Exploring Brain Activity in Novice Athletes During Closed and Open Skills in Table Tennis

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Abstract

This study investigated the neural correlates of closed and open-skill performance in novice table tennis players. Electroencephalography (EEG) was used to measure brain activity in 14 participants in a two-second window prior to movement onset by serving a ball (closed-skill) or returning a serve (open-skill) while attempting to hit a target. Results revealed distinct patterns of brain activity between the tasks. Linear mixed-effects models were used to compare EEG spectral power between Serve and Return trials and between successful and unsuccessful trials within each task. Return trials were associated with higher relative alpha power in the parietal and central regions, with additional exploratory effects at T7 and T8, compared with serve trials. Successful return trials were associated with lower relative occipital and parietal theta power than unsuccessful return trials. Successful serve trials were associated with higher relative central beta power and lower relative central and parietal theta power than unsuccessful serve trials. These findings suggest that novice table tennis performance is associated with task-specific differences in preparatory neural activity before movement onset. The study provides insights into the neural mechanisms underlying motor performance in novice athletes and highlights potential targets for training interventions aimed at improving skill acquisition and consistency.

Keywords: Electroencephalography, neural efficiency hypothesis, linear mixed-effects models

Introduction

The study of brain activity in sports is crucial for understanding the neurophysiological mechanisms involved in skilled motor performance (Babiloni et al., 2008; Del Percio et al., 2009). Electroencephalography (EEG) is well-suited for capturing real-time neural dynamics during motor preparation and execution (Hatfield et al., 1984; Loze et al., 2001, Morrone & Pedlar, 2024), and its relative portability has made it widely used in sports neuroscience (Filho, 2021; Park et al., 2015). Analysis of EEG spectral power across theta (4-8 Hz), alpha (8-12 Hz) and beta (12-25 Hz) frequency bands reveals differences between novices and experts, as well as between successful and unsuccessful performances (Baumeister et al., 2008; Doppelmayr et al., 2008; Wang et al., 2019; Filho, 2021, Fang et al., 2022).

The neural efficiency hypothesis suggests that skilled performers achieve superior performance through more selective recruitment of task-relevant neural resources and reduced engagement of unnecessary cortical processes (Babiloni et al., 2009; Del Percio et al., 2009; Filho et al., 2021; Guo et al., 2017, Li & Smith, 2021). This is supported by studies linking expertise with coordinated brain oscillations that support visuo-motor integration and top-down control (Cheron et al., 2016). Also supporting this view, elite athletes often exhibit hypoactivation (Budnik-Przybylska et al., 2021), with studies showing that reduced high-frequency alpha power and increased frontal-midline theta power are linked to better outcomes (Babiloni et al., 2008; Bertollo et al., 2020; Chuang et al., 2013; Wang et al., 2020). In closed-skill sports like golf and shooting, increased occipital alpha power is associated with effective inhibition

of irrelevant sensory input, and lower frontal beta power correlates with superior performance (Loze et al., 2001; Pluta et al., 2018). However, translating findings from closed-skill contexts to open-skill sports is challenging, and much of the current relevant work has focused on expert athletes engaged in closed-skill tasks; as such, research on novice athletes in open-skill sports is lacking. Because neural efficiency has been studied most extensively in expert performers, less is known about whether these efficiency related patterns of preparatory neural activity are already present in novices when task demands change or if this is something only later developed as part of skill acquisition.

Highly reactive sports such as table tennis require rapid integration of visual, auditory, and tactile cues, engaging premotor, motor, and visual areas to meet dynamic performance demands (Wolf et al., 2014, Shi et al., 2024) and more recent table-tennis research (Carius et al., 2023) has also linked expert performance with neural-efficiency patterns during sport-specific perceptual processing, such as demonstrating that experts can achieve superior performance with lower cortical resource usage. This supports the relevancy of the neural efficiency hypothesis to table tennis expertise while also highlighting the need to investigate novice performers directly. Within table tennis, serving and returning provide a useful contrast because they differ in environmental predictability and task complexity while remaining within the same sport. Serving is comparatively self-paced and predictable because the participant chooses when to initiate the action and can prepare a planned movement sequence. Returning a serve is more externally paced and reactive because the participant must anticipate the incoming ball, select an appropriate response, and execute the movement quickly. Although previous EEG research has predominantly compared experts to novices (Filho et al., 2021), few studies have examined the nuanced neural responses within novices themselves. Recent table-tennis neuroimaging work found that experts achieved higher target accuracy than novices while showing lower cortical resource use, suggesting that expertise-related neural efficiency in table tennis may be expressed through task-specific sensorimotor processes (Carius et al., 2023). Understanding the specific

neural states associated with different performance levels in novices may reveal whether the neural correlates of high-level performance observed in experts, like efficient resource allocation and inhibitory control, are only evident after extensive expertise or whether they begin to emerge during early skill performance. For instance, Visser et al. (2022) reported increased frontal theta power during continuous table tennis rallies in novices, indicating heightened attentional demands, but that study did not compare these results to novices performing closed-skill tasks. Therefore, comparing novice performance during serving and returning may help clarify whether task-related differences in preparatory EEG activity reflect early patterns of neural response allocation that are relevant to the neural efficiency hypothesis.

The present study addressed these gaps by examining pre-movement EEG activity in novice table tennis players during closed-skill serving and open-skill return trials. Theta, alpha, and beta activity were selected for analysis because these frequency bands have been linked to attentional, inhibitory, and sensorimotor processes relevant to sports performance. Theta activity has been associated with cognitive control, attentional focus, error monitoring, and the processing of changing environmental information during coordination and open-skill exercise (Chuang et al., 2013; Visser et al., 2022). Alpha activity was included because alpha oscillations are commonly interpreted in relation to attentional selection and cortical inhibition, including the suppression of task-irrelevant visual or neural processing (Mathewson et al., 2011; Uusberg et al., 2013). Beta activity was included because it has been associated with attentional arousal, alertness, and sensorimotor rhythms during pre-movement motor performance (Babiloni et al., 2008; Kamiński et al., 2012). Together, these frequency bands allowed us to examine whether preparatory EEG activity differed between serving and returning a serve and between successful and unsuccessful trials.The primary regions of interest were chosen because they correspond to neural processes likely to be involved in table tennis performance. Frontal regions were included because prior work has linked frontal EEG activity, particularly theta-band activity, with

attentional processing, decision making, executive function, and monitoring demands during coordination and open-skill exercise (Chuang et al., 2013; Visser et al., 2022). Occipital regions were included because table tennis requires visual tracking of the ball, anticipation of ball trajectory, and rapid processing of visual information during both serving and returning (Wolf et al., 2014; Visser et al., 2022; Studnicki & Ferris, 2023). Parietal regions were included because they are involved in visuospatial attention and sensorimotor integration, both of which are relevant when preparing to direct the ball toward a target. Recent EEG work during real world table tennis further supports the relevance of parieto-occipital electrocortical dynamics during table tennis (Studnicki & Ferris, 2023). Central regions were included because they are associated with sensorimotor preparation and motor execution, which are central to both the serve and return tasks (Babiloni et al., 2008; Wang et al., 2019). In addition to these primary regions, T7 and T8 were examined as exploratory lateral temporal electrodes because prior table-tennis EEG work has examined temporal-site alpha asymmetry and temporal premotor connectivity during sport-specific motor preparation (Wolf et al., 2015).

The primary aim of the present study was to compare the anticipatory period between closed-skill serve trials and open-skill return trials during the two-second window before movement onset. The secondary aims were to compare these same anticipatory windows before successful and unsuccessful serve and return trials. We hypothesized that pre-movement neural activity would differ between serve and return trials in the distribution of power within the 3 – 30 Hz range and across the selected regions of interest.

Additionally, we hypothesized that successful trials would be associated with distinguishable patterns of preparatory neural activity in both serving and returning. Framed within the neural efficiency hypothesis, these comparisons allowed us to examine whether different task demands and performance outcomes in novices were associated with task-specific patterns of preparatory neural resource allocation. These comparisons were planned to examine whether novice players show task and outcome related patterns of preparatory neural resource allocation that could provide insight into efficiency-like

processes during table tennis performance. T7 and T8 alpha activity were also examined as exploratory lateral temporal measures.

Materials and Methods

Participants

Fourteen right-handed, healthy novice participants (mean age: 24.25 years, SD: 11.69) were recruited for this study. For the purposes of this study, "novice" is used to indicate non-organized, non-competitive recreational players. Participants averaged 2.0 years (SD = 0.9, range = 1–3), with an estimated average total exposure of 156.0 hours (SD = 127.4, range = 52–468) and an average of 1.4 hours of play per week (SD = 0.7, range = 1–3). This exposure level is substantially below the thousands of accumulated practice hours typically represented in expertise research (Macnamara et al., 2016). Prior to any experiments taking place, the protocol was approved by the Institutional Review Board (IRB) at Mississippi State University (Starkville, MS, USA).

Experimental Protocol

After participants arrived in the lab, our EEG cap was placed on their head. EEG data were collected using a 64 channel BioSemi ActiveTwo EEG system at a sampling rate of 256 Hz, with the ActiveTwo AD box placed in a backpack to allow freedom of movement. The study involved two primary tasks, namely closed-skill (serving) and open-skill (returning a serve), with each participant performing 100 serves and 100 returns organized into five blocks of 20 trials per task. Task order was chosen randomly for each participant. For return trials, a study investigator served the ball to the participant. A standard table tennis setup was used, with a table measuring 274 cm by 152.5 cm and a height of 76 cm, and a designated square target area was marked with tape in the corner on the side of the table opposite the participant; prior to the beginning of the experiment, the participant was given the opportunity to warm

up and familiarize themselves with table tennis while wearing the EEG backpack. To familiarize the participants, they were asked to both serve the ball and return the ball and try to hit the ball into the target. The initial target size was 30x30cm. Participants were then asked to either serve or return the ball and attempt to hit the target ten times. The target size was incrementally adjusted in size until the participant was able to successfully hit the ball into the target approximately 50% of the time, or between four and six successful attempts (Wang et al., 2020).

During each experimental trial, participants remained still for 5 seconds before a 3 second countdown during which a trigger signal was sent to the EEG system to mark the onset of the 2 second pre-movement period. This two-second window prior to movement onset was the primary window from which EEG data was extracted and analyzed. To ensure consistency across participants, a five second timer was used prior to movement onset. Participants were instructed to remain as still as possible from the time the timer began until the time it sounded, then they were to either serve or attempt to return a serve once the timer sounded. After the countdown, participants initiated their movement to serve or return the ball, and shot outcomes were recorded. Shot outcomes were determined visually by the researchers. A successful attempt was defined as the ball landing within the designated target area on the table. An unsuccessful attempt was defined as the ball landing either directly on the boundary line of the target or completely outside the target area. Researchers observed the shots from beside the table to clearly view the ball's landing point.

EEG Data Analysis

The EEG electrode placement followed the standard 10-20 system (Jasper, H., 1958) consistent with current standardized EEG electrode layout nomenclature (Seeck et al., 2017). Two mastoid electrodes were used as the reference for each dataset. EEG data were processed in MATLAB 2021a using the latest version of the EEGlab toolbox(Delorme & Makeig, 2004). The data were band-pass filtered with

the EEGLAB Basic FIR filter between 3 and 30 Hz and subsequently re-referenced to the common average. This filter range was selected because the present analyses focused on theta, alpha, and beta activity, and the 3 Hz high-pass cutoff reduced the influence of slow drift and low-frequency movement-related contamination during this table tennis EEG paradigm. This pre-processing choice is also consistent with prior mobile EEG research in table tennis, which used the same 3–30 Hz band-pass filter range (Visser et al., 2022) and subsequently re-referenced to the common average. Channels exhibiting poor signal quality were identified using EEGlab's automatic channel rejection algorithm based on kurtosis with a threshold of 5 standard deviations (Delorme A., & Makeig, S (2004). To remove artifacts such as eye blinks, muscle activity, or cardiac signals, Independent Component Analysis (ICA) was performed using the default extended infomax runica algorithm. ICLabel (Pion-Tonachini et al., 2019) was used to classify each component as either a brain component, muscle component, heart component, eye component, line noise, channel noise, or other. Using a conservative threshold, components were removed when ICLabel assigned a probability of ≥ 90% to a non-brain component class. Components labelled as "Other" were manually inspected and removed only when their scalp topography, time series data, and/or power spectrum characteristics were consistent with non-brain activity. Although the same ICA component removal criteria was applied to all data, the exact number of ICA components removed per participant was not retained. Following ICA decomposition, channels previously identified by automated kurtosis-based rejection were interpolated before epoching and spectral analysis. Across the dataset, an average of 4.13 channels were rejected, corresponding to 6.45% of the 64-channel EEG montage. Using the trigger signals recorded during each trial, the EEG data for each shot were segmented into 2-second epochs immediately preceding movement initiation. This time window was selected to focus on the anticipatory neural activity associated with motor preparation while minimizing the influence of motion artifacts. These epochs were then further categorized into successful and unsuccessful trials based on whether the ball landed inside the designated target area.

Power spectral density (PSD) analysis was subsequently conducted on the cleaned data using Welch's method as implemented by MATLAB's pwelch function. The analysis employed a window length of 512 samples, no overlap, and a Fast Fourier Transform (FFT) length determined by the next power of 2 of the epoch length. PSD analysis was focused on the theta (4–8 Hz), alpha (8–12 Hz), and beta (12–25 Hz) frequency bands. For each epoch, both absolute and relative power values were calculated for the frontal, occipital, parietal, and central regions of interest. Frontal power was computed as the average of data from channels F3, F4, and Fz; occipital power was computed from channels O1, O2, and Oz; parietal power from channels P3, P4, and Pz; and central power from channels C3, C4, and Cz (Filho et al., 2021). In addition to these primary regions, the mean relative and absolute alpha power values for the lateral temporal electrodes T7 and T8 were calculated as exploratory measures. Because prior table-tennis EEG work has examined temporal alpha-power asymmetry during sport-specific motor performance, supplementary T7/T8 alpha-asymmetry values were also calculated using a right-minus-left convention, defined as T8 minus T7 relative alpha power (Wolf et al., 2015). Relative power was determined by dividing the sum of spectral power within the target frequency band by the total power in the 3–30 Hz range. Absolute and relative power were analyzed in parallel for each planned comparison and primary ROI.

Three planned comparisons were performed: (1) Serve vs Return, (2) Return Win vs Return Loss, and (3) Serve Win vs Serve Loss. For all primary ROIs, both absolute and relative power were calculated and analyzed. T7 and T8 alpha power was calculated and evaluated as exploratory temporal analyses. In the 2nd and 3rd comparisons, a "win" was defined as a trial in which the participant successfully hit the target (either on serve or return), and a "loss" was defined as a trial in which the target was missed.

For the Serve vs Return comparisons, all retained serve and return trials were averaged respectively to produce one mean Serve and Return value per participant and per variable. This approach avoided giving equal weight to varying numbers of successful and unsuccessful attempts. After preprocessing,

ICA decomposition, and component/artifact removal, 12 participants contributed usable serve data, 11 participants contributed usable return data, and 10 of those participants contributed usable data to both conditions. The Serve vs Return linear mixed model included 23 task-level observations, with task condition modelled as a fixed effect and the participant modelled as a random intercept.

For the Return Win vs Return Loss and Serve Win vs Serve Loss comparisons, trial-level data were analyzed. Trial outcome was modeled as a fixed effect, and participant was included as a random intercept to account for repeated measures within participants. This trial-level modeling approach was used because participants had naturally varying success rates and therefore contributed unequal numbers of successful and unsuccessful trials. Despite having unbalanced datasets, this analytical approach aligns with established EEG analysis methods (Delorme & Makeig, 2004; Maris & Oostenveld, 2007, Hesselmann, 2018; Tibon & Levy, 2015). When compared to other statistical analysis methods such as ANOVA, LMMs have an advantage in that they do not require balanced datasets like ANOVA, which would require that both conditions have the exact same participants. (Ward, 2020). This modelling approach has been validated in EEG research with repeated auditory stimuli and was adapted for FPVS data (Koerner & Zhang, 2017). It is especially useful for within-subject designs involving multiple conditions and can accommodate individual variability across trials (Magezi, 2015). This processing and analysis pipeline enabled us to account for the unbalanced datasets, and we were able to determine how neural activity varied with performance outcome and task type (closed-skill versus open-skill) in novice table tennis players. **Results**

Performance Results

Performance outcomes indicated that participants successfully hit the target on 51.5% of serve trials on average (SD = 16.3%, range = 18–70%). For return trials, participants successfully hit the target on 47.5% of trials on average (SD = 11.8%, range = 26–61%).

Usable Data

After preprocessing and artifact-related recording exclusion, 12 participants contributed usable serve data, 11 participants contributed usable return data, and 10 participants contributed usable data to both task conditions. For retained participant recordings, all 100 two-second pre-movement epochs were retained for analysis. Individual epochs were not selectively removed within otherwise retained Serve or Return recordings. The linear mixed model used for the Serve vs Return comparison included 23 task-level observations, with each observation reflecting the participant-level mean for that task. For the win vs loss comparisons, trial-level linear mixed-effects models used all retained serve trials from the 12 participants with usable serve data and all retained return trials from the 11 participants with usable return data.

The following results are organized according to the three planned comparisons: (1) Serve vs Return, (2) Return Win vs Return Loss, and (3) Serve Win vs Serve Loss. Both absolute and relative power variables were evaluated within the primary ROIs, and T7 and T8 were treated as exploratory lateral temporal analyses. Statistically significant effects from the final models were observed only in relative-power variables; therefore, the significant findings reported below are relative-power results. Absolute-power variables were evaluated in parallel but did not yield significant effects in the final models.

Serve vs Return

The linear mixed-effects model revealed that return trials were associated with higher relative alpha power at several regions of interest. Return trials showed higher relative alpha power in the parietal region (estimated difference = 3.851%, 95% CI [0.550%, 7.153%], p = 0.022, model-standardized

effect size = 1.015) and the central region (estimated difference = 2.881%, 95% CI [0.163%, 5.600%], p = 0.038, model-standardized effect size = 0.921). Exploratory analyses of lateral temporal electrodes revealed higher relative alpha power during return trials at T7 (estimated difference = 4.288%, 95% CI [0.593%, 7.983%], p = 0.023, model-standardized effect size = 1.004) and T8 (estimated difference = 3.418%, 95% CI [1.026%, 5.810%], p = 0.005, model-standardized effect size = 1.243). Effect sizes for linear mixed-effects models were calculated as model-standardized fixed-effect contrasts by dividing the estimated condition contrast by the residual standard deviation from the fitted model. These values express the estimated contrast in residual-standard-deviation units. Raw means, model estimated means, and other pertinent information are summarized in Table 1. Effect-size magnitudes were interpreted descriptively using the absolute value of the model-standardized contrast and conventional standardized mean-difference benchmarks: small = 0.20, medium = 0.50, and large = 0.80 (Lakens, 2013). Because these benchmarks are not specific to linear mixed-effects model contrasts, magnitude labels were used only as descriptive aids. Effects with absolute values below 0.20 were described as below the conventional small-effect threshold. The sign of the effect indicates the direction of the model-estimated contrast. Using these descriptive benchmarks, all significant Serve vs Return effects were large in magnitude. Significant results are visualized in Figure 1 and summarized in Table 1.

Return Win vs Return Loss

The next comparison was between Return Win and Return Loss. Using a trial-level linear mixed model, successful return trials were associated with lower relative occipital theta power than unsuccessful return trials (model-estimated difference = -1.416%, 95% CI [-2.376%, -0.456%], p = 0.004, model-standardized effect = -0.177). Successful return trials were also associated with lower relative parietal theta power than unsuccessful return trials (model-estimated difference = -0.970%, 95% CI [-1.823%,

-0.117%], p = 0.026, model-standardized effect = -0.136). Figure 2 displays these significant results, and Table 2 summarizes these results.

Serve Win vs Serve Loss

The final comparison was between Serve Win and Serve Loss. Using a trial-level linear mixed model, successful serve trials were associated with higher relative central beta power than unsuccessful serve trials (model-estimated difference = 0.983%, 95% CI [0.228%, 1.737%], p = 0.011, model-standardized effect = 0.158; below the conventional small-effect threshold). Successful serve trials were also associated with lower relative central theta power (model-estimated difference = -1.302%, 95% CI [-2.070%, -0.535%], p < 0.001, model-standardized effect = -0.206; small) and lower relative parietal theta power than unsuccessful serve trials (model-estimated difference = -0.931 percentage points, 95% CI [-1.796%, -0.065%], p = 0.035, model-standardized effect = -0.131; below the conventional small-effect threshold). Figure 3 displays these significant results and summarizes can be found in Table 2.

Exploratory T7/T8 Alpha Asymmetry

A supplementary exploratory T7/T8 relative alpha-asymmetry analysis, calculated as T8 minus T7 relative alpha power, did not reveal significant differences for Serve vs Return, estimated difference = −1.067, p = 0.434; Return Win vs Return Loss, estimated difference = −0.756, p = 0.171; or Serve Win vs Serve Loss, estimated difference = 0.444, p = 0.341.

Discussion

This study examined the neural correlates of motor performance in novice table tennis players by contrasting relatively closed-skill (serving) with relatively open-skill (returning) tasks and by comparing successful versus unsuccessful trials. The clearest finding was a shift toward greater

relative alpha power prior to return trials, particularly across the central and parietal regions, with additional lateral temporal involvement. While both absolute and relative power were analyzed, significant effects were only observed in the relative power variables. This is best interpreted as a redistribution of neural activity during the pre-movement phase rather than just an increase or decrease in overall cortical activation. The anticipatory period before returning a ball appears to be preceded by different preparatory neural mechanisms than the serve condition. The model-standardized effect-size interpretation should also temper the findings: the Serve vs Return relative-alpha effects were large, whereas most win/loss effects fell below the conventional small-effect threshold, with only the Serve Win vs Serve Loss central theta effect reaching the small range. Therefore, the win/loss findings should be interpreted cautiously despite statistical significance.

One plausible explanation for this pattern lies in the task constraints: serving a ball is associated with closed skills and is self-paced. The participant determines the timing of movement initiation, controls the tempo, and can execute a planned motor sequence under relatively stable conditions. In contrast, the return condition is externally paced. The participant must react to an incoming ball, judge its speed and trajectory, select an appropriate motor response, and execute that response effectively in a very short time window. From that perspective, the return condition likely places greater demands on the coordination of sensory sampling, visuospatial processing, and motor readiness.

The increase in central relative alpha power is especially informative in this context. The centrally located sensorimotor cortex is generally associated with movement preparation and execution, and in current sports-EEG literature, alpha activity is often discussed in terms of functional inhibition (Loze et al., 2001; Mathewson et al., 2011; Uusberg et al., 2013; Pluta et al., 2018). Higher central relative alpha power may reflect temporary regulation of sensorimotor excitability while the participant is preparing to react to the incoming ball. This pattern may reflect temporary inhibition within these

regions to prevent premature movement initiation or early commitment to a particular racket angle or return direction. An inhibitory effect in the central region does not necessarily imply that the motor system is disengaged. It may instead indicate that the motor system is being held in a controlled "ready to react" state until sufficient sensory information is available (i.e., the ball has started its movement toward the player).

The increase in relative alpha power in the parietal regions may be interpreted in a similar way. In a task such as returning a serve, the player must identify which features of the environment are behaviourally relevant and which can be ignored. The increase in relative parietal alpha power may therefore reflect the suppression of task-irrelevant spatial information, allowing the participant's attention to be directed toward only the task-relevant information for the incoming ball. This could include filtering interference from non-target locations or other non-useful information prior to reacting to the incoming ball. Taken together, these findings might best be interpreted as task-specific differences in preparatory neural activity before returning versus serving, rather than as a general neural signature of open skill vs closed-skill performance. The observed differences in neural activity prior to movement onset may reflect a combination of visual anticipation, motor preparation, response timing, and environmental predictability.

Although Return trials were associated with higher relative alpha power at both T7 and T8, the supplementary alpha-asymmetry analysis did not indicate a significant directional lateral temporal difference. Therefore, the exploratory lateral temporal effects are best interpreted as broader task-related alpha modulation at lateral temporal electrodes rather than evidence of T7/T8 hemispheric alpha asymmetry.

The neural efficiency hypothesis provides one framework for understanding this pattern. Prior work suggests that skilled performers often achieve better outcomes through more selective recruitment of task-relevant neural resources and reduced engagement of unnecessary processes (Del Percio et al., 2009; Guo et al., 2017; Cheron et al., 2016; Budnik-Przybylska et al., 2021; Filho et al., 2021). Although the present study did not include an expert comparison group, the return condition may represent the context in which novices are least efficient, because it imposes the greatest demand for rapid visuomotor updating under external control. Within that framework, the observed increase in relative alpha may reflect an efficiency-like preparatory strategy in which novices attempt to suppress irrelevant processing and stabilize the system before responding to a high-demand stimulus.

Successful returns were associated with a lower relative theta power in the occipital and parietal regions in the two-second anticipatory period prior to movement onset. Lower parietal and occipital theta power prior to successful return trials may therefore indicate that the participant was allocating neural resources in a different way, placing them in a unique preparatory state that correlated with successful attempts. In a reactive task associated with open-skills like returning a serve, the participant must be ready to quickly judge the incoming trajectory and speed of the incoming ball and react to the ball accordingly. Prior work has linked theta activity during open-skill table tennis to the demands of monitoring and processing unpredictable environmental stimuli (Visser et al., 2022).

The performance results from the serve condition presents a different picture. Successful serves were associated with lower relative central and parietal theta power, while central relative beta power increased. Because serving a ball is self-paced, successfully hitting a target is less likely to depend on the efficient processing of external information and more on executing an effective motor plan before movement onset. Central beta power has been linked to sensorimotor organization and motor planning in self-paced precision tasks (Wang et al., 2019; Pluta et al., 2018), so the increase in central relative

beta power before successful serves may reflect a more coherent sensorimotor plan that was ready to be executed, correlating with successful serve attempts. The accompanying reduction in central and parietal theta power prior to successful serve attempts may reflect a neural state in which the participant was using more neural resources to execute the plan rather than to think about the plan itself.

When considered alongside the broader shift toward relative alpha before return trials, these findings suggest that successful performance in novice players is associated with a different neural preparatory state than unsuccessful performance. For successfully returning a ball, this state appears to involve reduced relative occipital and parietal theta power, consistent with a more stable visuospatial preparatory state. For successfully serving a ball, it appears to involve a reduction in relative central and parietal theta power and an increase in central relative beta power, which is consistent with a more organized sensorimotor plan. This pattern is compatible with the neural efficiency hypothesis. Although the present study did not compare novices with experts directly, the data suggest that even within novices, successful trials may be associated with a more efficient neural state in which unnecessary monitoring is reduced, task-relevant processing is prioritized, and movement is initiated from a more stable preparatory state. These findings contribute to the understanding of motor skill development in novices and may help guide future training studies aimed at improving performance consistency.

These findings should be interpreted as task-specific rather than as a general neural signature of open-skill versus closed-skill performance. In the Serve vs Return analysis, returning was associated primarily with higher relative alpha power in parietal, central, and lateral temporal regions. This may reflect differences in alpha regulation during preparation for an externally paced response, including attention, sensorimotor preparation, or inhibition of task-irrelevant processing. However, serving and

returning differ not only in environmental predictability but also in motor timing and movement requirements. Therefore, the observed EEG differences may reflect a combination of visual anticipation, motor preparation, and response timing rather than open- versus closed-skill demands alone. This interpretation is consistent with recent real world table tennis EEG work showing different spectral power fluctuations in sensorimotor ROIs during serves and returns (Studnicki, Siedler, & Ferris, 2023). Although prior work has reported increased frontal and frontocentral theta during continuous table tennis, the present discrete serve-return paradigm produced a different spectral pattern, suggesting that EEG markers may depend strongly on the specific sport task being performed. Future studies should compare multiple open- and closed-skill tasks with more closely matched motor demands to determine which neural patterns generalize across sport contexts.

Limitations and Future Directions

Several limitations of our study warrant consideration. First, the sample size was modest (n = 14), and preprocessing and artifact rejection reduced the amount of usable data available for some comparisons. After artifact rejection, 12 participants contributed usable serve data, 11 contributed usable return data, and 10 contributed usable data to both task conditions for the Serve vs Return comparison. The Serve vs Return analysis included 23 task-level observations, while the Serve Win vs Serve Loss and Return Win vs Return Loss analyses used trial-level linear mixed-effects models with all available trials from participants who contributed usable data to the relevant task. Although linear mixed-effects models allowed us to retain unbalanced data and account for repeated observations within participants, the modest sample size still limits the precision and stability of the estimated effects. As a rough sensitivity benchmark, a fully paired within-subject comparison with n = 14 would have 80% power to detect effects of approximately dz = 0.81 or larger, suggesting that the study was primarily sensitive to relatively large effects. Because the primary analyses were conducted using linear mixed-effects models with unbalanced data, this value should be interpreted only as an approximate indication of study

sensitivity rather than as the exact power of the fitted models. The number of frequency-band, region, and task comparisons also increases the possibility of false-positive findings, while the modest sample size increases the possibility that smaller effects were not detected. For this reason, the reported confidence intervals should be considered alongside the p-values when interpreting the results, and both significant and non-significant findings should be interpreted cautiously. Effect-size estimates may also be less stable in a sample of this size. We also did not systematically control for participant fatigue, which has been shown to significantly impact reaction time and neural dynamics in athletes (Migliaccio et al., 2022).

Second, our study focused exclusively on novice athletes, which restricts the generalizability of the results to more experienced populations. Subsequent studies should compare novices and experts to better elucidate how neural efficiency develops with skill acquisition. Moreover, our experimental design was confined to a single sport and a specific set of motor tasks. Future research might expand the scope by including additional open-skill and closed-skill sports to determine whether the patterns we observed generalize across different activities. Exploring the longitudinal effects of training interventions on these neural markers could provide important insights into the mechanisms underlying motor skill acquisition and the potential for targeted cognitive and physical training programs.

Another possible limitation is that the present study cannot determine whether the observed EEG differences reflect task-specific neural preparation or more general fluctuations in attention. Because participants were novices and completed many repeated trials, unsuccessful attempts may have been influenced by transient attentional lapses, reduced sustained attention, fatigue, or momentary disengagement from the target rather than by inefficient visuomotor processing alone. Future studies should incorporate methods to account for attentional lapses and to directly measure participant attention; methods like eye tracking, reaction-time measures, subjective attention ratings, or fatigue monitoring seem appropriate.

Our sample was also limited to right-handed young adults, which may restrict the generalizability of the findings. This is particularly relevant because table tennis involves asymmetric upper-limb control, and handedness may influence movement strategy, hemispheric lateralization, and task-specific motor preparation during both serving and returning. Therefore, the present results may not generalize to left-handed or ambidextrous participants or to individuals who differ in sport expertise. Future studies should include more diverse samples and examine whether handedness moderates EEG activity during open and closed-skill sport performance. Additionally, although the target size was adjusted during calibration to achieve a roughly 50% success rate for each participant and task, final participant-level target sizes were not retained. Changes in the target size across participants could have contributed to performance variability and the observed effects.

Overall, our results underscore the critical roles of attentional focus, efficient resource allocation, and visuomotor integration in open-skill performance among novice athletes. These findings enhance our understanding of early motor skill acquisition and suggest potential targets for training interventions aimed at improving performance consistency.

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Declaration of Interest Statement

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Figures

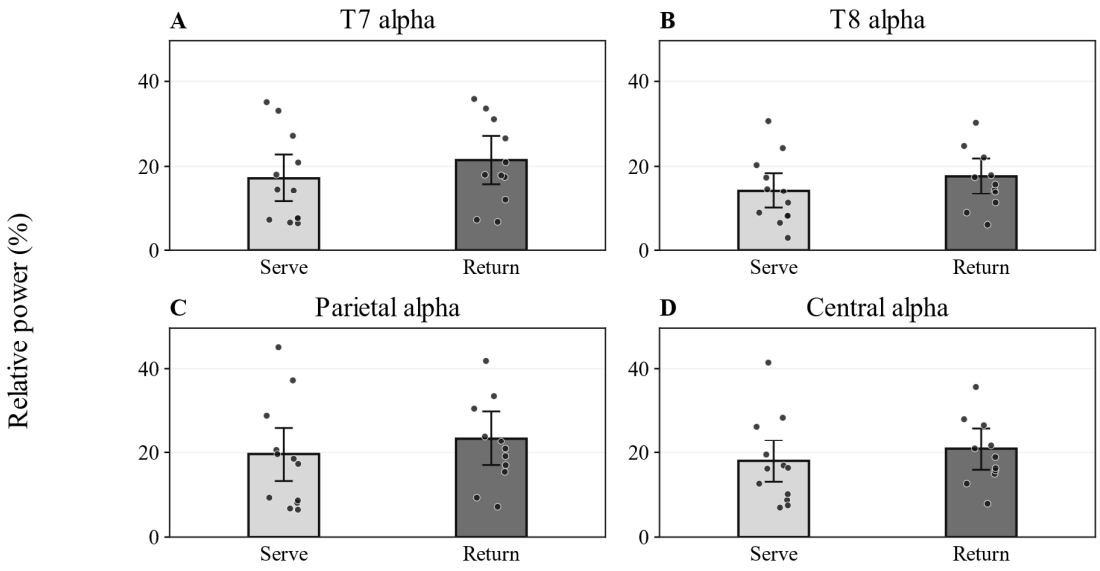

Figure 1: Serve vs Return Relative Alpha Power

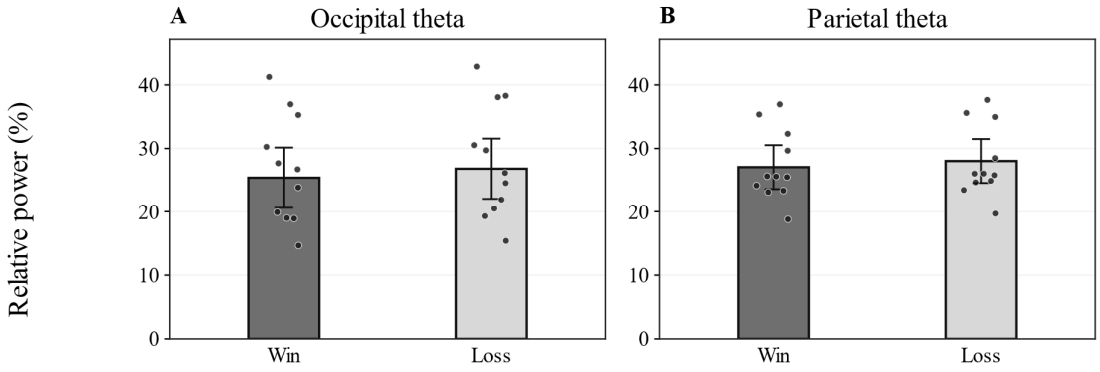

Figure 2: Return Win vs Loss Relative Theta Power

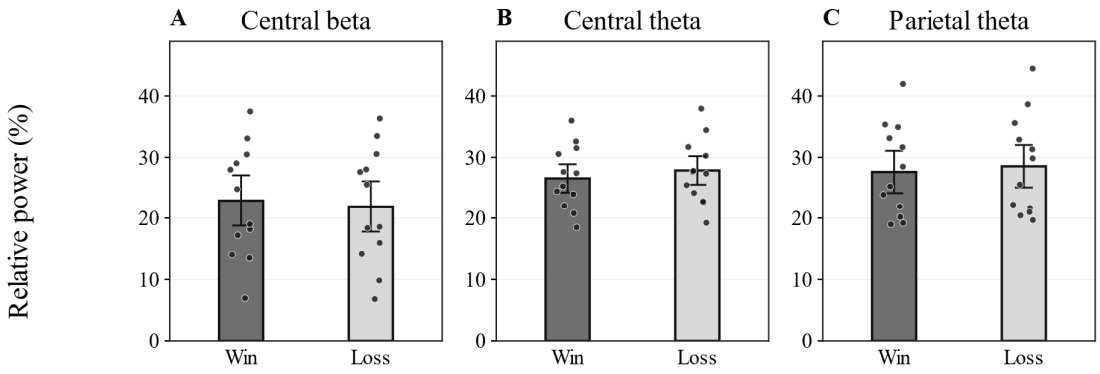

Figure 3: Serve Win vs Loss Relative Power

Figure Captions

Figure 1: Model-estimated relative alpha power during Serve and Return trials at T7, T8, parietal, and central regions. Bars represent model-estimated means from the linear mixed model, and error bars represent 95% confidence intervals. Dots represent participant-level descriptive means.

Figure 2: Model-estimated relative theta power during successful and unsuccessful Return trials at occipital and parietal regions. Bars represent model-estimated means from the trial-level linear mixed model, and error bars represent 95% confidence intervals. Dots represent participant-level descriptive means and are included for visualization only.

Figure 3: Model-estimated relative power during successful and unsuccessful Serve trials for central beta, central theta, and parietal theta. Bars represent model-estimated means from the trial-level linear mixed model, and error bars represent 95% confidence intervals. Dots represent participant-level descriptive means and are included for visualization only.

Tables

Table 1. Significant Differences in Mean Relative Alpha Power Between Serves and Returns

ROI	Raw Return Mean	Raw Serve Mean	Model-Estimated Return Mean	Model-Estimated Serve Mean	Model-Estimated Difference	95% CI	p-value	Effect Size
T7	20.667%	16.532%	21.480%	17.192%	4.288%	[0.593, 7.983]	0.023	1.004 (large)
T8	16.607%	13.908%	17.648%	14.230%	3.418%	[1.026, 5.810]	0.005	1.243 (large)
Parietal	21.953%	18.864%	23.463%	19.612%	3.851%	[0.550, 7.153]	0.022	1.015 (large)
Central	19.931%	17.580%	20.882%	18.001%	2.881%	[0.163, 5.600]	0.038	0.921 (large)

Table 2. Win vs Loss Linear Mixed-Effects Model Results

A. Return Win vs Loss Relative Theta Power

ROI	Raw Win Mean	Raw Loss Mean	Model-Estimated Win Mean	Model-Estimated Loss Mean	Model-Estimated Difference	95% CI	p-value	Effect Size
Occipital	26.194%	28.556%	25.384%	26.801%	-1.416%	[-2.376, -0.456]	0.004	-0.177
Parietal	26.947%	28.278%	27.050%	28.020%	-0.970%	[-1.823, -0.117]	0.026	-0.136

B. Serve Win vs Loss Relative Beta Power

ROI	Raw Win Mean	Raw Loss Mean	Model-Estimated Win Mean	Model-Estimated Loss Mean	Model-Estimated Difference	95% CI	p-value	Effect Size
Central	24.073%	20.311%	22.911%	21.929%	0.983%	[0.228, 1.737]	0.011	0.158

C. Serve Win vs Loss Relative Theta Power

ROI	Raw Win Mean	Raw Loss Mean	Model-Estimated Win Mean	Model-Estimated Loss Mean	Model-Estimated Difference	95% CI	p-value	Effect Size
Central	26.035%	28.467%	26.557%	27.859%	-1.302%	[-2.070, -0.535]	<0.001	-0.206
Parietal	27.400%	29.786%	27.610%	28.541%	-0.931%	[-1.796, -0.065]	0.035	-0.131

Table Captions

Table 1. Raw means are descriptive participant-level task means. Model-estimated means and differences are derived from the fitted linear mixed-effects model. The estimated difference is Return minus Serve. Model-standardized effects were calculated by dividing the fixed-effect contrast by the model residual standard deviation. Effect-size labels are descriptive aids based on conventional standardized mean-difference benchmarks.

Table 2. Raw means are descriptive trial-level means. Model-estimated means and differences are derived from the fitted trial-level linear mixed-effects models. Estimated differences are Win minus Loss contrasts. Model-standardized effects were calculated by dividing the fixed-effect contrast by the residual standard deviation from the fitted model. Values with absolute standardized effect sizes below 0.200 or -0.200 fall below the conventional small-effect threshold and should therefore be interpreted cautiously.