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The influence of kinematics and neuromuscular activity on stand-up paddling performance using cluster analysis

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ABSTRACT

This study classified stand-up paddle (SUP) practitioners by using cluster analysis of kinematic and neuromuscular activity. 14 male paddleboarders (24.2 ± 7.1 yrs) performed 3 submaximal trials of 65-m. Surface electromyography of *upper trapezius* (UT), *biceps brachii* (BB), *triceps brachii* (TB), *tibialis anterior*, and *gastrocnemius medialis*, on both sides of the body. Speed, stroke frequency, distance per stroke, and stroke index (SI) were also assessed. Clusters were discriminated between performances in different groups according to speed ($F = 4.24$, $p = 0.043$, $\eta^2 = 0.44$). The left UT of the left pull ($F = 7.20$, $p = 0.010$, $\eta^2 = 0.57$), the right TB of the left recovery ($F = 6.21$, $p = 0.016$, $\eta^2 = 0.53$), and the right TB of the left pull ($F = 5.80$, $p = 0.019$, $\eta^2 = 0.51$) were the main variables of the clusters. Best performers were characterised by high activations of the left UT during the left pull and the left TB during the right recovery, along with greater SI. Poor performers displayed low activations of right TB during the pull and recovery phases. Better performers showed high activations, in UT and TB during the pull and recovery phases, emphasising their role in SUP performance.

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1. Introduction

Stand-up paddle (SUP) is characterised by elements of surfing and paddle sports (Furness et al., 2017) and therefore involves multifactorial interactions across scientific domains (Mendez-Villanueva & Bishop, 2005). In recent years, research has tended to elucidate various aspects related to the physiological, musculoskeletal, and psychological effects of SUP, as well as its performance analysis (Furness et al., 2017; Schram, Hing, & Climstein, 2017; Schram, Hing, Climstein, & Furness, 2017; Willmott et al., 2020). For example, SUP races appear to involve a high aerobic demand and a significant impact of tactical decisions on variations in distance covered, peak speed, and heart rate (Schram, Hing, Climstein, & Furness, 2017).

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Indeed, elite SUP athletes have aerobic power levels comparable to other upper limb-dominant water-based sports (Schram et al., 2016a). The importance of technique for SUP performance was also highlighted (Schram et al., 2019). It was found that experienced paddlers tend to use different paddle stroke kinematics than inexperienced, relying less on shoulder range of motion and more on hip motion (Schram et al., 2019). Although the literature suggests that a combination of physiological, tactical, and technical factors may contribute to SUP performance, the study of performance and its determinants in SUP remains scarce (Castañeda-Babarro et al., 2022).

Identifying and predicting key determinants is common in other aquatic sports (e.g. López-Plaza et al., 2017; Morais et al., 2021). For example, energetics, anthropometrics, kinematics, and efficiency have been proposed as some of the main factors responsible for the variation in technique and performance in swimming (Morais et al., 2021; Silva et al., 2019; Zacca et al., 2018). Furthermore, the greater performance of highly trained kayakers and canoeists was found to be associated with superior physical fitness and body size (López-Plaza et al., 2017), while stroke parameters (i.e. speed fluctuations, propulsive forces, drag forces, paddling stroke rates) and velocity changes are important variables in predicting the paddling time in kayakers (Freitas, Conceição, Louro, et al., 2023; Gomes et al., 2022; Michael et al., 2009). Indeed, in sports such as rowing, kayaking, and swimming, stroke kinematics play a fundamental role in technique/mechanics and performance variability (Ettema et al., 2022; Gomes et al., 2022; Morais et al., 2014). For instance, being able to increase the stroke rate is important for enhancing race time and performance (Gomes et al., 2022). To do that, previous studies have demonstrated the importance of neuromuscular factors, such as force production, coordination, and activation patterns (Akbar et al., 2022; Gomes et al., 2015; Morais et al., 2021). Therefore, we can suggest that SUP performance depends on stroke kinematics, and understanding the influence of neuromuscular activity will be essential. However, the applicability of these findings to SUP remains uncertain given the unique biomechanics and environmental conditions of SUP.

While the existing literature has shed light on the multifactorial nature of performance in several aquatic sports, SUP presents unique challenges that require further investigation (Castañeda-Babarro et al., 2022; Freitas, Conceição, Šťastný, et al., 2023; Willmott et al., 2020). Despite the progress made in SUP research, there is still a need to understand the neuromuscular and biomechanical determinants that influence performance (Freitas, Conceição, Šťastný, et al., 2023; Tsai et al., 2020). By addressing this gap, the present research contributes to the existing body of knowledge but also has implications for SUP athletes, allowing for further understanding of the factors that can maximise their potential. Therefore, the purpose of this study was to classify and identify SUP performance based on kinematics and neuromuscular activity patterns by cluster analysis. This will allow us to understand which variables are related to better and poorer performances. It was hypothesised that the interplay between different variables would be responsible for the cluster formation, and not only variables from a specific domain.

2. Methods

2.1. Participants

Fourteen male recreational SUP participants, all right-handed, volunteered for this study (age: 24.2 ± 7.1 years, height: 1.73 ± 1.22 m, body mass: 58 ± 15.5 kg, wingspan: 1.79 ± 0.87; mean ± SD). Inclusion criteria included age requirements (>18 years), a minimum of 6 months of regular SUP experience (1–2 times per week), and were excluded if they had any health risks or conditions that affected paddling performance. Prior to testing, the participants were informed of the procedures and signed an institutionally approved written informed consent. This study was approved by the University Ethics Committee (CE-UBI-Pj-2022–042) and all the procedures were in accordance with the Declaration of Helsinki regarding human research.

2.2. Design and procedures

In this cross-sectional study, each participant performed three stand-up paddling trials at individual submaximal speed (i.e. at 75% of predicted maximal heart rate) during which kinematic (i.e. speed, stroke frequency [SF], distance per stroke [DPS], and stroke index [SI]) and neuromuscular activity (i.e. surface electromyography [EMG] of the *upper trapezius*, *biceps brachii*, *triceps brachii, tibialis anterior*, and *gastrocnemius medialis*) were measured.

All data were collected using the same paddleboard model (SUP Board Itiwit 10'32''5') and paddle (Itwit 170-220 cm). Before each trial, the height of the paddle was adjusted independently for each participant within a range of 1.7–2.2 m (Willmott et al., 2020). Trials were conducted in the same location, in calm water, free of current disturbance, and in a downwind direction. Wind speed was recorded daily and the average wind speed during the trials was 3.4 m/s (light breeze) as measured on the Beaufort Wind Scale and confirmed by the National Weather Service (2022). After a self-selected warm-up of 5 min, each participant completed a 65 m trial in a straight line, demarcated by two floaters indicating the start and end of the trial (Freitas, Conceição, Louro, et al., 2023). To maintain forward motion while paddling, participants were instructed to switch paddle sides after three strokes (Tsai et al., 2020). Participants were instructed to perform the trials at a moderate pace between 70 and 75% of the predicted maximum heart rate (Shookster et al., 2020). To ensure participants maintained their heart rate within the prescribed threshold, a familiarisation session was conducted before the test, where participants trained at a submaximal speed approximating 75% of their predicted maximum heart rate. During the test, participants controlled their heart rates using a Suunto Smartwatch 9 Peak along with the Suunto Smart Heart Rate Belt (Suunto, Vantaa, Finland), which continuously monitored their heart rates in real-time. If deviations from the target range occurred, participants adjusted their paddling intensity accordingly.

2.3. Neuromuscular analysis

Muscle activity on both sides of the body was assessed by surface EMG using a wireless system with built-in accelerometers (Miniwave, Cometa, Milano, Italy;

EMGandMotionsTools software 8.7.6.0) and probes equipped with a 7-g memory and a sampling rate of 2000 hz at 16 bits. To ensure accurate measurements, the skin was first gently shaved, rubbed with sandpaper, and cleaned with alcohol, following the protocol outlined by Afsharipour et al. (2019). This was done to prevent the interelectrode resistance from exceeding 5 KOhm. To protect the electrodes from water interference, transparent bandages with labels (Hydrofilm®, 10 cm x 12.5 cm, U.S.A.) were used to cover the electrodes as recommended (Hohmann et al., 2006). In addition, participants wore custom-made long-sleeved surfing suits (Decathlon, Olaian 3/2 mm, Villeneuve-d'Ascq, France) to protect the electrodes and sensors during the trials. EMG sensors (Kendall ™, ECG electrodes, 57 × 34 mm, 57 width mm × 34 length mm, gel area 201 mm^2, sensor area 80 mm^2, Dublin, Ohio, U.S.A.) were placed according to the SENIAM recommendations (Hermens et al., 2000) to analyse the *upper trapezius*, *biceps brachii*, *triceps brachii, tibialis anterior*, and *gastrocnemius* medialis muscles (Figure 1). These muscles were selected due to their importance in SUP (Ruess et al., 2013; Tsai et al., 2020).

Prior to the study evaluation, each subject performed three maximal voluntary isometric contractions for each muscle studied on dry land to assess the maximum voluntary contraction (MVC). The contractions were held for 5 seconds, followed by 5 minutes of rest, and verbal encouragement was given to the subjects. The maximum value of the three measurements was used to normalise the EMG signals (Boettcher et al., 2008; Hermens et al., 2000). MVC procedures were performed using the manual resistance applied by the examiner and according to the guidelines of the Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles (SENIAM) and Noraxon (Scottsdale, Arizona, U.S.A.) companies (Al-Qaisi & Aghazadeh, 2015; Dyson et al., 1996). The detailed procedures for MVC assessment for each muscle can be found

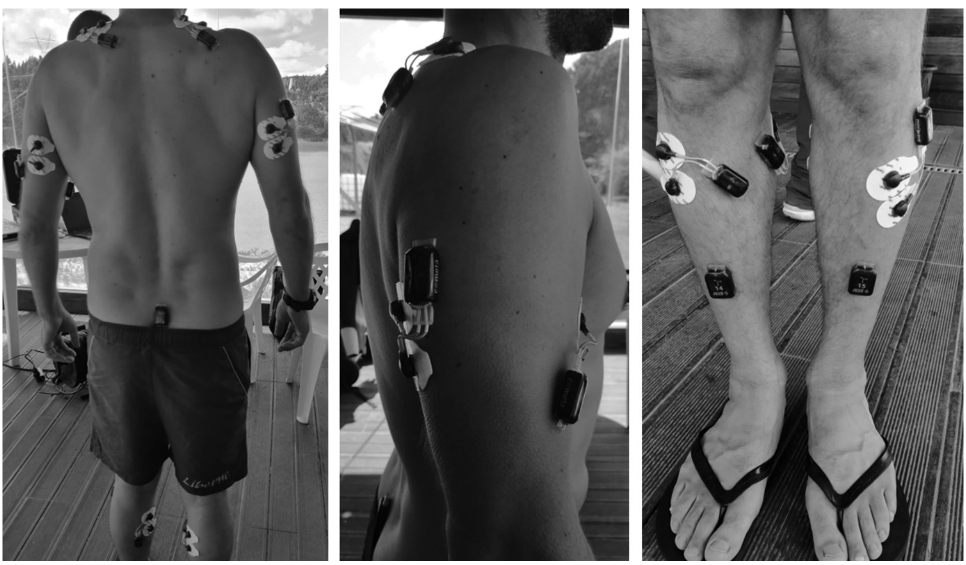

Figure 1. Participant equipped with surface electromyography electrodes.

in a previous study by Freitas, Conceição, Šťastný, et al. (2023). The maximum value of the resulting EMG was determined and averaged across the trials for each test.

During the trials, the EMG measurement was synchronised with a digital video camera (Panasonic, DC-FZ 1000II, Osaka, Japan) mounted on a tripod (Falcon Eyes, FT-120, Hoogeveen, The Netherlands) perpendicular to the course at a distance of 20 metres. To synchronise the data, the subjects had to stand on the board in a T-position for 5 seconds and then tap on their arm *biceps brachii* three times before starting the trials. Each video was edited according to the trials and then the data was synchronised with the EMG software (EMG and Motion Tools, V8, Cometa, Bareggio Mi, Italy). The pull and recovery phases of the stroke were determined as previously reported elsewhere (Freitas, Conceição, Šťastný, et al., 2023; Michael et al., 2009; Tsai et al., 2020). To ensure accuracy, event times were verified by a second observer, which increased the reliability of the measurements associated with the different phases performed by the upper limb. The first six cycle strokes of both sides were excluded from the analysis, as well as the first stroke of each cycle, to eliminate paddle transfer from side to side, which affects the cycle parameters. Four left and four right cycle strokes were then analysed.

Signal processing was initiated by filtering the MVC file. The EMG sensors received raw EMG data that was filtered using a low-pass filter with a cut-off frequency of 400 hz and a 4th order Butterworth filter, and a high-pass filter with a cut-off frequency of 20 hz and a 4th order Butterworth filter. After signal rectification, a smoothing technique was applied using a Root Mean Square envelope with a 50 ms window. The maximum MVC activation values (µV) were then calculated for each muscle and presented as percentage MVC (% MVC). Finally, the last processing step involved applying the same filters to the signal obtained from each trial and applying the MVC to the trial file.

2.4. Kinematics analysis

The same cycle strokes used for EMG analysis were used for the kinematic evaluation. After image acquisition, during the subsequent analysis phase, the Kinovea ® software (version 0.9.5) was used for video editing, duration registration, and kinematic analysis based on sagittal plane images. The choice of the sagittal plane was motivated by its ability to provide a comprehensive view of the paddling motion, considering the kinematic characteristics of the paddling motion. As shown above, four cycle strokes were analysed for both the left and right sides of each subject. The use of Kinovea ® software for kinematic analysis is well supported by previous research, which has demonstrated its accuracy in frame-by-frame video analysis and its strong agreement with other motion capture systems in various sports applications, including paddling and stroke analysis (e.g. Fernandes et al., 2024; Fernández-González et al., 2020). The kinematic parameters analysed were calculated as follows: speed was derived as distance divided by time, SF (in Hz) as the number of cycles per second, DPS (in m) as the total distance divided by the number of strokes, and SI (in m^2/s) as the product of DPS and speed, providing comprehensive scientific support for performance assessment (Abellán-Aynés et al., 2023)

2.5. Statistical analysis

Normality of data distribution was analysed using the Shapiro-Wilk test. The mean and standard deviation were calculated as descriptive statistics. Cluster modelling was performed based on the k-means approach (non-hierarchical). This allows the definition of several clusters to be used in advance. The k-means defines a centroid (i.e. the mean of a group of points/subjects) based on their similarities (Rein et al., 2010). Standardised z-scores were used to ensure consistent comparison of data sets with different magnitudes and/or units. All variables were tested in the modelling, except those related to EMG. For these, the correlation between speed and muscle activity was first verified with the Spearman correlation coefficient ($p < 0.05$). The variables that showed a significant correlation were tested in the cluster modelling. One-way ANOVA was used to identify the main determinants responsible for the formation of the clusters ($p < 0.05$). The total eta-squared (η^2) was chosen as the effect size index and was considered as: (i) no effect if $0 < \eta^2 < 0.04$; (ii) minimal if $0.04 < \eta^2 < 0.25$; (iii) moderate if $0.25 < \eta^2 < 0.64$ and; (iv) strong if $\eta^2 > 0.64$ (Ferguson, 2009). Bonferroni post-hoc correction ($p < 0.017$) was used to identify differences between clusters whenever suitable. The significance level was set at $\alpha = 0.05$. Stepwise discriminant analysis was used to validate the clusters.

3. Results

The elbow method was used to test several cluster solutions (from 2 to 9), where the three-cluster solution presented the highest power. Cluster 1 was labelled as the cluster with poor performances, cluster 2 with medium performances, and cluster 3 with best performances. Participants maintained trial intensity around 75% of the predicted maximum heart rate, with no differences between clusters (cluster 1: 140.50 ± 42.23 bpm; cluster 2: 148.80 ± 3.90 bpm; cluster 3: 139.40 ± 13.67 bpm; F = 0.230, $p = 0.798$, $\eta^2 = 0.00$). Table 1 presents the descriptive and inferential data of the variables tested after the cluster modelling. Speed (F = 4.24, $p = 0.043$, $\eta^2 = 0.44$) presented significant differences between clusters. The left *upper trapezius* of the left pull (F = 7.20, $p = 0.010$, $\eta^2 = 0.57$), the right *triceps brachii* of the left recovery (F = 6.21, $p = 0.016$, $\eta^2 = 0.53$), and the right *triceps brachii* of the left pull (F = 5.80, $p = 0.019$, $\eta^2 = 0.51$) were the main variables responsible for the formation of the clusters. Cluster 1 (poor performers) was characterised by low activations of the right *triceps brachii* during the left pull, right *triceps brachii* during the left recovery, and right *triceps brachii* during the right pull. Cluster 2 (medium performers) was characterised by a small DPS, and large activations of the right and left *triceps brachii* during the left pull. Cluster 3 (best performers), besides the fast speeds, was also characterised by large activations of the left *upper trapezius* during the left pull, a greater SI, and large activations of the left *triceps brachii* during the right recovery.

Stepwise discriminant analysis was used as a qualitative assessment of clustering. This extracted two functions including the left *upper trapezius* of the left pull and the right *triceps brachii* of the left pull. Function 1 was mainly defined by the left *upper trapezius* of the left pull explaining 84.6% of the variance ($\Lambda = 0.203$, X2 = 16.722, $p = 0.002$). Function 2 was mainly defined by the right *triceps brachii* of the left pull explaining 15.4% of the variance ($\Lambda = 0.695$, X2 = 3.821, $p = 0.051$). The discriminant analysis

Table 1. Descriptive (mean ± SD – standard deviation) and clustering statistics.

	Cluster 1 ($N = 4$)		Cluster 2 ($N = 7$)		Cluster 3 ($N = 3$)			
	Mean ± SD	z-score	Mean ± SD	z-score	Mean ± SD	z-score	F-ratio (p)	η^2
Speed [m/s]	1.07 ± 0.19	−0.5931	1.16 ± 0.16	−0.1605	1.45 ± 0.18	1.1654	4.24 (0.043)	0.44
SF [Hz]	0.55 ± 0.10	−0.8342	0.70 ± 0.13	0.3377	0.69 ± 0.06	0.3242	2.35 (0.141)	0.30
DPS [m]	1.96 ± 0.20	0.3588	1.69 ± 0.18	−0.5824	2.11 ± 0.40	0.8805	3.68 (0.060)	0.40
SI [m^2/s]	2.10 ± 0.46	−0.2130	1.96 ± 0.29	−0.4231	3.09 ± 0.95	1.2713	5.14 (0.026)	0.48
Right pull [%MVC]								
Left *Upper trapezius*	23.92 ± 13.62	−0.0493	23.39 ± 7.19	−0.1093	27.15 ± 6.95	0.3207	0.17 (0.841)	0.03
Left *Triceps brachii*	6.46 ± 1.61	−0.8224	11.48 ± 5.65	0.1613	14.33 ± 3.38	0.7202	2.85 (0.100)	0.34
Right *Triceps brachii*	5.92 ± 2.87	−0.9106	11.93 ± 4.69	0.4247	11.02 ± 2.30	0.2231	3.14 (0.083)	0.36
Right *Biceps brachii*	5.97 ± 1.29	−0.9019	8.73 ± 2.49	0.0817	11.34 ± 2.20	1.0119	5.29 (0.025)	0.49
Right recovery [%MVC]								
Left *Triceps brachii*	27.20 ± 17.15	−0.3732	28.58 ± 14.91	−0.2923	53.66 ± 1.84	1.1798	3.82 (0.055)	0.41
Right *Triceps brachii*	18.71 ± 10.07	−0.8853	36.95 ± 16.61	0.2505	42.49 ± 9.84	0.5959	3.05 (0.088)	0.36
Left pull [%MVC]								
Left *Upper trapezius*[a]	6.41 ± 2.77	−0.7667	10.14 ± 4.32	−0.1114	18.05 ± 4.79	1.2823	7.20 (0.010)	0.57
Left *Triceps brachii*	5.88 ± 3.05	−0.8240	14.63 ± 7.06	0.4949	10.97 ± 4.92	−0.0562	2.85 (0.100)	0.34
Right *Triceps brachii*	7.33 ± 3.30	−1.0752	17.39 ± 6.00	0.5225	15.45 ± 0.97	0.2143	5.80 (0.019)	0.51
Left *Biceps brachii*	6.51 ± 3.09	−0.8513	9.62 ± 2.85	0.1217	11.95 ± 1.15	0.8511	3.63 (0.061)	0.40
Left recovery [%MVC]								
Left *Triceps brachii*	20.61 ± 5.48	−0.8949	34.17 ± 11.68	0.4046	32.55 ± 2.56	0.2490	2.94 (0.094)	0.35
Right *Triceps brachii*	23.20 ± 16.23	−1.0145	45.72 ± 14.38	0.1854	59.51 ± 7.64	0.9201	6.21 (0.016)	0.53

SF – stroke frequency; DPS – distance per stroke; SI – stroke index; HR – heart rate; %MVC- percentage of maximal voluntary contraction; η^2 – eta square (effect size index). Superscripts: a – post-hoc differences between cluster 1 and 3.

showed a good compactness/separation with a correct classification of the original groups (71.4%) and a correct classification of the cross-validated groups (71.4%) (Figure 2). The following classification functions are available:

$$\text{Cluster 1} = -4.340 + (0.432 \cdot R\ Triceps\ LP) + (0.516 \cdot L\ Upper\ Trapezius\ LP) \quad (1)$$

$$\text{Cluster 2} = -13.936 + (0.954 \cdot R\ Triceps\ LP) + (0.896 \cdot L\ Upper\ Trapezius\ LP) \quad (2)$$

$$\text{Cluster 3} = -21.075 + (0.972 \cdot R\ Triceps\ LP) + (1.381 \cdot L\ Upper\ Trapezius\ LP) \quad (3)$$

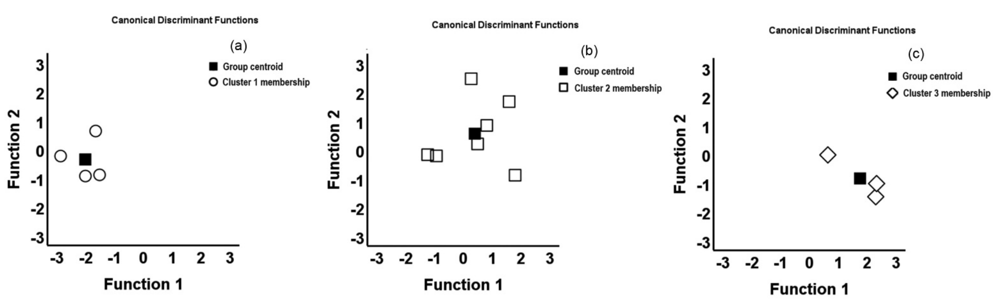

Figure 2. Territorial map for each cluster. Panel (a) – cluster 1; Panel (b) – cluster 2; Panel (c) – cluster 3.

Where R Triceps LP is the right *triceps brachii* activation during the left pull (in % MVC), and L Upper Trapezius LP is the left *upper trapezius* activation during the left pull (in % MVC).

4. Discussion

The purpose of this study was to classify and identify SUP performance based on kinematics and neuromuscular activity patterns by cluster analysis. The results showed that the clustering adequately discriminated the performances between the different groups according to speed. Faster performances were associated with unique neuromuscular activation patterns during the pull and recovery phases, as well as higher speeds. Furthermore, the determinants that characterised each cluster were different according to the speed of the trials.

The cluster analysis allowed us to distinguish between the speed of the participants clearly, and in this way, it was possible to identify the variables that characterised each group, particularly neuromuscular activity in different muscles and kinematic factors. Previous findings have shown some differences between experienced and inexperienced paddlers, suggesting that those with better performance used a more efficient SUP stroke, possibly due to a larger catch angle and longer stroke length, resulting in higher peak power output (Brown et al., 2011; Schram et al., 2016b, 2019). In this study, the best performers were distinguished by significant muscle activations and higher stroke indices. Specifically, these individuals demonstrated large activations of the left *upper trapezius* during the left pull and the left *triceps brachii* during the right recovery, in addition to higher speed and SI values. These findings highlight the interplay between muscle activation and kinematic efficiency in achieving optimal SUP performance. In contrast, the poor performers showed lower activations of key muscles during both the pull and recovery phases, including the right *triceps brachii* during the left pull, the right pull, and the right recovery phases. This insufficient muscle engagement during key phases of the stroke cycle indicates possible inefficiencies in force production and coordination, which may limit performance.

Increased activation of the left *upper trapezius* during the left pull likely helps create a more efficient stroke by stabilising the shoulder and reducing energy loss. This contributes to the higher speeds and SI values observed in the best performers. Additionally, the *triceps brachii* plays a key role in extending the arm during the recovery phase of a stroke, which prepares the paddle for the next stroke. This activation supports arm extension, torso twisting, and preparation for force application during the pull. Increased activation during these phases improves stroke efficiency by ensuring proper positioning (Tsai et al., 2020). Higher activation in this muscle during the recovery phase ensures that the paddler positions the paddle quickly and effectively, reducing cycle time while maintaining stroke efficiency (Freitas, Conceição, Šťastný, et al., 2023). This activation of the contralateral *triceps brachii* (left triceps during right recovery) may reflect advanced coordination and timing among opposing muscle groups, which is often seen in skilled athletes (Schram et al., 2016a).

Interestingly, the poor and medium performers displayed low muscle activation during the pulling phase, suggesting that inefficiencies in this phase contribute significantly to slower speeds. In contrast, the recovery phase played a decisive role for the best performers, with high muscle activity during this phase supporting better stroke preparation and overall efficiency. Therefore, the attention to the recovery phase and the work of the muscles during this phase of the stroke should not be neglected. This is even more important as it is known that the recovery phase can take up the majority of the stroke time in SUP (Freitas, Conceição, Šťastný, et al., 2023).

According to the stepwise discriminant analysis, the formation of the clusters could be resolved by including the data from the right *triceps brachii* activation and left *upper trapezius* during the left pull. This means that information about these variables allows accurate classification of participants into the faster, medium, or slower group of paddlers. *Triceps brachii* and *upper trapezius* activity, particularly during the left pull and recovery phases, emerged as a consistent determinant across analyses, highlighting its critical role in SUP performance.

Although research on this topic is scarce, and this was the first study to use cluster analysis to examine neuromuscular activity and kinematics in SUP, some limitations must be acknowledged. The participants were recreational paddleboarders, which may not reflect the results of more experienced SUP athletes. It would be beneficial to replicate this study with different participants and genders to better understand the differences and determinants of SUP performance. This should also be understood when maximal effort is required. Additionally, expanding the analysis to include more muscles would provide a deeper understanding of performance variability in SUP. Despite these challenges, the contributions of this research are noteworthy and point the way for future research in SUP.

5. Conclusion

This study used clustering modelling to categorise and identify SUP practitioners into subgroups based on performance, differentiating between faster, medium, and slower performers, and examining how neuromuscular activation and kinematics affect performance. One of the key findings of this research is that faster SUP performers were characterised by higher speed and greater SI, coupled with specific neuromuscular activation patterns during both the pull and recovery phases of the stroke. The determinants that characterised each cluster were distinct and highlighted critical neuromuscular contributions to performance variability. Among the muscles analysed, the main variables influencing the formation of clusters were the low activations of muscles during the pull and recovery phases for poor performers (*triceps brachii*), and large activation for the best performers (*upper trapezius* and *triceps brachii*). The stepwise discriminant analysis further reinforced the significance of specific muscle activations, particularly the left *upper trapezius* during the left pull and the right *triceps brachii* during the left pull, as key predictors for differentiating between performance groups. These findings emphasise that neuromuscular engagement, especially during the pull phase, along with effective preparation for the recovery phase, is crucial for achieving higher SUP performance. The implications of this study extend beyond the academic context to help SUP practitioners and coaches optimise technique and SUP performance by further understanding performance variability and its biomechanical determinants.

Disclosure statement

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Author contributions

All authors contributed equally to the manuscript and read and approved the final version of the manuscript.

Ethics approval and consent to participate

All procedures were approved by the Ethics Committee of the University.

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