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Research report

Brain complexity in motion: Multiscale entropy analysis on mobile EEG data to assess motor performance

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ABSTRACT

Multiscale entropy (MSE) as a measure of brain complexity provides substantial insights into the adaptability of the brain. However, it is often applied to resting-state electroencephalography (EEG) or in static tasks. The current study assessed the reliability, validity and classification accuracy of MSE computed on mobile EEG data for linking brain complexity to motor performance within a kicking task. Eleven novice participants underwent repeated measurements to assess test-retest reliability, while the data from 15 novices and 15 football players were used to evaluate known-groups validity, convergent validity and classification accuracy. EEG data were recorded using 65 active electrodes and MSE estimates were computed for 64 time scales on preprocessed data. Results showed poor to excellent reliability for MSE estimates, exhibiting channel- and scale-specific variations, with reliability generally higher at fine-to-mid scales. Experts exhibited significantly lower entropy at coarse scales in left frontal and at fine scales in centroparietal regions compared to novices. Negative correlations were found between entropy estimates and kicking accuracy. Receiver operating characteristic curves of entropy estimates and their principal components demonstrated moderate to good classification accuracy between expertise levels. These findings suggest MSE as a promising metric for investigating brain complexity in movement contexts, revealing distinct patterns of complexity associated with motor performance. Future research across diverse tasks and populations is crucial to further elucidate this relationship and explore the applied potential of MSE.

1. Introduction

The human brain is a complex and highly dynamic system, constantly processing, integrating, and adapting information in response to both internal states and external stimuli (Tononi et al., 1994; McIntosh and Kovacevic, 2008). This complexity refers to the richness and variability of neural activity, which emerges from intricate interactions occurring across neural networks. Such complexity provides a valuable window into the brain’s information processing capacity (Sporns et al., 2000a; 2000b). Beyond rhythmic oscillations commonly observed in neural activity, the brain's intrinsic complexity also manifests in temporal irregularities within neural signals, which can be detected through electroencephalography (EEG) recordings. These irregular patterns are supposed to carry critical information about the brain's underlying dynamics, reflecting how neural processes integrate across multiple temporal and spatial scales. Traditional linear EEG metrics, however, oversee this complexity by assuming stationarity and linear relationships within neural signals. As a result, these approaches may not fully capture the brain's dynamic and non-linear nature, which is recognized as essential for healthy, efficient, and flexible functioning (Breakspear, 2017; Wang et al., 2020).

Multiscale entropy (MSE) analysis has emerged as a powerful nonlinear tool to analyze irregularities in EEG time series and to assess the complexity of the brain (Costa et al., 2002; Keshmiri, 2020). Unlike conventional entropy measures, which evaluate randomness of a signal at a single time scale, MSE considers the structure of neural signals over multiple time scales, capturing both fast and slow dynamics to provide deeper insights into local and distributed neural communication (McIntosh et al., 2014). The application of MSE on EEG signals has demonstrated that increased or decreased brain complexity at specific

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time scales can be distinctive for various conditions, including neurological pathologies (Chenxi et al., 2016; Hwang et al., 2024; Mizuno et al., 2010;), cognitive states such as fatigue and vigilance (Al-Shargie et al., 2021; Liu et al., 2023), physical activity levels of elderlies (Wang et al., 2014) and sport-specific cognitive skills of athletes (Wang et al., 2020). Compared with other nonlinear metrics such as fractal dimension or Lyapunov exponents, the scale-resolved approach in MSE is particularly relevant for expertise-related motor tasks, where fast processes and slower integrative dynamics jointly shape performance (Cavanagh and Frank, 2014; Kilavik et al., 2013; Wang et al., 2020). Despite its extensive application on EEG signals, MSE has been predominantly used in resting-state or static conditions, leaving its potential in movement-related contexts largely unexplored.

Given that human movement is an emergent behavior shaped by continuous interactions between the nervous system, body, and environment, the brain's complexity may provide crucial insights into motor control and adaptability (Sporns et al., 2000a). For example, in sports, athletes need to process external sensory information, such as the maneuvers of other players, the trajectory of the ball and spatial positioning, to produce congruent and effective motor actions. Effective movement execution requires the integration of sensory information, motor planning, action, and real-time feedback processing, all of which contribute to the overall complexity of neural activity (Lungarella and Sporns, 2006; Yarrow et al., 2009). An optimal level of complexity - situated at a critical edge between randomness and regularity - is suggested to reflect an efficient balance between neural flexibility and stability (Cocchi et al., 2017). While excessively high complexity might indicate neural noise reducing the efficiency of sound sensory-motor integration, excessively low complexity might reflect loss of adaptive capacity and reduced responsiveness to environmental changes (Cocchi et al., 2017; O'Byrne and Jerbi, 2022). Still, complexity in neural signals should not be considered strictly linear, where higher complexity always corresponds to better adaptability, rather, its significance is context-dependent. Skilled athletes, for instance, may exhibit lower cortical complexity in stable conditions and familiar motor tasks due to optimized neural efficiency, whereby repetitive practice and expertise allow their neural processes to require fewer resources and less redundant computation to achieve the same outcome (Hung et al., 2008). On the other hand, a higher complexity level in dynamic conditions may indicate a more adaptive and flexible neural system, capable of efficiently integrating sensory inputs, predicting upcoming actions, and responding to external perturbations accurately (Faisal et al., 2008). The ability of MSE to quantify these complex, multi-scale processes may propose it as a promising metric for understanding the context-dependent reciprocal dynamics between cortical complexity and motor performance.

Despite these insights, EEG recordings with motor tasks inherently introduce methodological challenges, including movement artifacts and signal variations, with the need for tailored preprocessing steps (Cohen, 2015; Gorjan et al., 2022). Applying MSE to such data necessitates a rigorous consideration of preprocessing steps, such as using optimal band-pass filtering parameters, artifact rejection techniques and sampling rates, all of which have been shown to influence entropy estimates significantly (Kosciessa et al., 2020; Puglia et al., 2022). While some perspectives argue for minimal preprocessing to preserve raw signal characteristics (Okazaki et al., 2015), mobile EEG demands effective artifact mitigation strategies to ensure reliable entropy estimates. Given these methodological challenges and the presented context, the current study aims to evaluate a) the test-retest reliability of MSE estimates on mobile EEG data recorded during a soccer kicking task and b) the validity and classification accuracy of MSE, particularly in revealing interactions between cortical complexity and motor performance. The acknowledged reliability, validity and classification performance of MSE can highlight its potential as a tool for tracking complexity in motor performance contexts.

2. Methods

2.1. Participants

The sample sizes used in the present study were determined based on two previously published studies employing the same task and participant groups (Piskin et al., 2024a, 2024b). In these studies, the identical EEG datasets with the same participants demonstrated substantial test-retest reliability for the cortical dynamics associated with the kicking task (Piskin et al., 2024a), as well as significant group differences between novices and experts (Piskin et al., 2024b). These findings support that the current sample sizes provide sufficient statistical sensitivity for the analysis of test-retest reliability of cortical dynamics and group differences observed in these dynamics.

The data of 11 healthy novice participants (3 females, 8 males; mean age: 27.42 ± 3.68 years) were considered for the reliability analysis. The inclusion criteria matched those of the novice group described below. For the validity analysis, 15 healthy novice participants (7 female / 8 male; mean age: 26.87 ± 3.54 years) and 15 healthy amateur football players (6 female / 9 male; mean age: 22.40 ± 3.62 years) were recruited. Novice participants met the following inclusion criteria: (i) aged between 18 and 35 years, (ii) right-dominant in the lower extremity as determined by the Lateral Preference Inventory (Coren and Porac, 1978), (iii) no current or previous participation in football (Baumeister et al., 2008; Silva et al., 2022), (iv) no regular involvement in any sport requiring running, cutting, or pivoting within the last year (Wang et al., 2024), and (v) no neurological diseases, previous orthopedic injuries, or use of psychotropic medication. The Marx Activity Scale (Marx et al., 2001) and an additional questionnaire confirmed that their physical activity was limited to recreational levels. For football players, the inclusion criteria were: (i) aged between 18 and 35 years, (ii) right-dominant in the lower extremity (Coren and Porac, 1978), (iii) actively playing football for at least 10 years, (iv) training at least twice per week and playing one game per week, and (v) free from neurological diseases, previous orthopedic injuries, and psychotropic medication use. Participation in sports and activity levels were assessed using custom questionnaires and the Marx Activity Scale (Marx et al., 2001). In both studies, participants had normal or corrected vision during the experiments. Prior to participation, they gave written informed consent after being fully informed about the study's purpose and procedures. The study adhered to the Declaration of Helsinki and received approval from the local ethics committee.

2.2. Experimental procedures

The present study utilized a short-distance kicking task previously employed in the aforementioned studies (Piskin et al., 2024a, 2024b). Participants performed the task in a standardized laboratory setting while wearing laced sneakers. The objective of the task was to kick a FIFA size five ball using the inside of the right foot toward a designated target, represented by the frontal surface of a rectangular wooden block (10 × 15 cm). To maintain consistency across trials, the initial position of the participants was standardized. They were instructed to place their left foot next to, and their right foot behind the ball. The optimal distance between the left foot and the ball was determined individually during familiarization trials and marked on the floor to ensure a standard position throughout the experiment. Participants were instructed to execute the kicks with a focus on accuracy while maintaining a natural kicking pattern. No verbal feedback or additional instructions were provided during the trials to avoid interfering with their performance. Each participant completed six blocks of 15 trials, resulting in a total of 90 kicks. The number of on-target and missed kicks was recorded to determine the accuracy rate for each participant, which was subsequently used to examine the relationship between accuracy performance and cortical complexity.

For the reliability analysis, measurements were repeated with a one-week interval to assess the consistency of MSE estimates over time. In contrast, measurements were conducted only once for the validity analysis to compare cortical complexity between the two groups and their relation to accuracy performance.

2.3. EEG recording and preprocessing

Cortical activity was continuously recorded using 65 active Ag/AgCl electrodes (actiCap, Brain Products, Germany) positioned according to the international 10–20 system. The AFz and FCz electrodes served as the ground and reference, respectively (Pivik et al., 1993). EEG signals were wirelessly transmitted and digitized at a sampling rate of 500 Hz via a mobile amplifier (LiveAmp, Brain Products, Germany). Additionally, a 3D accelerometer (Brain Products, Germany) was affixed posteriorly to the lateral malleolus to capture synchronized acceleration data of the kicking foot.

EEG preprocessing was conducted offline using the EEGLAB toolbox (version 2021.1.2b, Delorme and Makeig, 2004) for MATLAB (version R2020b, The MathWorks, USA). Due to the lack of tested pipelines for MSE analysis in mobile EEG settings, this study implemented the preprocessing pipeline from our previous research that yielded reliable results for the previously described EEG correlates of the same task (Piskin et al., 2024a, 2024b).

Sinusoidal line noise was eliminated using the Cleanline plugin (Mullen, 2012), followed by band-pass filtering between 3 and 30 Hz using a finite impulse response filter. Noisy channels were automatically detected and removed based on a combination of kurtosis, probability, and spectral properties, with a z-score threshold of 5 ($n_{NOVICEreliability1} = 0.36 \pm 0.67$, $n_{NOVICEreliability2} = 0.45 \pm 0.82$, $n_{NOVICE} = 0.27 \pm 0.59$, $n_{EXPERT} = 0.67 \pm 1.59$, Nicolas-Alonso et al., 2015). Spherical spline interpolation was applied to maintain channel consistency across datasets. The data were subsequently re-referenced to the common average and downsampled to 256 Hz.

Epoching was performed based on kick onset detection, determined through a linear computational cost approach (Killick et al., 2012). The acceleration signal of the kicking foot along the x-axis was rectified and smoothed using a Gaussian-weighted moving average filter with a window length of 1000 data points (Mendi et al., 2013). Kick onsets were identified as abrupt deviations in the mean signal using the *ischange* function in MATLAB. The signal was then epoched for a time window of −500–2500 ms relative to kick onset with baseline correction applied from −500–0 ms. Epochs exceeding + /-75 μV in any of the channels were rejected.

An adaptive mixture independent component analysis (Palmer et al., 2011) was applied to further clean the data, by decomposing the EEG signal into maximally independent components (ICs). Source localization of ICs was performed using the DIPFIT plugin (Oostenveld and Oostendorp, 2002), with a standardized four-shell spherical head model (BESA, Germany). Brain-related ICs were identified based on spatial localization, residual variance (<15 %), and classification of the ICLabel plugin (Pion-Tonachini et al., 2019) with at least 90 % brain activity. Non-brain components, including those linked to muscle activity, eye movements, and line noise, were subsequently removed. Comparable artifact-removal strategies including independent component analysis and ICLabel classification have successfully implemented in mobile EEG studies to mitigate movement- and muscle-related contamination during motor tasks (Gebel et al., 2020; Klug et al., 2022; Piskin et al., 2024a, 2024b; Protzak and Gramann, 2021).

2.4. Computation of multiscale entropy estimates on preprocessed EEG data

A modified MSE analysis was applied to the preprocessed EEG data using a custom algorithm, following the methodology for sparse EEG data established by Grandy et al. (2016). To standardize data length across sessions and participants, 80 clean epochs were randomly selected using the POP_SELECT function in EEGLAB, which corresponded to the minimum number of retained epochs across datasets after rejection. For each subject, the selected epochs were concatenated, and entropy estimates were computed on the residuals of the resulting signal, obtained by subtracting the intra-individual average across trials. This approach has produced reliable entropy estimates for discontinuous EEG data previously (Grandy et al., 2016; Puglia et al., 2022).

Considering kick-related activity detectable in 0–2500 ms upon kick onset as shown by previous studies (Piskin et al., 2024a, 2024b), the analysis focused on this time frame. Ultimately, this procedure resulted in a total number of 51200 (80 ×640) data points per channel. Time series were generated across 64 time scales through a coarse-graining procedure defined as:

$$y_j^T = 1/T + \sum_{i=(j-1)T+1}^{jT} x_i, 1 \le y_j \le N/T$$

where T corresponds to the time scale, yj denotes the constructed time series after coarse-graining, xi is a data point within that series, and N shows the length of the original time series (Costa et al., 2002). The selection of 64 time scales is intended to capture relevant frequency dynamics associated with kick-related cortical activity. Coarse-graining acts as a form of filtering at time scales, indicated by high and low frequencies in Fourier transformations. Given that the first scale aligns with the sampling rate (256 Hz), higher scales progressively capture lower frequencies (Puglia et al., 2022; von Stein and Sarnthein, 2000). The number of scales was set to 64 to also ensure the inclusion of lower frequencies, as these have previously been linked to kicking-related processes (Piskin et al., 2024a, 2024b). This allowed for a comprehensive entropy assessment across a broad frequency spectrum while maintaining sufficient resolution in the frequency domain. Sample entropy was then estimated for each channel as:

$$S_E(m, N, r) = \ln\frac{A}{B} = \ln\frac{\sum_{i=1}^{N-m} n_i^m}{\sum_{i=1}^{N-m} n_i^{m+1}}$$

with the following parameters: m = embedding dimension, N = total number of data points, r = similarity criterion, and n = number of vectors close to a template vector i with a dimension of m (Costa et al., 2002). The embedding dimension was set to m = 2 (Grandy et al., 2016), and the similarity criterion was dynamically adjusted for each scale as r = 0.50 × SD to prevent bias toward lower entropy values at coarser scales (Kosciessa et al., 2020; Puglia et al., 2022). A 64 × 64 entropy matrix (scales × channels) was computed for each participant and used in further analysis.

To evaluate whether group differences in MSE could be explained by differences in the amplitude variance of the input EEG signal, MSE was recomputed after normalizing the residual EEG time series to zero mean and unit variance prior to coarse-graining. This linear transformation preserves the temporal structure relevant for entropy estimation while eliminating between-subject differences in signal magnitude (Costa et al., 2005; Miskovic et al., 2019). MSE was then estimated using the identical pipeline applied in the primary analysis.

2.5. Statistical approaches for reliability, validity, and classification accuracy

2.5.1. Test-retest reliability analysis of multiscale entropy estimates

The test–retest reliability of entropy values was assessed using intraclass correlation coefficients (ICC), computed with the *ICC* function in MATLAB (Salarian, 2023). ICC estimates and their 95 % confidence intervals (CI) were derived from a two-way mixed effects model, based on single measurements and absolute agreement (McGraw and Wong, 1996). ICC values were interpreted as: 0.5–0.75 indicating moderate reliability, 0.75–0.9 good reliability, and > 0.9 excellent reliability (Koo and Li, 2016). A reliability map was generated to visualize the spatial and temporal reliability distribution with EEG channels on the x-axis and scales on the y-axis. Each value in the entropy matrices was mapped to its corresponding ICC estimate, providing an overview of reliability variations across EEG channels and time scales.

2.5.2. Known-groups and convergent validity of multiscale entropy estimates

Two complementary approaches were used to assess the known-groups and convergent validity of entropy estimates in differentiating between expertise levels. First, group differences in sample entropy were examined using independent *t*-tests at each channel x scale combination (Davidson, 2014). To control for multiple comparisons across the entropy matrix, *p*-values were adjusted using the Benjamini–Hochberg false discovery rate (FDR) procedure (Benjamini and Hochberg, 1995). To evaluate whether group differences in MSE could be attributed to differences in the variance of the input EEG signals, or to variance in the entropy estimates themselves, two variance analyses were conducted. For each participant and channel, the residual EEG time series used for entropy estimation were concatenated (Grandy et al., 2016; Puglia et al., 2022), and the variance of the resulting signal vector was computed. Group differences in this residual variance were assessed using independent *t*-tests. In addition, scale-wise variances of the entropy estimates were also calculated to account for their potential contribution to the group differences. These entropy variances were likewise compared using independent *t*-tests.

Second, a correlational analysis was conducted to examine the relationship between brain complexity and accuracy performance. Pearson's correlation coefficient was computed between entropy values at scales showing significant group differences and the accuracy rate. This approach aimed to determine whether higher or lower entropy values were associated with enhanced accuracy, providing further insight into the functional relevance of MSE measures (Masson et al., 2003). Statistical significance was set at an alpha value of 0.05 in all analyses.

2.5.3. Computation of receiver operating characteristic (ROC) curves on entropy estimates and their principal components

In addition to examining group differences, a sensitivity analysis was conducted to assess the classification robustness of MSE estimates using ROC curves (Linden, 2006). This procedure was implemented to confirm that the observed effects were not driven by specific parametric assumptions, potential outliers, or variations in the computed estimates (Hajian-Tilaki, 2013). ROC curves were first computed for the time scales where significant group differences were observed to evaluate the discriminative capacity of entropy values. The corresponding area under the curve (AUC) values were obtained using the *perfcurve* function in MATLAB, which evaluates classification performance based on true positive and false positive rates (Fawcett, 2004; Zweig and Campbell, 1993). In the current analysis, the true class labels were assigned as 0 for novices and 1 for experts. Based on conventional thresholds, AUC values between 0.5 and 0.6 were interpreted as indicating weak, values between 0.6 and 0.8 suggesting moderate, and values above 0.8 reflecting good classification accuracy (Guo et al., 2013; Koç et al., 2007; Thorsen et al., 2013). This initial step assessed whether entropy values alone were capable of distinguishing novices from experts.

Next, principal component analysis (PCA) was applied to the entropy estimates of channels that showed significant group differences to reduce the dimensionality of the multiscale data while preserving essential information. This approach accounted for variations across time scales and helped identify the most informative patterns in the entropy values (Jolliffe, 2002; Sun and Niu, 2019). By transforming the data into principal components (PC), PCA minimized potential bias introduced by random noise or irrelevant variance across scales, ensuring that the primary sources of variation relevant to cohort differences were captured. Since entropy values varied with scale, z-score standardization (*zscore* function in MATLAB) was performed to ensure comparability across time scales and eliminate potential scale-related bias in the data. PC scores and coefficients were computed using the *pca* function in MATLAB. AUC values were also calculated for each PC score**,** following the same procedure as for entropy values. The PC with the maximum AUC was identified as the component best capturing cohort-specific variance. Finally, for this PC, the 10 highest coefficients were examined to determine the dominant time scales contributing to its variance and to assess whether these scales aligned with those where significant group differences were observed.

3. Results

3.1. Accuracy performance

In the novice group, the accuracy rate did not significantly differ between Session I (M = 63.94, SD = 12.04) and Session II (M = 66.19, SD = 12.45). An ICC value of 0.56 (95 % CI = −0.002–0.86) indicated moderate reliability.

The comparison of groups revealed that the accuracy rate was significantly higher in experts (84.74 ± 8.60) compared to novices (62.87 ± 12.08; $t(28) = -5.71$, $p < 0.01$).

3.2. Test-retest reliability of multiscale entropy estimates

ICC values ranged from poor to excellent reliability, exhibiting channel- and scale-specific variability. Notably, higher reliability estimates were observed at lower time scales with decreasing estimates towards higher time scales. The representative reliability map is provided in Fig. 1.

3.3. Differences in entropy estimates between expertise levels and their correlation with accuracy

Novices exhibited overall higher entropy estimates, yielding significant differences in seven channels located in the left frontal and centroparietal regions (Fig. 2). In frontal channels (Fp1, AF3, F1, F3, FC3), significant differences were found at mid and coarse scales (Fig. 3), whereas in centroparietal channels (CP1 and CP3), entropy estimates were significantly higher at fine scales (Fig. 4). Visual inspection of EEG time series demonstrated that *z*-score normalization attenuated overall amplitude while preserving temporal structure. Example traces are provided in Supplementary Material S1. Entropy curves computed from these normalized residuals replicated those derived from the original data, with the same group differences across channels and scales, and are presented both for the original and normalized data in Supplementary Material S2. No group differences were found in the variances of residuals and entropy estimates.

Furthermore, Pearson's correlation analysis revealed significant negative correlations between entropy values and accuracy rate for the channels AF3, F1, F3, FC3 and CP3 in a subset of scales where significant differences between groups were observed (Table 1, Fig. 5).

3.4. Classification performance of entropy estimates in differentiating expertise levels

The AUC analysis revealed that entropy estimates of channels and scales with significant group differences exhibited weak to moderate classification accuracy. The application of PCA on standardized entropy estimates resulted in 29 PCs, providing a more comprehensive assessment of entropy variations across multiple scales. PCs with the maximum AUC values demonstrated moderate to good classification accuracy. For the channels F1, F3, FC3, CP1 and CP3 the scales with the highest coefficients contributing to these PCs overlapped with those where significant differences were observed (Table 1). The scale-wise

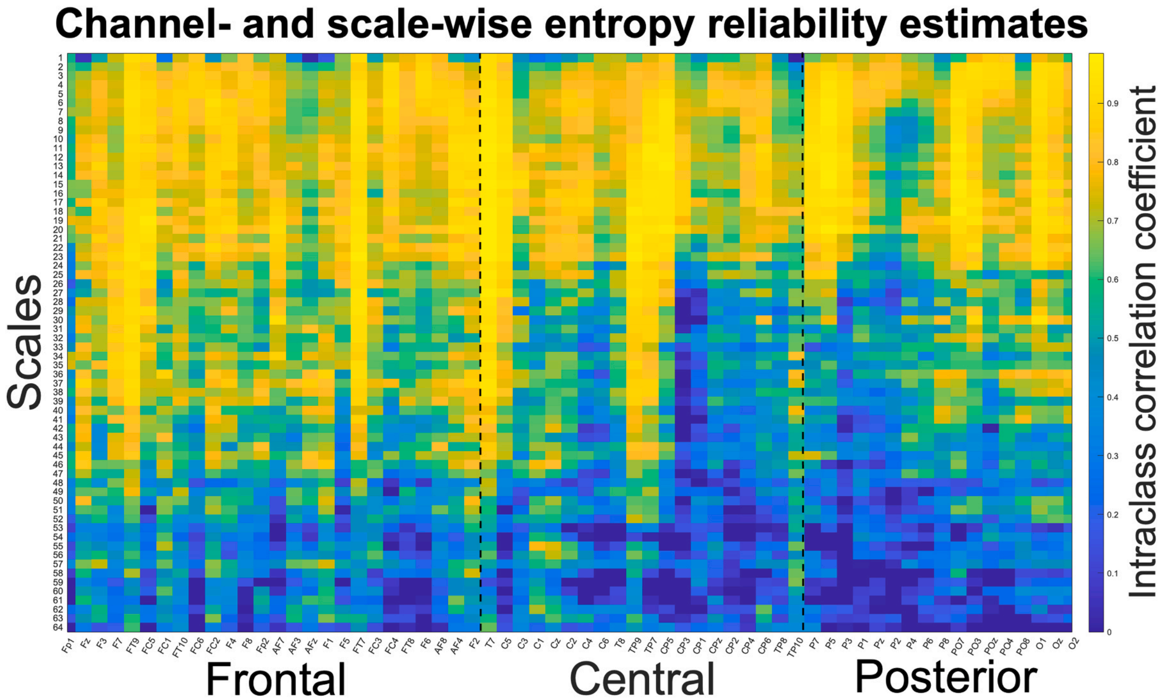

Fig. 1. Test–retest reliability map of multiscale entropy (MSE) estimates across EEG channels (x-axis) and temporal scales (y-axis). The heatmap illustrates intraclass correlation coefficients (ICC), with yellow indicating higher reliability and blue indicating lower reliability. This spatiotemporal reliability map provides an overview of the consistency of cortical complexity across two sessions during the kicking task.

coefficients of the computed PCs are provided in the Supplementary Material S3.

4. Discussion

The current study assessed the reliability, known-groups and convergent validity, and classification performance of MSE analysis to explore its potential in characterizing brain complexity during movement, specifically in distinguishing enhanced performance during a soccer kicking task. The results demonstrated that MSE estimates can capture consistent complexity patterns with channel- and scale-specific variations. Validity was supported by significant differences in entropy values between novices and experts, particularly in frontal and centroparietal regions, and by significant negative correlations between entropy estimates and kicking accuracy. The classification performance of MSE to expertise levels was assessed through AUC values of ROC curves for both entropy estimates and their PCs. The PCs with the highest classification accuracy predominantly reflected the same time scales where group differences were most pronounced, suggesting that MSE has the potential to differentiate between expertise levels with substantial performance.

4.1. Test-retest reliability of entropy estimates as a task-related complexity measure

MSE estimates demonstrated a spectrum of test-retest reliability values across channels and time scales, with a general trend towards lower estimates at coarser time scales. Understanding the sources of this variability is crucial for interpreting the longitudinal stability of entropy estimates. These factors contributing to this variability might be broadly categorized into those related with individual neural variability and those inherent to MSE analysis.

Neurophysiologically, neural consistency in movement-related brain dynamics is often region-specific, with task-relevant regions showing higher consistency due to their recurrent involvement in motor execution, while other regions may exhibit greater variability due to individual learning effects or fluctuating engagement across sessions (Domingos et al., 2023; Espenhahn et al., 2017; Malcolm et al., 2019; Piskin et al., 2024a). As the reliability analysis was conducted on the data of novice participants, the estimates may have been influenced by neural adaptation to the task across sessions. Despite insignificant differences across sessions, the moderate reliability found for pass accuracy could also support this, potentially reflecting a habituation effect. Motor learning involves dynamic changes in cortical activity as individuals refine their movement execution, leading to increased neural variability in regions undergoing substantial neuroplastic modifications (Berchicci et al., 2017; Bütefisch et al., 2000; Orban de Xivry and Lefèvre, 2015). Channels showing lower reliability estimates may correspond to brain regions involved in adaptation and learning, where participants initially relied on diverse movement strategies before gradually converging on more consistent patterns over time (Aliakbaryhosseinabadi et al., 2021; Titone et al., 2022; Wu et al., 2014; Wenger et al., 2017). Conversely, brain regions consistently engaged in the task likely yielded more stable entropy estimates, reflecting functionally consistent neural processes across sessions. Furthermore, the current findings also showed that the reliability of MSE estimates is inherently scale-specific. For instance, the reliability estimates of centroparietal channels were higher at finer scales, suggesting a consistent pattern of faster, local processing in this region (Gu et al., 2022). This implies that the stability of entropy estimates for a particular brain region could vary depending on the congruence between the scale analyzed and the intrinsic operational timescale of that region during the task.

From a methodological perspective, a key factor inherent to MSE analysis is the coarse-graining process, which systematically alters signal frequency composition with increasing scale by acting as a low-pass filter, attenuating high-frequency components and narrowing bandwidth (Donoghue et al., 2020; Kosciessa et al., 2020). For complex EEG signals arising from multiscale neural interactions (Ibáñez-Molina et al., 2020; Linkenkaer-Hansen et al., 2001), this can lead to loss of multiscale information, potentially reducing entropy estimates and their consistency (Costa et al., 2002; Courtiol et al., 2016; Kaur et al., 2019). At higher scales, increased signal smoothing can make entropy estimates

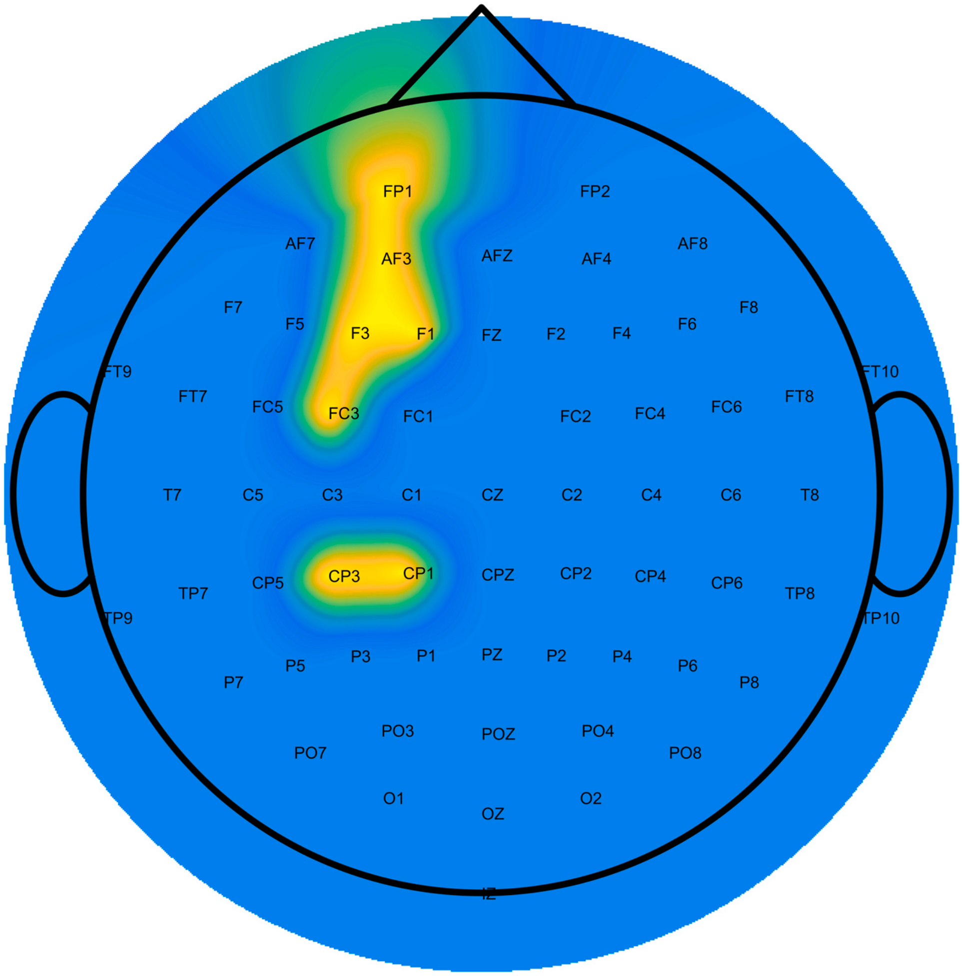

Fig. 2. Topography of significant differences observed between the groups for entropy estimates. Experts demonstrated lower complexity in left frontal and centroparietal regions.

more susceptible to minor fluctuations or low-frequency noise (Daud and Sudirman, 2022), although some channels might still capture task-relevant low-frequency patterns (Tseng and Lo, 2020). Critically, the progressive reduction of data points at coarser scales inherently increases statistical uncertainty, contributing significantly to greater variability in entropy estimates (Costa et al., 2005; Gow et al., 2015; Kaur et al., 2019).

In summary, the observed test-retest reliability of MSE estimates may be shaped by an interplay between neurophysiological factors such as learning-induced neural adaptations, and methodological aspects like the scale-dependent nature of MSE and the coarse-graining process. Despite channel and scale-specific fluctuations in reliability, the capacity of MSE to capture consistent patterns of task-related complexity supports its potential use in longitudinal studies tracking changes over time.

4.2. The validity of entropy estimates in revealing dynamics between cortical complexity and motor performance

The present study demonstrated that MSE estimates differentiated between expertise levels, capturing significant differences at specific channels and time scales. The diverging complexity profiles at fine and coarse scales suggest that expertise may be associated with alterations in task-related brain complexity, reflecting functional adaptations in neural processes engaged during movement execution (Bays and Wolpert, 2007; Berchicci et al., 2017; Piskin et al., 2024b). Although statistically significant effects were limited to a small number of scales, the consistent lower entropy values across portions of the entropy curves, together with the spatial clustering of channels showing differences, support that this pattern is unlikely to be random and is broadly consistent with existing literature showing that skilled motor performance is accompanied by reduced neural noise and computational redundancy in sensorimotor processes (Bays and Wolpert, 2007; Cocchi et al., 2017; Costa et al., 2005; Del Percio et al., 2009; Hristovski et al., 2011; Hung et al., 2008; Lutzenberger et al., 1995).

Further elaborating on these findings, the differences in complexity between experts and novices were confined to specific channels and time scales rather than appearing across the entire entropy curve. The observed differences were primarily located in left frontal and left centroparietal regions, which aligns with their established roles in goal-directed movements of the lower limb such as kicking (Palucci Vieira et al., 2022; Piskin et al., 2024a, 2024b). Centroparietal regions, encompassing sensorimotor and posterior parietal areas, contribute to sensory feedback integration and precise motor actions (Witham et al., 2010; Tan et al., 2014). In these regions, group differences emerged at multiple fine scales, which capture fast, local neural interactions detectable at high frequencies and related to motor preparation, execution, and sensorimotor modulation (Kosciessa et al., 2020; McIntosh et al., 2014; Engel and Fries, 2010; Kilavik et al., 2013). Although the number of significant scales was limited, the presence of clustered fine-scale effects in the contralateral hemisphere may indicate more stable, specialized and efficient sensorimotor processes in experts during kicking, characterized by reduced neural noise and enhanced modularity (Gallen and D'Esposito, 2019; Hung et al., 2008; Del Percio et al.,

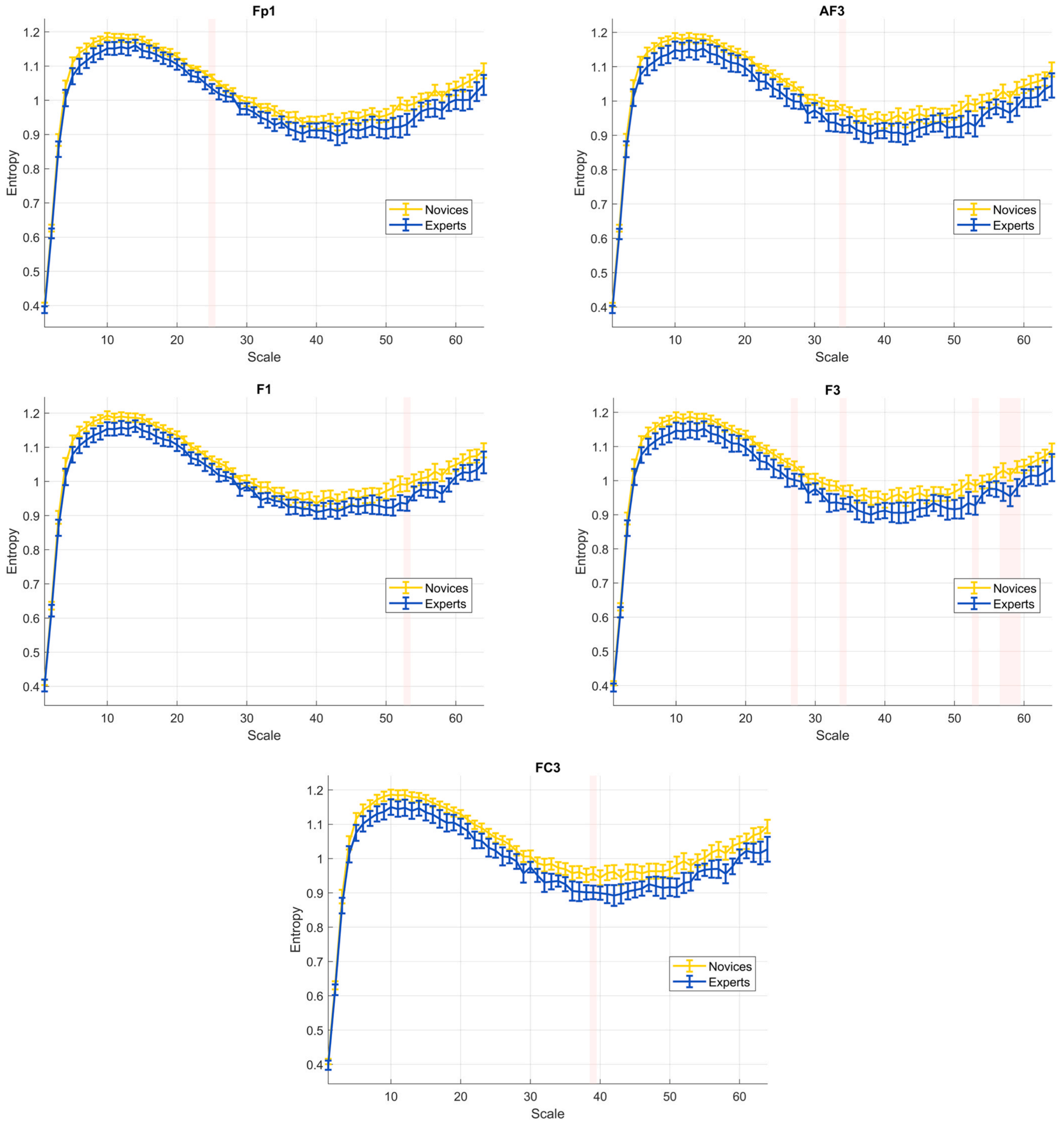

Fig. 3. Entropy curves of frontal channels for novices and expert players. Expert players demonstrated overall lower entropy estimates with occasional significant differences at middle and coarse scales.

2009).

In contrast, group differences in frontal regions were observed mainly at middle to coarse ranges and typically at isolated scales. While these effects were modest, they coincided with a broader, non-significant trend towards lower complexity in experts across wider scale ranges (Costa et al., 2005). Such a pattern at middle and coarse scales may suggest the reduced contribution of the frontal cortex to long-range, large-scale neural integration represented by slow dynamics (Courtiol et al., 2016; Vakorin et al., 2011). The frontal cortex, including dorsolateral prefrontal and supplementary motor areas, plays a key role in action preparation, decision-making, and movement adaptation (Pascual-Leone et al., 1995; Tanji, 2001). These functions often involve low-frequency dynamics (Cavanagh and Frank, 2014; Ofner et al., 2017), which are captured at coarse scales in MSE analysis. Thus, although less pervasive than the fine-scale centroparietal effects, the frontal findings may similarly reflect expertise-related refinement in higher-order processes supporting improved kicking performance (Costa et al., 2005).

Importantly, the gradual progression from coarse-scale differences at frontal sites to fine-scale differences at centroparietal sites is consistent

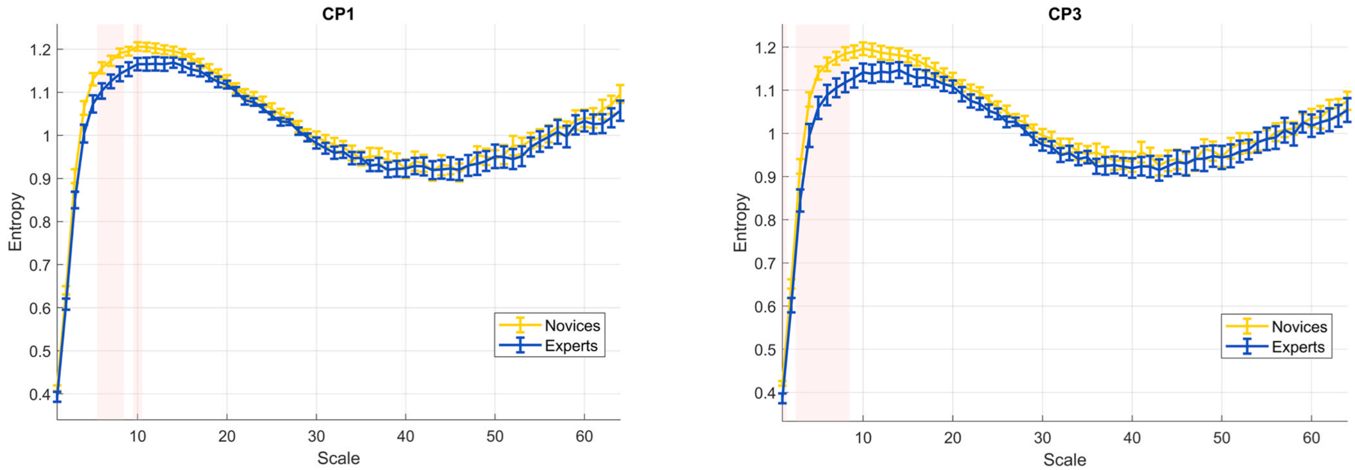

Fig. 4. Entropy estimates of centroparietal channels for novices and experts. Expert players demonstrated overall lower entropy estimates with clustered significant differences at fine scales.

Table 1
Channels and scales with significant group differences, the correlation between their entropy estimates and accuracy rate, and area under the curve (AUC) values derived from raw entropy estimates and their principal components (PC). Scales are highlighted in bold if they exhibited both significant group differences and the highest PC coefficients.

Channel	Scales with significant differences	Correlation with accuracy rate (Pearson's r, significance level)	AUC	Maximum AUC across PCs (dimension)	First 10 scales contributing to PCs with highest coefficients in descending order
Fp1	25	-	0.70	0.76 (23)	29, 52, 36, 47, 15, 44, 53, 45, 42, 19
AF3	34	r = -0.36, p = 0.02	0.68	0.76 (12)	48, 58, 64, 44, 45, 31, 27, 30, 55, 15
F1	53	r = -0.43, p = 0.02	0.65	0.75 (24)	**53,** 34, 52, 14, 26, 56, 44, 27, 21, 15
F3	27	-	0.67	0.73 (13)	**58, 59,** 55, **57,** 26, **34,** 19, 38, 1, 20
	34	r = -0.42, p = 0.02	0.60		
	53	-	0.57		
	57	-	0.65		
	58	-	0.63		
	59	r = -0.40, p = 0.04	0.62		
FC3	39	r = -0.43, p = 0.02	0.68	0.80 (19)	22, 27, 64, 57, **39,** 51, 38, 62, 45, 5
CP1	6	-	0.76	0.72 (2)	3, 4, **6,** 5, **7,** 2, 11, **8,** 9, **10**
	7	-	0.76		
	8	-	0.75		
	10	-	0.78		
CP3	1	-	0.74	0.74 (2)	**3, 7,** 2, 11, 10, **6, 4, 8,** 9, 5
	3	-	0.74		
	4	-	0.75		
	5	-	0.77		
	6	-0.37 (p = 0.04)	0.76		
	7	-0.40 (p = 0.03)	0.77		
	8	-0.39 (p = 0.04)	0.78		

with the spatial gradients expected under volume conduction and highlights that MSE is sensitive to region- and scale-specific complexity dynamics rather than producing arbitrary scale effects (Michel and Brunet, 2019; Nunez and Srinivasan, 2006). Although the overall complexity profiles remain largely consistent across channels with novices showing higher entropy throughout, the ranges at which group differences become most pronounced vary systematically across regions, reflecting the distinct temporal characteristics of frontal and sensorimotor cortical processes.

A further finding supporting these interpretations was the negative correlation between MSE-derived entropy estimates and kicking accuracy. Although the correlations were small, they followed a consistent direction across channels and scales that also differentiated experts from novices, indicating that the degree of brain complexity may be functionally related to performance. In this context, lower complexity may reflect more stable and refined cortical processing with reduced task-irrelevant neural variability, thereby contributing to enhanced accuracy. This interpretation is consistent with the findings of Hung et al. (2008), who similarly reported reduced neural complexity in expert shooters and an inverse relationship between accuracy and complexity. While neural variability is essential for adaptability, excessive or unstructured complexity can hinder precise motor output in highly constrained or repetitive tasks (Faisal et al., 2008; Hung et al., 2008). Taken together, the scale-dependent and region-specific patterns of group differences, along with their modest correlations with accuracy, suggest that the entropy profile associated with motor expertise may reflect a nuanced reorganization of task-related brain complexity. Nevertheless, interpretations of particularly frontal effects should remain cautious, as entropy estimates at higher scales may be more susceptible to noise and reduced signal stability, as also suggested by the reliability estimates.

4.3. The classification performance of entropy estimates to differentiate expertise levels

To further evaluate the discriminatory power of entropy for differentiating expertise levels, ROC curve analysis was applied to individual entropy values and their PCs for channels and scales exhibiting significant group differences. The results yielded predominantly moderate to good classification accuracy, suggesting that MSE may have the potential to distinguish between expert and novice performers. While the identified differences at coarse frontal and fine centroparietal scales point to distinctive complexity profiles, the AUC values provide a direct measure of discriminatory power, reflecting the degree to which the spatiotemporal distributions of entropy values diverge between groups. Channels in frontal and centroparietal regions that showed both higher classification performance and significant group differences may correspond to cortical sites whose complexity characteristics are more consistently shaped by expertise (Del Percio et al., 2009; Berchicci et al.,

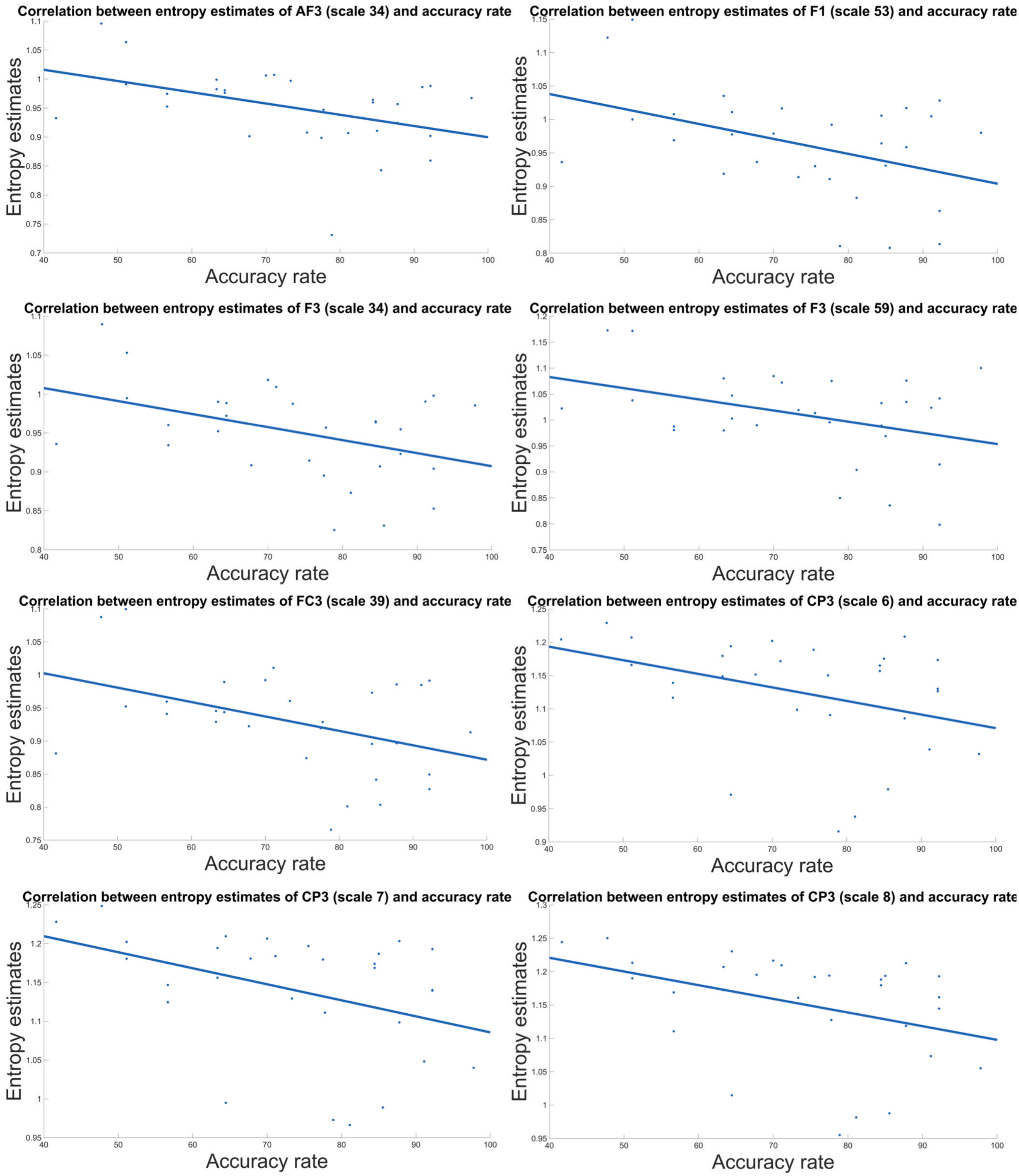

Fig. 5. Scatter plots for entropy estimates and kicking accuracy. Entropy estimates were negatively correlated with kicking accuracy suggesting lower complexity as a predictor for enhanced kicking accuracy.

2017). Moreover, because MSE captures neural dynamics across multiple temporal resolutions, some scales may inherently be more sensitive than others in classifying expertise-related complexity patterns (Wang et al., 2020). At the same time, channels with higher within-group variability may reach significance at single scales without necessarily providing strong standalone classification performance, highlighting the importance of considering both effect size and variability when interpreting ROC results.

To address these considerations and integrate information across multiple scales while reducing dimensionality, PCA-based classification was also conducted in the current study. Notably, the highest AUC values did not always correspond to the first PCs. Although first-order

PCs account for the largest share of variance and reflect global patterns in the data, they do not necessarily encode the features most relevant for distinguishing levels of expertise. Higher-order PCs can instead capture subtle but task-relevant differences between groups or conditions (Daffertshofer et al., 2004; Jolliffe and Cadima, 2016; Parra et al., 2005), which is consistent with the present findings showing that certain higher-order PCs exhibited superior classification performance. Importantly, most PCs with the highest AUC values had their largest coefficients at scales where significant group differences emerged, reinforcing that entropy characteristics at specific scales constitute key discriminative features. Although higher-order PCs improved classification accuracy by isolating subtle distinctions, their contributions were interpreted with caution to avoid overfitting and to consider implications for generalizability.

Collectively, the present study provides the first assessment of the reliability, validity, and classification accuracy of MSE derived from mobile EEG in a dynamic sports context. The findings demonstrate substantial test-retest reliability and support the validity of MSE as a measure sensitive to motor performance and having a potential to differentiate expertise levels in sports by characterizing distinct patterns of brain complexity. Beyond their theoretical relevance, these findings may also have practical applications. Entropy-based complexity profiles could serve as sensitive markers of motor proficiency, providing a foundation for paradigms in training and performance assessment. Moreover, given the demonstrated longitudinal consistency of entropy estimates, MSE may offer a promising avenue for monitoring complexity changes over time, for example following targeted training or rehabilitation interventions. Future work across diverse tasks, populations, and longitudinal designs is essential for clarifying the relationship between cortical complexity and motor performance and for establishing the applied potential of MSE in training and recovery contexts.

4.4. Methodological limitations and recommendations for future implementation of MSE analysis in mobile settings

The methodological limitations of the present study should be acknowledged when interpreting the findings and considering future implementations of MSE analysis on mobile EEG data. A first consideration concerns the characteristics of the experimental task, which may influence the interpretation of complexity. The current paradigm involved a predictable motor task focused on accuracy, providing an appropriate context for observing how lower complexity in experts might relate to reduced neural noise and refined sensorimotor processes. However, the functional interpretation of neural complexity is known to depend on task context (Ibáñez-Molina et al., 2018; Liang et al., 2014). For instance, in tasks requiring high adaptability or processing of unpredictable stimuli, increased complexity may be advantageous (Liang et al., 2014). Future studies should therefore investigate how neural complexity, as measured by MSE, varies across tasks with systematically different cognitive-motor demands and degrees of environmental predictability.

Task characteristics may also explain why significant group differences appeared at single scales in frontal channels, even when broader trends indicated lower complexity among experts across a wider range of scales. These characteristics could likewise have influenced the magnitude of the observed effects and correlations. Rather than comparing entropy values scale-wise, future research could employ statistical approaches that consider the entire curve. When integrating multiple scales into a single complexity index (e.g., AUC), researchers must carefully account for opposing trends across different scale ranges (McIntosh et al., 2014; Mizuno et al., 2010). Such opposing trends could cancel each other out when aggregated into a single metric, thereby masking meaningful group differences at specific scale ranges.

Another consideration relates to EEG preprocessing procedures and the inherent nature of EEG signals. Following preprocessing steps previously validated for reliable linear EEG dynamics during the same motor task (Piskin et al., 2024a), the present study used a single pair of high- and low-pass filter cutoff frequencies. Filtering parameters are known to influence entropy estimates by altering the underlying frequency composition of the signal (Puglia et al., 2022). Given the potential artifacts inherent to mobile EEG recordings, particularly those arising from physiological sources or movement-related noise, future studies should systematically test how different cutoff frequencies affect entropy measures. Filtering can also remove interactions occurring near cutoff frequencies, particularly affecting the finest and coarsest scales (Kosciessa et al., 2020; Puglia et al., 2022). Scales corresponding to frequencies outside the filtered range may contain irrelevant or distorted information. In the context of the present findings, the 3–30 Hz filter may have contributed to the lower entropy observed at the finest scales, where high-frequency (>30 Hz) components are attenuated, and to the stabilization of coarse-scale estimates through the removal of slow drifts (<3 Hz). Consequently, scale-specific differences identified in frontal and centroparietal regions should be interpreted considering the reduced frequency content at the extremes of the filtered bandwidth. Additionally, analyses targeting specific frequency bands (Azami et al., 2017) should consider the maximum frequency reliably captured by the number of available data points at each temporal scale (Gow et al., 2015; Puglia et al., 2022). Careful selection of appropriate scales is therefore essential for meaningful interpretation of MSE results.

Relatedly, the coarse-graining procedure inherent to MSE analysis acts similar to a low-pass filter, progressively attenuating higher-frequency components at coarser scales. This introduces a bias toward emphasizing slower brain dynamics while diminishing interactions between fast and slow neural processes at higher scales. Future research may benefit from modified MSE variants that apply adaptive filtering strategies designed to preserve relevant frequency content throughout successive coarse-graining steps (Kosciessa et al., 2020).

Finally, it is important to recognize that EEG signals represent summed electrical potentials from underlying neural populations. Due to volume conduction, activity from a single neural source can be detected by multiple electrodes, particularly those in close proximity (Nunez and Srinivasan, 2006). As a result, apparent entropy differences in adjacent channels may in part reflect shared influence from common neural sources rather than fully independent local processes.

In summary, addressing these methodological considerations will enhance the interpretability and robustness of future MSE analyses conducted using mobile EEG systems.

5. Conclusion

The present study aimed to evaluate the reliability and validity of MSE derived from mobile EEG data recorded during a short-distance kicking task to assess its potential use in mobile contexts. Reliability estimates were overall substantial, although scale- and channel-specific variations were observed. Significant differences in entropy values between experts and novices, along with a significant entropy-accuracy correlation, supported both known-groups and convergent validity of MSE. Experts exhibited overall lower complexity, notably at coarse frontal and fine centroparietal scales, suggesting that refined neural processing contributes to performance in stable contexts. Furthermore, MSE demonstrated acceptable classification accuracy to differentiate expertise levels. Collectively, these findings propose MSE as a potential metric for investigating brain complexity within movement contexts. Future research across diverse tasks and populations is needed to further clarify the relationship between brain complexity and movement.

CRediT authorship contribution statement

Gjergji Cobani: Writing – review & editing, Investigation, Data curation. **Daghan Piskin:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tim Lehmann:** Writing – review & editing, Formal analysis. **Daniel Büchel:**

Writing – review & editing. **Jochen Baumeister:** Writing – review & editing, Supervision, Project administration.

Ethics

The ethics committee of Paderborn University approved the conduction of the study in line with the Declaration of Helsinki. All participants were informed about the purpose and procedures of the study and gave written consent prior to participation.

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Declaration of Competing Interest

The authors declare that they have no competing interests.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.brainresbull.2026.111769.

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