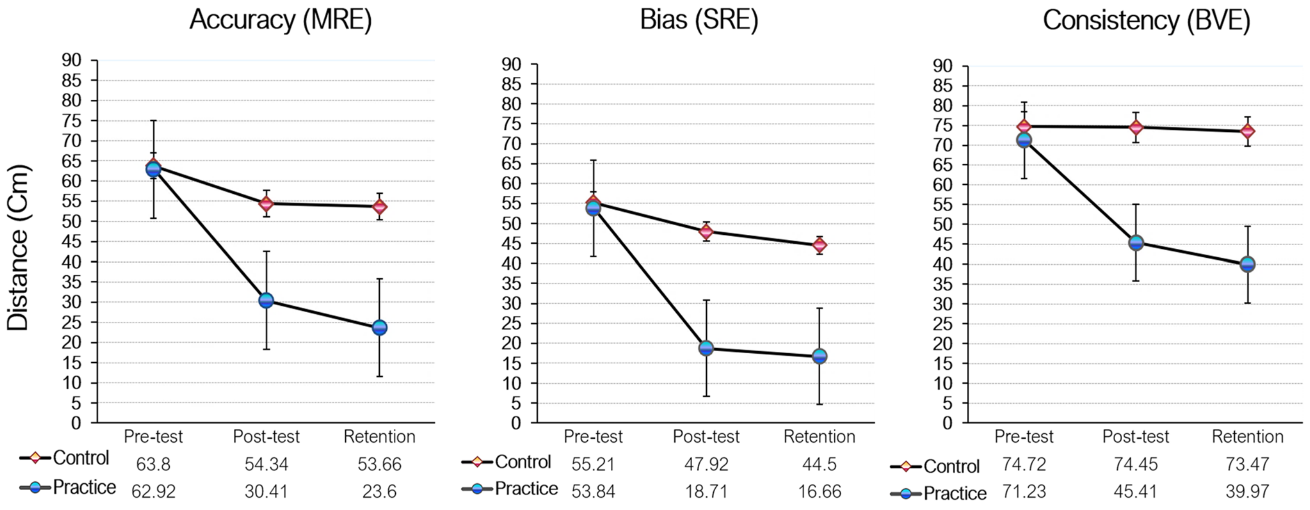

Fig. 8 The figure presents the average scores for the practice and control groups in the variables of accuracy (MRE), bias (SRE), and consistency (BVE). The data reveals that the practice group's scores for MRE, SRE, and BVE significantly decreased from the pre-test to the post-test, as well as from the pre-test to the retention test when compared to the control group. In contrast, the average scores for the control group did not show any significant decrease in the MRE, SRE, or BVE variables during the pre-test and retention test

post- and, retention- test for the three dependent variables (MRE, SRE, and BVE).

Between-subjects ANOVA on MRE, SRE, and BVE showed a significant main effect of the group, and the performance of the practice and the control groups have a significant difference. Pairwise comparisons indicated that MRE, $F(1,28) = 5.270$, $p = 0.029$, $\eta p2 = 0.158$, and power = 0.601; SRE, $F(1,28) = 4.358$, $p = 0.05$, $\eta p2 = 0.157$, and power = 0.625; and BVE, $F(1,28) = 9.172$, $p = 0.005$, $\eta p2 = 0.247$, and power = 0.832, decreased significantly from pre-test to post-test, as well as from pre-test to retention test in the practice group in comparison to the control group (see Fig. 8).

Discussion

The present study aimed to investigate the motor learning process across cognitive, neurophysiological, and behavioral domains. Specifically, it examined cognitive structures, low and high alpha wave power, and motor performance outcomes in both practice and control groups.

The adaptation of cognitive structures in motor learning

Based on our first hypothesis, we expected physical practice to develop cognitive structures relevant to task performance, potentially leading to improved skill execution. The cognitive findings of our study support this hypothesis, as the practice group developed a more organized and complex cognitive structure, which is essential for skill acquisition. This enrichment in cognitive structures was accompanied by improved performance outcomes, reinforcing the idea that physical practice facilitates cognitive development relevant to task execution. These findings align with previous research, indicating that motor learning is associated with functional adaptations in cognitive structures (Schack, 2004; Schack & Frank, 2021). Notably, we discovered that the basic action concepts (BACs) associated with the beginning and end of the golf putting skill were significant. These include BAC 1, BAC 2, BAC 3, BAC 5, BAC 6, BAC 12, BAC 13, BAC 14, BAC 15, and BAC 16. In contrast, the BACs located in the middle of the sequence—BAC 4, BAC 7, BAC 8, BAC 9, BAC 10, and BAC 11—were not significant. This finding supports the "serial position effect," also known as the "primacy-recency effect," which suggests that items presented at the beginning and end of a sequence are recalled more easily than those in the middle (Magill & Anderson, 2017; Raanaas & Magnussen, 2006).

Existing literature supports the idea that cognitive structures can become increasingly organized and complex through various practice methods, including physical, observational, mental practice, and combined approaches. Instructions—whether implicit or explicit—along with psychological interventions, such as cognitive and behavioral routines, facilitate these functional changes (Frank et al., 2018; Land et al., 2014; Simonsmeier et al., 2018). For example, previous studies have shown significant functional changes in the cognitive structures of participants engaged in physical practice on the golf putting task, whereas no similar improvements were noted in the control group (Frank et al., 2013). Additionally, research exploring the effects of different focus instructions (internal vs. external) on mental representation development indicated that participants instructed with an external focus exhibited more substantial advancements in their mental representation (Land et al., 2014). Another study has examined the influence of mental and physical practice on cognitive structures, quiet eye behavior, and performance results in three conditions physical, combined (physical and mental), and no practice. The findings of this study have shown that the combined practice group exhibited more accurate cognitive structures and maintained longer periods of quiet eye behavior compared to the no-practice group (Frank et al., 2016). Furthermore, Fazeli et al. (2017) examined cognitive structures involved in golf putting using both blocked and random practice methods, discovering that the random practice group's cognitive structures closely resembled those of proficient golfers. Moreover, Kim et al (2017). demonstrated that cognitive structures improved with observational and mental practice, revealing a significant positive correlation between cognitive structure development and motor performance. Meier et al. (2020) explored the influence of analogy and explicit instructions on cognitive structures and performance in intermediate-level tennis players, finding that both instructional methods enhanced cognitive structures in tennis serve performance. Collectively, these findings underscore the critical role of cognitive structures in motor skill learning (Schack & Frank, 2021). Based on our cognitive results and the research literature in this field, we conclude that cognitive concepts (such as basic action concepts), structures, and knowledge are formed during the motor learning process, ultimately leading to a more complex and organized cognitive architecture for golf putting skill over time.

The adaptation of neurophysiological structures in motor learning

In our research, we hypothesized that the motor learning process involves simultaneous cognitive, neurophysiological, and behavioral adaptations. Therefore, our second objective was to investigate brain function to assess the neurophysiological changes associated with motor learning. We anticipated that physical practice would lead to an increase in both low alpha power (8–10 Hz) and high alpha power (10–12 Hz) across the brain's frontal, central, and parietal regions, which are associated with successful motor execution. Specifically, we measured low alpha power (8–10 Hz) and high alpha power (10–12 Hz) in areas responsible for motor planning, motor control, and integrative functions. Our neurophysiological results indicated significant increases in both low and high alpha power within the frontal, central, and parietal regions for the practice group, while the control group showed no significant changes. However, it is important to acknowledge that these interpretations are based on an average across a 4-s epoch, which may mask specific effects occurring during the preparatory and execution phases of movement. Our findings support our hypothesis and align with previous research indicating that learning and expertise are associated with changes in brain wave patterns.

For example, researchers have noted changes in brain wave patterns associated with learning and expertise. Landers et al. (1994) reported an increase in alpha power in the left hemisphere following learning. Kerick et al. (2001) observed an increase in alpha power in the temporal and occipital regions. Haufler et al. (2000) found increased alpha power in the left hemisphere of skilled individuals before shooting, with no difference in the right hemisphere. Taliep and John (2014) discovered that skilled individuals exhibit more alpha power in the left temporal region compared to novices. Parr et al. (2019) observed skilled individuals exhibit more alpha power in various brain regions. Additional research supports our findings, Smith et al. (1999) observed increased theta power in the middle frontal region and increased alpha power in the occipital region after practicing a computer game. Kim et al. (2014) found greater neural activity in the supplementary motor area (SMA), temporoparietal area, superior frontal area, and cerebellum in elite and expert archers compared to novice archers. Recently, Abdoli et al. (2024) reported that skilled golfers demonstrate more mu rhythm in the central areas (motor cortex) than their novice counterparts.

Specifically, numerous studies have highlighted the significance of frontal alpha activity in cognitive functions, particularly in relation to attentional focus, which is essential for effective exercise performance. For instance, Blomstrand and Engvall(2021) and Smith et al. (2010) demonstrate that increased frontal alpha activity is linked to improved attentional focus during complex motor tasks. This correlation is further supported by Hosang et al. (2022), who notes that enhanced cognitive processing during exercise facilitates greater alpha modulation in frontal regions. Additionally, Ammar et al. (2024) emphasizes that while alpha frequency (8–13 Hz) in the parietal-occipital region generally increases irrespective of the motor learning model, variations in alpha activity across other frontal and motor areas depend on the specific learning paradigms employed. This suggests a nuanced relationship between frontal alpha activity and performance, which can vary based on training context. Supporting this premise, research by Enders et al. (2016) and Gutmann et al. (2018) indicates overall increases in alpha activity across frontal areas during endurance tasks, suggesting that heightened alpha may improve coordination and cognitive processing among skilled practitioners. Similar findings by Gallicchio et al. (2016) in shooting indicate that higher alpha levels in non-motor areas, combined with lower alpha in motor regions, correlate with improved shooting accuracy, suggesting that increased frontal alpha activity aids in maintaining focus and managing cognitive load.

These researchers believe that increased frontal alpha activity is linked to improved cognitive functions, such as attentional focus and cognitive control, which are essential for effective task execution. Taken together, this body of evidence suggests that experts exhibit higher alpha, theta, mu, and SMR power in certain brain regions such as frontal, temporal, central, parietal, and occipital (Abdoli et al., 2024; Baumeister et al., 2008; Bertollo et al., 2020; Cheng et al., 2015; Cooke et al., 2014; Del Percio et al., 2009; Parr et al., 2019, 2021). This indicates that expertise and successful performance are characterized by an increase in brain wave power in these regions (Hatfield et al., 1984; Kerick et al., 2001; Loze et al., 2001).

In contrast to the increase of alpha power in different regions of the brain, some studies have shown that experts have lower alpha power than amateurs. For example, some researchers believe that with the increase in skill level, the alpha power in the central regions (Babiloni et al., 2008; Cooke et al., 2014) or in the middle frontal, central (motor sensory), and parietal regions also decreases (Wang et al., 2020). A reduction in alpha power is especially reported at the left temporal region which researchers believe may reflect cognitive analysis of the task (Deeny et al., 2003). For example, Hatfield and Hillman (Hatfield & Hillman, 2001) and Janelle et al. (Janelle et al., 2000) observed that left temporal alpha power is lower in experts compared to novices. Hatfield and colleagues (Hatfield et al., 1984) also recorded the brain activity of elite shooters during shooting and found that during a verbal task, the alpha power between the right (T4) and left (T3) temporal lobes was higher, whereas the alpha power between these two locations was lower during doing a spatial task. Considering that Hatfield and colleagues observed that brain activity decreases in the left hemisphere compared to the right hemisphere, they inferred that this decrease indicates the efficiency of information processing (Hatfield et al., 1984). Also, Neuper and Pfurtscheller (2001) and Pfurtscheller (1992) found that alpha activity diminishes over motor areas of the cortex before and during movement, reflecting the brain's preparation for motor tasks and a strategic reallocation of cognitive resources to areas directly involved in during movement execution. Cooke et al. (2014) and Hatfield et al. (2004) explain that in precision sports, skilled athletes often show decreased frontal alpha activity as they concentrate their cognitive efforts on executing movements accurately. This decline helps suppress irrelevant cognitive processes, enhancing motor control. The findings by Brady (2004) further support this perspective, indicating that expert performers exhibit lower frontal alpha activity during high-stakes situations, which may aid their ability to manage distractions and maintain focus.

The dual perspective on alpha activity reveals a complex interplay between cognitive processes and motor control. On one hand, the increase in alpha activity can signify enhanced attentional focus and cognitive engagement necessary for skilled performance. On the other hand, the decrease in alpha activity suggests a dynamic reallocation of cognitive resources aimed at optimizing motor execution. Understanding this delicate balance is key to enhancing training methodologies and cognitive strategies. Researchers propose that experts demonstrate greater neural efficiency than novices through more effective cortical functioning, resulting in expert-level performance achieved with minimal energy expenditure in cognitive-motor processes (Deeny et al., 2009). This aligns with *the psychomotor efficiency hypothesis* proposed by Hatfield and Hillman (2001), which posits that experts exhibit more appropriate cortical processing when performing tasks. Such efficient processing inhibits irrelevant cognitive-motor processes while enhancing those that are relevant, ultimately leading to successful performance (Hatfield & Hillman, 2001; Hatfield et al., 1984; Hatfield 2018). During the motor learning process, neuronal circuits undergo refinement: unused and unnecessary neural connections and networks diminish or are lost, while those utilized become strengthened, and new connections are formed. This dynamic is supported by recent findings indicating that the neural networks associated with task execution increase as skill levels improve (Hedrick et al., 2024). Our neurophysiological results corroborate this, showing increases in both low and high alpha power in the frontal region—associated with motor planning processes (Haufler et al., 2000)—the central region—linked to motor execution (Schinke et al., 2016)—and the parietal region—integral for integrating sensorimotor information for planning (Ferri et al., 2015) and executing motor actions (Medendorp & Heed, 2019).

Altogether, we infer that as skill levels and motor learning progress, the neural connections and networks related to task execution not only increase but also undergo significant reorganization, resulting in the formation of new connections. This suggests that neural connections, structures, and networks are formed, developed, and strengthened over time due to repetitive practicing of a specific skill (golf putting task) and the continuous involvement of neural activities in the regions responsible for executing the skill. In this study, an increase in alpha power in the relevant regions during execution and control of the skill represents this construction and formation. We propose that because the brain can undergo significant neurophysiological changes over time, the process of constructing neurophysiological structures is essentially the learning process from the neural domain. This perspective emphasizes that motor learning is not merely a cognitive or behavioral outcome but is deeply rooted in the evolving neural architecture that underpins skill acquisition and performance.

The adaptation of behavioral structures in motor learning

Researchers suggest that motor learning leads to changes in motor behavior (Schmidt et al., 2018). Therefore, we investigated the hypothesis that motor learning encompasses changes beyond just cognitive and neurophysiological dimensions. Accordingly, we expected physical practice to reduce performance errors, including inaccuracies, biases, and inconsistencies. The behavioral results demonstrated that the practice group showed a significant reduction in execution errors over time, while the control group did not exhibit any improvement in motor performance errors. This finding supports our hypothesis that physical practice enhances performance by reducing errors and improving skill execution.

These findings support previous research by Frank et al. (2013), who studied the effects of physical practice on motor performance in a golf putting task, revealing significant improvements in the practice group compared to the control group. Moreover, various methods of practice and instructions have been found to enhance motor performance in golf putting task. For example, studies have shown that external attention, as opposed to internal attention, leads to increased motor performance (accuracy) in golf putting task (Bell & Hardy, 2009; Land et al., 2014; Wulf & Su, 2007; Wulf et al., 1999). An experiment assessed whether internal or external attention instructions influence skill development; findings suggested that the external focus group performed with greater accuracy in golf putting task (Land et al., 2014). Additionally, a study by Frank et al. (2016) examined the effect of different practice methods (including physical, a combination of physical and mental, and no practice) on golf putting skill. The study found that both physical practice and combined practice led to significant improvements in performance compared to no practice. In a study conducted by Fazeli et al. (2017), two groups were tested on their motor performance in golf putting skill using random and blocked practice methods. The study indicated that the group that practiced with random methods performed better than the group that practiced with blocked methods. Kim et al. (2017) conducted a study to examine the motor performance of individuals in the golf putting task under four physical, observational, mental, and no-practice conditions. Their findings revealed that performance accuracy was improved and developed through the use of observational and mental practice. Furthermore, Schmidt et al. (2021) compared different practice groups in novice golfers, including a contextual interference group, a differential learning group, an identical differential learning group, and a control group. They found that all practice groups showed improved performance at post-test, with the variable practice groups demonstrating more stable retention compared to the control group. Based on the behavioral results that demonstrate a reduction in performance errors over time, along with improved consistency and accuracy in the practice group (see Figs. 7 and 8), we propose that the process of constructing behavioral structures and modifying motor behavior can be viewed as integral to the motor learning process from a behavioral perspective.

A holistic approach to understanding motor learning dynamics

Our main hypothesis is that motor learning involves simultaneous cognitive, neurophysiological, and behavioral adaptations, which will increase with practice. The findings from this study provide compelling evidence in support of this hypothesis. After practice, the practice group exhibited a more organized and complex cognitive structure, increased alpha power in key brain regions, and a significant reduction in performance errors compared to the control group. Our findings suggest that motor learning leads to simultaneous cognitive, neurophysiological, and behavioral changes. Therefore, from a *holistic perspective* of the motor learning process, we propose that motor learning involves the concurrent development of knowledge and/or cognitive, neurophysiological, and behavioral structures over time.

The cognitive, neurophysiological, and behavioral adjustments observed in our study highlight the complex relationship between cognitive processes and motor behavior, supporting *the perceptual-cognitive approach* to motor learning. This approach emphasizes how cognition and action are interconnected, suggesting that effective motor learning depends on the dynamic interaction between these two domains (Schack, 2004). Specifically, successful motor learning relies on the ability to plan and execute actions based on anticipated perceptual outcomes (Prinz, 1997). *The perceptual-cognitive approach* argues that motor actions are not solely generated by internal motor programs; instead, they are strategically planned and executed in accordance with expected perceptual effects (e.g., Frank et al., 2024; Hoffmann, 1993; Hommel et al., 2001; Jeannerod, 2001; Knuf et al., 2001; Kunde, 2001; Prinz, 1997; Schack, 2004). This contrasts with *the ecological approach*, which primarily focuses on environmental influences and organisms do not need cognitive structures or mental representations to perceive their surroundings or to perform actions (Gibson, 1979; Turvey, 1991). Instead, *the perceptual-cognitive approach* acknowledges the crucial role of cognitive structures and environmental affordances (e.g., Hoffmann, 1993; Hommel et al., 2001; Jeannerod, 2001; Knuf et al., 2001; Kunde, 2001; Prinz, 1997; Schack, 2004), leading to a comprehensive understanding of how these factors interact throughout the motor learning process. Furthermore, this approach recognizes that cognitive structures evolve over time, enabling individuals to progress from simple representations to more complex and organized frameworks as they gain experience (Schack, 2004; Schack & Frank, 2021). Consequently, it underscores the importance of cognitive flexibility and the development of rules related to sensory parameters and the consequences of movement—areas that are often overlooked in *the ecological approach*. Such cognitive flexibility is crucial for refining skills in response to changing conditions and task demands; whereas, movement variability remains a challenge that *the cognitive approach* has yet to adequately address.

Recognizing the valuable contributions of *the perceptual-cognitive approach*, our "*holistic motor learning approach"* aims to expand this understanding by integrating cognitive, neurophysiological, and behavioral dimensions. While we appreciate these insights, we propose that motor learning encompasses more than cognitive structures alone; it also involves significant changes in neurophysiological and behavioral structures. Our *holistic approach* maintains the core principles of *the perceptual-cognitive approach* while emphasizing the simultaneous interplay of cognitive, neurophysiological, and behavioral changes during the motor learning process. This broader approach captures the complexity of motor learning, highlighting that effective skill acquisition is influenced by a multifaceted array of factors that work together. By considering these dimensions, our holistic approach enhances the existing framework, providing a broader perspective that addresses the complex nature of human motor learning and enriches emerging theories in the literature.

Limitations and future directions

During the retention phase of the study, we faced challenges with participant retention, as some individuals chose to opt out of EEG recordings due to concerns about fatigue. To respect their autonomy and adhere to ethical standards, we allowed participants to perform the golf skill task without EEG recording on the final day (the retention phase). While this decision prioritized participant choice, it resulted in the absence of neurophysiological data for our analysis during this phase. The lack of brain activity assessment in the retention phase may limit our insights into long-term learning processes. Nevertheless, our findings enhance the understanding of immediate learning dynamics and the interaction between cognitive and motor performance. Future research should focus on strategies to improve participant comfort and retention, enabling a more comprehensive analysis of neurophysiological data throughout all learning phases.

Additionally, the absence of kinematic data in our study (due to some challenges) limited our ability to fully understand the motor learning process. While we assessed motor performance through execution errors, future research incorporating kinematic measures could provide deeper insights into movement quality and the strategies involved in skill acquisition and retention. These limitations should be considered when interpreting our findings.

Conclusion

This study provides compelling evidence that motor learning involves significant cognitive, neurophysiological, and behavioral adaptions. 1. Our cognitive findings indicate that the practice group developed a more organized and complex cognitive structure compared to the control group. 2. Our neurophysiological findings revealed increases in both low and high alpha power in the frontal, central, and parietal brain regions in the practice group, while the control group exhibited no notable changes. 3. Our behavioral findings demonstrated that the practice group showed a reduction in execution errors over time, in contrast to the control group, which displayed no improvement in motor performance.

This study offers a more comprehensive understanding of the motor learning process by highlighting the simultaneous development of cognitive, neurophysiological, and behavioral aspects. This *holistic perspective* enhances theoretical insights and provides practical implications for coaches and athletes. It allows them to design effective training programs that address the multifaceted nature of skill acquisition. Future research should continue to explore the connections between these dimensions to clarify the complexities of motor learning further.

Author contributions The authors' contributions are as follows: —Conceptualization: N.A—Investigation: N.A—Methodology: N.A—Formal analysis: N.A—Project administration: A.SK—Validation: A.SK—Writing—original draft preparation: N.A—Writing—review, and editing: A.SK, H.TT, M.Gh, T.S— All authors reviewed the manuscript.

Data availability No datasets were generated or analyzed during the current study; whereas we had written that we were not permitted to publish the data.

Declarations

Conflict of interest The authors declare no competing interests.

References

Abdoli, N., Saberi Kakhki, A., Taheri Torbati, H. R., & Ghoshuni, M. (2024). The comparison of the mu rhythm power of novice and expert people during the execution of Golf Putting Skill. *Journal of Sports and Motor Development and Learning*. https://doi.org/10.22059/jsmdl.2024.371049.1762. in press.

Adams, J. A. (1971). A closed-loop theory of motor learning. *Journal of Motor Behavior, 3*(2), 111–150. https://doi.org/10.1080/00222895.1971.10734898

Ammar, A., Boujelbane, M., Simak, M., Fraile-Fuente, I., Rizz, N., Washif, J., & Schöllhorn, W. (2024). Unveiling the acute neurophysiological responses to strength training: An exploratory study on novices performing weightlifting bouts with different motor learning models. *Biology of Sport, 41*(2), 249–274. https://doi.org/10.5114/biolsport.2024.133481

Anderson, J. (1983). *The architecture of cognition*. Harvard University Press.

Anderson, J. R. (1982). Acquisition of cognitive skill. *Psychological Review, 89*(4), 369–406. https://doi.org/10.1037/0033

Babiloni, C., Del Percio, C., Iacoboni, M., Infarinato, F., Lizio, R., Marzano, N., Crespi, G., Dassù, F., Pirritano, M., & Gallamini, M. (2008). Golf putt outcomes are predicted by sensorimotor cerebral EEG rhythms. *The Journal of Physiology, 586*(1), 131–139. https://doi.org/10.1113/jphysiol.2007.141630

Baumeister, J., Reinecke, K., Liesen, H., & Weiss, M. (2008). Cortical activity of skilled performance in a complex sports related motor task. *European Journal of Applied Physiology, 104*, 625–631. https://doi.org/10.1007/s00421-008-0811-x

Bell, J. J., & Hardy, J. (2009). Effects of attentional focus on skilled performance in golf. *Journal of Applied Sport Psychology, 21*(2), 163–177. https://doi.org/10.1080/10413200902795323

Bernstein, N. A. (1967). *The coordination and regulation of movement*. Pergamon Press.

Bertollo, M., Doppelmayr, M., & Robazza, C. (2020). Using brain technologies in practice. In *Handbook of Sport Psychology* (pp. 666–693). https://doi.org/10.1002/9781119568124.ch32

Bläsing, B. E., Güldenpenning, I., Koester, D., & Schack, T. (2014). Expertise affects representation structure and categorical activation of grasp postures in climbing. *Frontiers in Psychology, 5*, 1008. https://doi.org/10.3389/fpsyg.2014.01008

Blomstrand, P., & Engvall, J. (2021). Effects of a single exercise workout on memory and learning functions in young adults—A systematic review. *Translational Sports Medicine, 4*(1), 115–127. https://doi.org/10.1002/tsm2.190

Brady, F. (2004). Contextual interference: A meta-analytic study. *Perceptual and Motor Skills, 99*(1), 116–126. https://doi.org/10.2466/PMS.99.4.116-126

Cheng, M.-Y., Huang, C.-J., Chang, Y.-K., Koester, D., Schack, T., & Hung, T.-M. (2015). Sensorimotor rhythm neurofeedback enhances golf putting performance. *Journal of Sport and Exercise Psychology, 37*(6), 626–636. https://doi.org/10.1123/jsep.2015-0166

Cooke, A., Kavussanu, M., Gallicchio, G., Willoughby, A., McIntyre, D., & Ring, C. (2014). Preparation for action: Psychophysiological activity preceding a motor skill as a function of expertise, performance outcome, and psychological pressure. *Psychophysiology, 51*(4), 374–384. https://doi.org/10.1111/psyp.12182

Deeny, S. P., Haufler, A. J., Saffer, M., & Hatfield, B. D. (2009). Electroencephalographic coherence during visuomotor performance: A comparison of cortico-cortical communication in experts and novices. *Journal of Motor Behavior, 41*(2), 106–116. https://doi.org/10.3200/JMBR.41.2.106-116

Deeny, S. P., Hillman, C. H., Janelle, C. M., & Hatfield, B. D. (2003). Cortico-cortical communication and superior performance in skilled marksmen: An EEG coherence analysis. *Journal of Sport and Exercise Psychology, 25*(2), 188–204. https://doi.org/10.1123/jsep.25.2.188

Del Percio, C., Babiloni, C., Bertollo, M., Marzano, N., Iacoboni, M., Infarinato, F., Lizio, R., Stocchi, M., Robazza, C., & Cibelli, G.

(2009). Visuo-attentional and sensorimotor alpha rhythms are related to visuo-motor performance in athletes. *Human Brain Mapping, 30*(11), 3527–3540. https://doi.org/10.1002/hbm.20776

Delorme, A., & Makeig, S. (2004). EEGLAB: Una caja de herramientas de código abierto para el análisis de la dinámica de EEG de un solo ensayo, incluido el análisis de componentes independientes. *J. Neurosci. Métodos, 134*, 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Denis, D., Rowe, R., Williams, A. M., & Milne, E. (2017). The role of cortical sensorimotor oscillations in action anticipation. *NeuroImage, 146*, 1102–1114. https://doi.org/10.1016/j.neuroimage.2016.10.022

Doppelmayr, M., Finkenzeller, T., & Sauseng, P. (2008). Frontal midline theta in the pre-shot phase of rifle shooting: Differences between experts and novices. *Neuropsychologia, 46*(5), 1463–1467. https://doi.org/10.1016/j.neuropsychologia.2007.12.026

Edwards, W. H. (2010). *Motor learning and control: From theory to practice*. Cengage Learning.

Enders, H., Cortese, F., Maurer, C., Baltich, J., Protzner, A. B., & Nigg, B. M. (2016). Changes in cortical activity measured with EEG during a high-intensity cycling exercise. *Journal of Neurophysiology, 115*(1), 379–388. https://doi.org/10.1152/jn.00497.2015

England, A., Brusseau, T., Burns, R., Koester, D., Newton, M., Thiese, M., & Chase, B. (2019). The cognitive structure of the basketball free throw in adolescent physical education students. *Motor Control, 23*(4), 472–484. https://doi.org/10.1123/mc.2018-0035

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*(4), 11491160. https://doi.org/10.3758/BF03193146

Fazeli, D., Taheri, H., & Saberi Kakhki, A. (2017). Random versus blocked practice to enhance mental representation in golf putting. *Perceptual and Motor Skills, 124*(3), 674–688. https://doi.org/10.1177/0031512517704106

Ferri, S., Rizzolatti, G., & Orban, G. A. (2015). The organization of the posterior parietal cortex devoted to upper limb actions: An fMRI study. *Human Brain Mapping, 36*(10), 3845–3866. https://doi.org/10.1002/hbm.22882

Fitts, P. M., & Posner, M. I. (1967). *Human performance*.

Fox, N. A., Bakermans-Kranenburg, M. J., Yoo, K. H., Bowman, L. C., Cannon, E. N., Vanderwert, R. E., Ferrari, P. F., & van IJzendoorn, M. H. (2016). Assessing human mirror activity with EEG mu rhythm: A meta-analysis. *Psychological Bulletin, 142*(3), 291–313. https://doi.org/10.1037/bul0000031

Frank, C., Guillot, A., & Vogt, S. (2024). Imagery and motor learning: A special issue on the neurocognitive mechanisms of imagery and imagery practice of motor actions. *Psychological Research Psychologische Forschung*. https://doi.org/10.1007/s00426-024-01982-5

Frank, C., Land, W. M., & Schack, T. (2013). Mental representation and learning: The influence of practice on the development of mental representation structure in complex action. *Psychology of Sport and Exercise, 14*(3), 353–361. https://doi.org/10.1016/j.psychsport.2012.12.001

Frank, C., Land, W. M., & Schack, T. (2016). Perceptual-cognitive changes during motor learning: The influence of mental and physical practice on mental representation, gaze behavior, and performance of a complex action. *Frontiers in Psychology, 6*, 1981. https://doi.org/10.3389/fpsyg.2015.01981

Frank, C., Linstromberg, G.-L., Hennig, L., Heinen, T., & Schack, T. (2018). Team action imagery and team cognition: Imagery of game situations and required team actions promotes a functional structure in players' representations of team-level tactics. *Journal of Sport and Exercise Psychology, 40*(1), 20–30. https://doi.org/10.1123/jsep.2017-0088

French, K. E., & Thomas, J. R. (1987). The relation off knowledge development to children's basketball performance. *Journal of Sport and Exercise Psychology, 9*(1), 15–32. https://doi.org/10.1123/jsp.9.1.15

Gallicchio, G., Cooke, A., & Ring, C. (2016). Lower left temporal-frontal connectivity characterizes expert and accurate performance: High-alpha T7–Fz connectivity as a marker of conscious processing during movement. *Sport, Exercise, and Performance Psychology, 5*(1), 14–24. https://doi.org/10.1037/spy0000055

Ghasemian, M., Taheri, H., Saberi Kakhki, A., & Ghoshuni, M. (2017). Electroencephalography pattern variations during motor skill acquisition. *Perceptual and Motor Skills, 124*(6), 1069–1084. https://doi.org/10.1177/0031512517727404

Gibson, J. J. (1979). *The theory of affordances. The ecological approach to visual perception*. Houghton Mifflin.

Greenough, W. T., Black, J. E., & Wallace, C. S. (1987). Experience and brain development. *Child Development*. https://doi.org/10.2307/1130197

Gromeier, M., Schack, T., & Koester, D. (2022). Effects of age and expertise on mental representation of the throwing movement among 6-to 16-year-olds. *Frontiers in Psychology, 13*, 799316. https://doi.org/10.3389/fpsyg.2022.799316

Gutmann, B., Zimmer, P., Hülsdünker, T., Lefebvre, J., Binnebößel, S., Oberste, M., & Mierau, A. (2018). The effects of exercise intensity and post-exercise recovery time on cortical activation as revealed by EEG alpha peak frequency. *Neuroscience Letters, 668*, 159–163. https://doi.org/10.1016/j.neulet.2018.01.007

Hancock, G. R., Butler, M. S., & Fischman, M. G. (1995). On the problem of two-dimensional error scores: Measures and analyses of accuracy, bias, and consistency. *Journal of Motor Behavior, 27*(3), 241–250. https://doi.org/10.1080/00222895.1995.9941714

Hatfield, B. D. (2018). Brain dynamics and motor behavior: A case for efficiency and refinement for superior performance. *Kinesiology Review, 7*(1), 42–50. https://doi.org/10.1123/kr.2017-0056

Hatfield, B. D., & Hillman, C. H. (2001). The psychophysiology of sport: A mechanistic understanding of the psychology of superior performance. In R. N. Singer, H. A. Hausenblas, & C. M. Janelle (Eds.). *Handbook of sport psychology*, 2nd ed. (pp. 362–386). Wiley.

Hatfield, B. D., Haufler, A. J., Hung, T. M., & Spalding, T. W. (2004). Electroencephalographic studies of skilled psychomotor performance. *Journal of Clinical Neurophysiology, 21*(3), 144–156. https://doi.org/10.1097/00004691-200405000-00003

Hatfield, B. D., Landers, D. M., & Ray, W. J. (1984). Cognitive processes during self-paced motor performance: An electroencephalographic profile of skilled marksmen. *Journal of Sport and Exercise Psychology, 6*(1), 42–59. https://doi.org/10.1123/jsp.6.1.42

Haufler, A. J., Spalding, T. W., Santa Maria, D., & Hatfield, B. D. (2000). Neuro-cognitive activity during a self-paced visuospatial task: Comparative EEG profiles in marksmen and novice shooters. *Biological Psychology, 53*(2–3), 131–160. https://doi.org/10.1016/S0301-0511(00)00047-8

Hedrick, N. G., Wright, W. J., & Komiyama, T. (2024). Local and global predictors of synapse elimination during motor learning. *Science Advances, 10*(11), eadk0540. https://doi.org/10.1126/sciadv.adk0540

Hoffmann, J. (1993). *Vorhersage und Erkenntnis [Prediction and reason]*. Hogrefe.

Hoffmann, J., Stoecker, C., & Kunde, W. (2004). Anticipatory control of actions. *International Journal of Sport and Exercise Psychology, 2*(4), 346–361. https://doi.org/10.1080/1612197X.2004.9671750

Hommel, B. (2009). Action control according to TEC (the theory of event coding). *Psychological Research PRPF, 73*(4), 512–526. https://doi.org/10.1007/s00426-009-0234-2

Hommel, B., & Elsner, B. (2009). Acquisition, representation, and control of action. In E. Morsella, J. A. Bargh, & P. M. Gollwitzer (Eds.), *Oxford handbook of human action* (pp. 371–398). Oxford University Press.

Hommel, B., Müsseler, J., Aschersleben, G., & Prinz, W. (2001). The theory of event coding (TEC): A framework for perception and action planning. *Behavioral and Brain Sciences, 24*(5), 849–878. https://doi.org/10.1017/S0140525X01000103

Hommel, B., & Wiers, R. W. (2017). Towards a unitary approach to human action control. *Trends in Cognitive Sciences, 21*(12), 940–949. https://doi.org/10.1016/j.tics.2017.09.009

Hosang, L., Mouchlianitis, E., Guérin, S. M., & Karageorghis, C. I. (2022). Effects of exercise on electroencephalography-recorded neural oscillations: a systematic review. *International Review of Sport and Exercise Psychology*. https://doi.org/10.1080/1750984X.2022.2103841

James, W. (1890). *Habit*. H. Holt.

James, W. (1892). *Principles of psychology: Briefer course*. Holt.

Janelle, C. M., Hillman, C. H., Apparies, R. J., Murray, N. P., Meili, L., Fallon, E. A., & Hatfield, B. D. (2000). Expertise differences in cortical activation and gaze behavior during rifle shooting. *Journal of Sport and Exercise Psychology, 22*(2), 167–182. https://doi.org/10.1123/jsep.22.2.167

Jasper, H. H. (1958). Ten-twenty electrode system of the international federation. *Electroencephalography and Clinical Neurophysiology, 10*, 371–375.

Jeannerod, M. (2001). Neural simulation of action: A unifying mechanism for motor cognition. *NeuroImage, 14*(1), S103–S109. https://doi.org/10.1006/nimg.2001.0832

Kao, S.-C., Huang, C.-J., & Hung, T.-M. (2014). Neurofeedback training reduces frontal midline theta and improves putting performance in expert golfers. *Journal of Applied Sport Psychology, 26*(3), 271–286. https://doi.org/10.1080/10413200.2013.855682

Keele, S. W., & Posner, M. I. (1968). Processing of visual feedback in rapid movements. *Journal of Experimental Psychology, 77*, 155–158. https://doi.org/10.1037/h0025754

Kelly, A. C., & Garavan, H. (2005). Human functional neuroimaging of brain changes associated with practice. *Cerebral Cortex, 15*(8), 1089–1102. https://doi.org/10.1093/cercor/bhi005

Kerick, S. E., McDowell, K., Hung, T.-M., Santa Maria, D. L., Spalding, T. W., & Hatfield, B. D. (2001). The role of the left temporal region under the cognitive motor demands of shooting in skilled marksmen. *Biological Psychology, 58*(3), 263–277. https://doi.org/10.1016/S0301-0511(01)00116-8

Kim, T., Frank, C., & Schack, T. (2017). A systematic investigation of the effect of action observation training and motor imagery training on the development of mental representation structure and skill performance. *Frontiers in Human Neuroscience, 11*, 499. https://doi.org/10.3389/fnhum.2017.00499

Kim, W., Chang, Y., Kim, J., Seo, J., Ryu, K., Lee, E., Woo, M., & Janelle, C. M. (2014). An fMRI study of differences in brain activity among elite, expert, and novice archers at the moment of optimal aiming. *Cognitive and Behavioral Neurology, 27*(4), 173–182. https://doi.org/10.1097/WNN.0000000000000042

Knuf, L., Aschersleben, G., & Prinz, W. (2001). An analysis of ideomotor action. *Journal of Experimental Psychology: General, 130*(4), 779–198. https://doi.org/10.1037/0096-3445.130.4.779

Kunde, W. (2001). Response-effect compatibility in manual choice reaction tasks. *Journal of Experimental Psychology: Human Perception and Performance, 27*(2), 387–394. https://doi.org/10.1037/0096-1523.27.2.387

Land, W. M., Frank, C., & Schack, T. (2014). The influence of attentional focus on the development of skill representation in a complex action. *Psychology of Sport and Exercise, 15*, 30–38. https://doi.org/10.1016/j.psychsport.2013.09.006

Landers, D. M., Han, M., Salazar, W., Petruzzello, S. J., et al. (1994). Effects of learning on electroencephalographic and electrocardiographic patterns in novice archers. *International Journal of Sport Psychology, 25*(3), 313–330.

Lashley, K. S. (1917). The accuracy of movement in the absence of excitation from the moving organ. *American Journal of Physiology, 43*, 169–194. https://doi.org/10.1152/AJPLEGACY.1917.43.2.169

Lebiere, C., & R Anderson, J. (1993). *A connectionist implementation of the ACT-R production system*

Lex, H., Schütz, C., Knoblauch, A., & Schack, T. (2015). Cognitive representation of a complex motor action executed by different motor systems. *Minds and Machines, 25*, 1–15. https://doi.org/10.1007/s11023-014-9351-9

Loze, G. M., Collins, D., & Holmes, P. S. (2001). Pre-shot EEG alpha-power during expert air-pistol shooting; A comparison of best and worst shots. *Journal of Sport Sciences, 19*, 727–733. https://doi.org/10.1080/02640410152475856

Magill, R., & Anderson, D. I. (2017). *Motor learning and control*. McGraw-Hill Publishing.

McMorris, T. (2014). *Acquisition and performance of sports skills*. Wiley.

McPherson, S. L., & Kernodle, M. W. (2003). Tactics, the neglected attribute of expertise: Problem representations and performance skills in tennis. In *Expert performance in sports: Advances in research on sport expertise* (pp. 137–167). https://doi.org/10.2466/30.10.25.PMS.115.5.567-580

Medendorp, W. P., & Heed, T. (2019). State estimation in posterior parietal cortex: Distinct poles of environmental and bodily states. *Progress in Neurobiology, 183*, 101691. https://doi.org/10.1016/j.pneurobio.2019.101691

Meier, C., Frank, C., Gröben, B., & Schack, T. (2020). Verbal instructions and motor learning: How analogy and explicit instructions influence the development of mental representations and tennis serve performance. *Frontiers in Psychology, 11*, 2. https://doi.org/10.3389/fpsyg.2020.00002

Morizawa, Y. M., Matsumoto, M., Nakashima, Y., Endo, N., Aida, T., Ishikane, H., & Matsui, K. (2022). Synaptic pruning through glial synapse engulfment upon motor learning. *Nature Neuroscience, 25*(11), 1458–1469. https://doi.org/10.1038/s41593-022-01184-5

Neuper, C., & Pfurtscheller, G. (2001). Event-related dynamics of cortical rhythms: Frequency-specific features and functional correlates. *International Journal of Psychophysiology, 43*(1), 41–58. https://doi.org/10.1007/s00421-008-0811-x

Oldfield, R. C. (1971). The assessment and analysis of handedness: The Edinburgh inventory. *Neuropsychologia, 9*(1), 97–113. https://doi.org/10.1016/0028-3932(71)90067-4

Parr, J. V., Gallicchio, G., & Wood, G. (2021). EEG correlates of verbal and conscious processing of motor control in sport and human movement: A systematic review. *International Review of Sport and Exercise Psychology*. https://doi.org/10.1080/1750984X.2021.1878548

Parr, J. V. V., Vine, S. J., Wilson, M. R., Harrison, N. R., & Wood, G. (2019). Visual attention, EEG alpha power and T7-Fz connectivity are implicated in prosthetic hand control and can be optimized through gaze training. *Journal of Neuroengineering and Rehabilitation, 16*, 1–20. https://doi.org/10.1186/s12984-019-0524-x

Petrini, K., Pollick, F. E., Dahl, S., McAleer, P., McKay, L. S., Rocchesso, D., & Puce, A. (2011). Action expertise reduces brain activity for Cogn Affect Behav Neurosci (2015) 15:381–394 393 audiovisual matching actions:an fMRI study with expertdrummers. *NeuroImage, 56*, 1480–1492. https://doi.org/10.1016/j.neuroimage.2011.03.009

Pfurtscheller, G. (1992). Event-related synchronization (ERS): An electrophysiological correlate of cortical areas at rest.

Electroencephalography and Clinical Neurophysiology, 83(1), 62–69. https://doi.org/10.1016/0013-4694(92)90133-3

Prinz, W. (1984). Modes of linkage between perception and action. In W. Prinz, & A. F. Sanders (Eds.), *Cognition and motor processes* (pp. 185–193). Springer. https://hdl.handle.net/11858/00-001M-0000-0010-C752-C

Prinz, W. (1997). Perception and action planning. *The European Journal of Cognitive Psychology, 9*, 129–154. https://doi.org/10.1080/713752551

Prinz, W., Heuer, H., & Sanders, A.: Ideo-motor action. In *Perspectives on perception and action* (pp. 47–76).

Proctor, R. W., & Dutta, A. (1995). *Skill acquisition and human performance*. Sage Publications, Inc.

Raanaas, R. K., & Magnussen, S. (2006). Serial position effects in implicit memory. *European Journal of Cognitive Psychology*, 18(03), 398–414. https://www.researchgate.net/publication/233554621

Schack, T. (2004). The cognitive architecture of complex movement. *International Journal of Sport and Exercise Psychology, 2*(4), 403–438. https://doi.org/10.1080/1612197X.2004.9671753

Schack, T. (2012). Measuring mental representations. In *Handbook of measurement in sport and exercise psychology* (pp. 203–214).

Schack, T., & Hackfort, D. (2007). Action-theory approach to applied sport psychology. *Handbook of sport psychology* (pp. 332–351). https://doi.org/10.1002/9781118270011

Schack, T., & Frank, C. (2021). Mental representation and the cognitive architecture of skilled action. *Review of Philosophy and Psychology, 12*, 527–546. https://doi.org/10.1007/s13164-020-00485-7

Schack, T., & Mechsner, F. (2006). Representation of motor skills in human long-term memory. *Neuroscience Letters, 391*(3), 77–81. https://doi.org/10.1016/j.neulet.2005.10.009

Schinke, R. J., McGannon, K. R., & Smith, B. (Eds.). (2016). *Routledge international handbook of sport psychology*. Routledge.

Schmidt, M., Kemena, M., & Jaitner, T. (2021). Null effects of different amounts of task variation in both contextual interference and differential learning paradigms. *Perceptual and Motor Skills, 128*(4), 1836–1850. https://doi.org/10.1177/00315125211022302

Schmidt, R. A. (1975). A schema theory of discrete motor skill learning. *Psychological Review, 82*, 225–260. https://doi.org/10.1037/h0076770

Schmidt, R. A., Lee, T. D., Winstein, C., Wulf, G., & Zelaznik, H. N. (2018). *Motor Control and Learning: A behavioral emphasis*. Human Kinetics.

Schmidt, R. A., & White, J. L. (1972). Evidence for an error detection mechanism in motor skills: A test of Adams' closed-loop theory. *Journal of Motor Behavior, 4*, 143–153. https://doi.org/10.1080/00222895.1972.10734930

Seo, J., Kim, Y. T., Song, H. J., Lee, H. J., Lee, J., Jung, T. D., & Chang, Y. (2012). Stronger activation and deactivation in archery experts for differential cognitive strategy in visuospatial working memory processing. *Behavioral Brain Research, 229*, 185–193. https://doi.org/10.1016/j.bbr.2012.01.019

Simonsmeier, B. A., Frank, C., Gubelmann, H., & Schneider, M. (2018). The effects of motor imagery training on performance and mental representation of 7-to 15-year-old gymnasts of different levels of expertise. *Sport, Exercise, and Performance Psychology, 7*(2), 155. https://doi.org/10.1007/s002210050738

Smith, M. E., McEvoy, L. K., & Gevins, A. (1999). Neurophysiological indices of strategy development and skill acquisition. *Cognitive Brain Research, 7*(3), 389–404. https://doi.org/10.1016/S0926-6410(98)00043-3

Smith, P. J., Blumenthal, J. A., Hoffman, B. M., Cooper, H., Strauman, T. A., Welsh-Bohmer, K., & Sherwood, A. (2010). Aerobic exercise and neurocognitive performance: A meta-analytic review of randomized controlled trials. *Psychosomatic Medicine, 72*(3), 239–252. https://doi.org/10.1097/PSY.0b013e3181d14633

Taliep, M. S., & John, L. (2014). Sport expertise: The role of precise timing of verbal-analytical engagement and the ability to detect visual cues. *Perception, 43*(4), 316–332. https://doi.org/10.1068/p7530

Thomas, K. T., & Thomas, J. R. (1994). Developing expertise in sport: The relation of knowledge and performance. *International Journal of Sport Psychology, 25*, 295–295.

Turvey, M. (1991). Action and perception from an ecological point of view. In R. Daugs, H. Mechling, K. Blischke, N. Olivier (Eds.), *Sportmotorisches Lernen und Techniktraining* (pp. 78–95).

Velentzas, K., Heinen, T., & Schack, T. (2011). Routine integration strategies and their effects on volleyball serve performance and players' movement mental representation. *Journal of Applied Sport Psychology, 23*(2), 209–222. https://doi.org/10.1080/10413200.2010.546826

Wang, K.-P., Cheng, M.-Y., Chen, T.-T., Huang, C.-J., Schack, T., & Hung, T.-M. (2020). Elite golfers are characterized by psychomotor refinement in cognitive-motor processes. *Psychology of Sport and Exercise, 50*, 101739. https://doi.org/10.1016/j.psychsport.2020.101739

Weigelt, M., Ahlmeyer, T., Lex, H., & Schack, T. (2011). The cognitive representation of a throwing technique in judo experts–technological ways for individual skill diagnostics in high-performance sports. *Psychology of Sport and Exercise, 12*(3), 231–235. https://doi.org/10.1016/j.psychsport.2010.11.001

Welch, P. (1967). The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms. *IEEE Transactions on Audio and Electroacoustics, 15*(2), 70–73. https://doi.org/10.1109/TAU.1967.1161901

Williams, A. M., Davids, K., Burwitz, L., & Williams, J. G. (2005). 'Perception and action in Sport. *Journal of Human Movement Studies, 22*, 147–204.

Woodworth, R. S. (1899). The accuracy of voluntary movement. In *Psychological review monographs* (Vol. 3, Whole No. 13). https://doi.org/10.1037/0033-2909.127.3.342

Wulf, G., Lauterbach, B., & Toole, T. (1999). The learning advantages of an external focus of attention in golf. *Research Quarterly for Exercise and Sport, 70*(2), 120–126. https://doi.org/10.1080/02701367.1999.10608029

Wulf, G., & Prinz, W. (2001). Directing attention to movement effects enhances learning: A review. *Psychonomic Bulletin & Review, 8*(4), 648–660. https://doi.org/10.3758/bf03196201

Wulf, G., & Su, J. (2007). An external focus of attention enhances golf shot accuracy in beginners and experts. *Research Quarterly for Exercise and Sport, 78*(4), 384–389. https://doi.org/10.1080/02701367.2007.10599436

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