



Article

Stroke Frequency Effects on Coordination and Performance in Elite Kayakers

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Abstract

Objectives: This study aimed to assess stroke coordination and biomechanics in elite U23 male kayakers under valid on-water conditions (instrumented K1 kayak on a competition lake) across race-relevant stroke frequencies (60, 80, and 100 strokes·min⁻¹). **Methods:** To achieve our aims, twelve male athletes (age 21.00 ± 0.47 years) completed 500 m trials at three randomized paddle frequencies (60, 80, 100 strokes·min⁻¹) with 10 min of passive recovery in-between. Data were collected with inertial measurement units, and a customized seat/footrest with integrated strain-gauge sensors. **Results:** Principal Component Analysis identified four key components: Mechanical Work, Mechanical Energy, Stroke Variability (PCI, Phase Coordination Index), and boat acceleration, accounting for 76% of total variance. Linear mixed-effects models (within-subject LME; Participant random intercept; Satterthwaite df) revealed that Mechanical Work ($\chi^2 = 17.10$, $p < 0.001$) and Mechanical Energy ($\chi^2 = 53.10$, $p < 0.001$) increased significantly with stroke frequency. Phase Coordination Index showed a significant increase at 60 and 100 strokes·min⁻¹ ($\chi^2 = 16.78$, $p < 0.001$; $t = 4.78$, $p < 0.001$), while boat acceleration was not significantly affected ($\chi^2 = 4.95$, $p = 0.08$). The PCI correlated negatively with Mechanical Work ($r = -0.37$, $p = 0.022$) and positively with boat acceleration ($r = 0.39$, $p = 0.010$). Effect sizes were moderate to large ($\eta^2 = 0.18$ – 0.36 ; corresponding 95% confidence intervals are reported in the main text). For the primary mechanical indicator (Paddle Factor), the mixed-effects model yielded a marginal $R^2 = 0.57$, reflecting the proportion of variance explained by cadence. **Conclusions:** Approximately 80 strokes·min⁻¹ may represent a condition in which coordination metrics appear comparatively favorable. These findings are exploratory and hypothesis-generating, not prescriptive. No causal inference can be drawn, and any training application attempts should await replication in larger, longitudinal and randomized studies.

Keywords: kayaking biomechanics; stroke frequency; movement variability; bilateral coordination; wearable sensors; on-water assessment; performance optimization



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1. Introduction

Kayaking demands precise coordination of upper limb movements and trunk rotation [1]. The rhythmic nature of paddling presents a unique opportunity to investigate motor control strategies and movement variability in a context distinct from terrestrial locomotion [2], becoming a subject of interest in sports biomechanics and motor control research. Understanding the factors that influence paddling efficiency and coordination is crucial for optimizing performance and developing evidence-based training protocols for kayak athletes [1].

Movement variability, once considered merely noise or error in motor output, is now recognized as an essential feature of the sensorimotor system that allows for adaptability and task-specific optimization [3]. In cyclic activities, such as kayaking, analyzing movement variability can provide insights into the level of motor control and coordination exhibited by athletes [4]. Research has shown that skilled performers typically demonstrate lower levels of variability in key kinematic and kinetic parameters compared to their less experienced counterparts [5]. This reduction in variability is thought to reflect a more refined and efficient motor strategy, allowing for greater consistency and precision in movement execution [5].

However, the relationship between movement variability and performance is not strictly linear [6]. While excessive variability may indeed be detrimental to performance, some degrees of variability are necessary for adaptation to changing environmental conditions and task demands [6]. This concept of “optimal variability” suggests the presence of a sweet spot in terms of movement consistency that allows for both stability and flexibility in motor output [7].

The concept of gait variability, initially developed in the context of bipedal locomotion, has proven to be a valuable tool for assessing motor control and coordination in cyclic activities [8]. Gait variability metrics, such as the Phase Coordination Index (PCI), provide quantitative measures of the consistency and symmetry of movement patterns over multiple cycles [9]. While these metrics have been successfully applied to various forms of human locomotion, including walking, running, and cycling, their application to upper limb-dominated activities, such as kayaking, remains limited [10].

One of the key parameters in kayaking performance is paddle stroke frequency, which directly influences both the propulsive forces generated and the metabolic demands placed on the athlete. Previous research has shown that manipulating stroke frequency can have a significant impact on physiological responses, biomechanical efficiency, and overall performance in kayaking [11,12]. However, the relationship between stroke frequency and movement coordination, particularly in terms of upper limb and trunk kinematics, remains poorly understood [11,13].

The selection of an optimal paddle stroke frequency represents a complex optimization problem, balancing the need for maximal power output with considerations of energy expenditure, fatigue resistance, and movement coordination [14]. While higher stroke frequencies may enable greater power generation in the short term, they also increase the metabolic cost of paddling and may lead to an earlier onset of fatigue [14]. Conversely, lower stroke frequencies may be more economical in terms of energy expenditure but may not provide sufficient propulsive force to maintain competitive speeds [15]. Given the cyclical nature of kayaking, it is plausible that certain stroke frequencies may facilitate more stable and coordinated movement patterns, potentially leading to improved performance and reduced risk of injury [16].

A significant challenge in sports science research is balancing the need for controlled experimental conditions with the desire for real water conditions. Laboratory-based studies, while offering precise measurement capabilities, may not fully capture the complexities

of real-world athletic performance [17]. This is particularly true for water-based sports, such as kayaking, where environmental factors, including water conditions, wind, and temperature, can significantly influence performance and movement patterns [18]. In the context of kayaking, field-based assessments using inertial measurement units (IMUs) and instrumented paddles have shown promise in capturing detailed information about stroke mechanics and movement patterns during on-water paddling [19].

Despite the growing body of research on human locomotion and motor control, a significant gap remains in our understanding of upper limb-dominated cyclic activities, particularly in the context of water-based sports such as kayaking. While previous studies [20,21] have investigated the physiological and biomechanical aspects of kayaking performance, little attention has been paid to the role of movement variability and coordination in determining paddling efficiency and effectiveness. Thus, it is plausible to hypothesize that an optimal stroke frequency can be identified in real water conditions, considering the variability metrics.

The aim of this study was to assess stroke coordination and biomechanics in elite U23 kayakers under real water conditions (instrumented K1 kayak on a competition lake), across race-relevant stroke frequencies (60, 80, 100 strokes·min⁻¹).

This approach provides controlled measurement accuracy while maintaining practical relevance through the use of realistic paddling posture, mechanics, and cadence typical of competition.

Based on the literature and the identified research gap, we hypothesized that

- (1) increasing paddle stroke frequency would lead to higher mechanical work and energy expenditure;
- (2) stroke variability would decrease as stroke frequency increases, reflecting greater technical stability; and
- (3) an intermediate frequency (around 80 strokes·min⁻¹) would represent an optimal balance between efficiency, coordination, and performance.

This study adopts a real-water conditions approach by conducting assessments in a real-world kayaking environment, using advanced sensor technology to capture detailed kinematic and kinetic data.

To clarify the study framework, the following prespecified outcomes and inferential priorities were established.

The primary outcome was the *Mechanical Work* component (PC1) extracted from the Principal Component Analysis, representing the latent construct of work and power transfer during paddling. *Mechanical Energy* (PC2), *Stroke Variability* (PC3), and *Boat Acceleration* (PC4) were defined as co-primary components within the same family, and were controlled for multiplicity using Holm–Bonferroni adjustment.

The secondary outcomes included variable-level indices, the *Phase Coordination Index* (PCI), and correlational analyses with training experience (HRWEEK) and transmission efficiency (TE).

Accordingly, the primary hypothesis (H1) focused on frequency-dependent increases in *Mechanical Work* and *Mechanical Energy*; H2 addressed a decrease in coordination variability (PCI) with increasing stroke frequency; and H3 explored the possibility that an intermediate cadence (~80 strokes·min⁻¹) would represent an optimal compromise between efficiency and coordination.

The inferential strategy was based on within-subject linear mixed-effects models (LME) with *Participant* as random intercept and *Satterthwaite* degrees of freedom approximation, which are fully consistent with the Statistical Analysis section.

2. Materials and Methods

2.1. Participants

Twelve male kayaker athletes (age 21.0 ± 0.5 years, body mass 79.5 ± 6.9 kg, body height 180.9 ± 4.7 cm, training experience 9.9 ± 4.0 years, with a weekly training of 18.0 ± 6.3 h, 10 right-hand dominant, 2 left-hand dominant) voluntarily participated in this study.

Inclusion criteria were Nationally Ranked Italian athletes aged 20–21 years, >4 training sessions per week, >4 years of training experience. The subjects were healthy without any muscular, neurological, or tendinous injuries and did not report the use of any drugs. The diet control in pre-study was designed to eliminate the risk of any major differences between diets in total protein, carbohydrates, saturated, and unsaturated fats. The experimental protocol was approved by the local Ethics Committee. All participants provided written informed consent, in accordance with the principles set out in the Declaration of Helsinki. After being informed of procedures, methods, benefits, and possible risks related to the study, each participant reviewed and signed informed consent to participate in the study, in accordance with ethical standards and the Helsinki Declaration.

This study was approved by the local Ethics Committee institution and conducted in agreement with the ethical guidelines.

2.2. Experimental Setting

Testing was carried out on a single day for all participants using a crossover study design on the same 500 m regatta course. Environmental conditions were monitored throughout the session; no rainfall occurred, wave height remained low, and wind was light and approximately aligned with the course, ensuring that hydrodynamic and aerodynamic conditions remained as constant as possible across all trials. No bouts were performed under strong crosswinds, whitecaps, or boat traffic. Average air temperature was 17°C , humidity 71%, wind speed $4\text{ km}\cdot\text{h}^{-1}$, and water temperature 13°C , on a lake typically used for national competitions.

All participants were in good health at the time of testing. Each kayaker performed on an individual kayak (Olympic K1 Vanquish—Nelo™, Size XL–L–M) equipped with seat and foot sensors [13], each integrating four strain gauges (100 Hz). Signals were transmitted via Bluetooth to a laptop running CoreMeter™ 0.9 software (Latina, Italy), which was calibrated and checked with different loads before each trial.

Each participant performed a standardized 10 min warm-up, consisting of paddling for 10' at self-selected stroke, followed by 5 min of active muscular dynamic stretching [22]. Subsequently, each participant performed 500 m time trials at three randomly ordered stroke frequencies (60, 80, 100 strokes·min^{−1}) using a metronome (Tempo Trainer PRO, FINIS Inc., Livermore, CA, USA) with 10 min of passive recovery between trials. Each Kayaker started in a square (3 m) delimited by 4 boats. At the start signal, the kayaker followed the path of the boats, staying 3 m between the right and left boats. Boats were placed at a distance of 50 m from the start line up to the 500 m finish line.

The use of an instrumented kayak setup in a competition lake allowed the replication of race-specific paddling posture, boat hydrodynamics, and stroke rhythm, in a real water condition that balance experimental control with real-world relevance.

All measurements were conducted by the same researcher using standardized instructions without performance feedback. Trials were performed in randomized order (60, 80, and 100 strokes·min^{−1}) to avoid learning or order effects. Data files were coded anonymously before analysis to minimize researcher influence.

2.3. Measurement

The biomechanical data collection was carried out using a multisensory acquisition system designed to capture both force distribution and movement dynamics during kayak paddling. Two custom-built measurement modules were integrated into the kayak (Figure 1A): one at the seat (Figure 1B) and the other at the footrest (Figure 1C). Each module included four strain-gauge-based load cells (sampled at 100 Hz) to quantify the vertical and horizontal force components applied by the athlete. These force measurements enabled the calculation of key variables, such as mechanical work, power output (W), and center of pressure dynamics (2D displacement and velocity), at both the seat and foot interfaces. These parameters were further used to compute indices of efficiency, coordination, and symmetry.

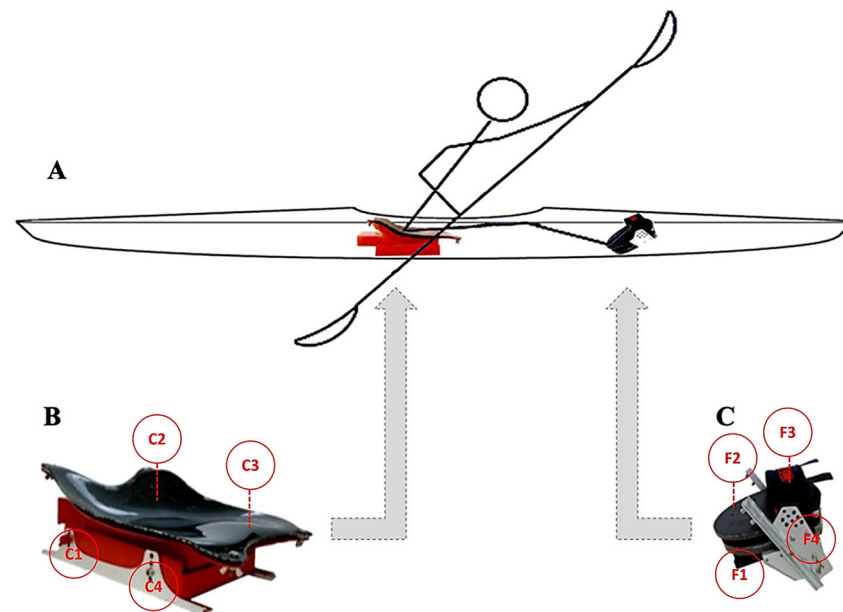


Figure 1. Schematic representation of the instrumented kayak: (A) athlete–kayak overview; (B) seat assembly (20 × 20 cm) with four uniaxial strain-gauge cells located at the corners (Nintendo Wii Balance Board RVL-021, Nintendo Co., Ltd., Kyoto, Japan); (C) footrest assembly (20 × 20 cm) with four uniaxial strain-gauge cells. A triaxial accelerometer (ADXL330, Analog Devices, Wilmington, NC, USA) was aligned with the longitudinal axis of the hull. Mounting locations of strain-gauge cells and accelerometer are indicated. Channel labels (Seat C1–C4; Foot F1–F4) correspond to calibration entries in Table S1 and coordinates shown in Supplementary Figure S1.

Additionally, a triaxial accelerometer (Analog Devices ADXL330, Wilmington, NC, USA) was integrated into the seat (Figure 1B) and placed longitudinally along the kayak hull to measure forward acceleration (ACC , $m \cdot s^{-2}$) throughout the stroke cycle. This data contributed to identifying variations in boat dynamics associated with changes in stroke frequency and was later used as one of the key factors in Principal Component Analysis (PCA). The integration of a sensorized footrest and seat with inertial data provided a detailed view of the mechanical output and postural contributions of the athlete during each paddling trial.

These validation results ensured that the mechanical work and power estimates derived from these force and displacement signals (see Section 2.6) were based on linearly calibrated, time-synchronized data with negligible bias (<1%), fully comparable to laboratory-grade force platforms [23,24].

Strain-gauge system, calibration, and telemetry.

Seat and footrest modules incorporated a strain-gauge-based load-cell system implemented using a Nintendo Wii Balance Board (model RVL-021, Nintendo Co., Ltd., Kyoto,

Japan), hosting four uniaxial strain-gauge cells positioned at the four corners of each platform (see Figure 1).

Calibration followed a multi-point linear protocol with certified masses according to [24], generating load–voltage calibration curves for each cell and for the overall center of pressure (CoP). This procedure reduced CoP error from -10.5 to -0.05% , confirming high linearity and sensitivity. Cross-axis effects were minimized through symmetric mechanical mounting and verified as negligible within the operative range.

Telemetry and sampling.

Data were streamed via Bluetooth HID at ~ 50 – 100 Hz and later time-aligned and resampled to 100 Hz prior to zero-lag low-pass filtering (5 Hz) to correct for small irregularities in sampling frequency. No data dropouts or synchronization mismatches were observed in the acquisition logs.

Geometric and computational adaptation (CoreMeter dual-module 20×20 cm system).

The original Wii Balance Board (WBB, RVL-021) electronics and load cells were mechanically redistributed into two independent rigid modules (seat and footrest), each built as a 20×20 cm plate carrying four uniaxial sensors. Each module was managed by CoreMeter™ software, which handles both devices as synchronized HID streams and performs geometry scaling and dimensionless CoP (Center of Pressure) computation.

Raw 4-channel force vectors (F_i) were converted to normalized coordinates within the $[-1, +1]$ range using

$$x^*CoP = \frac{\sum_i F_i x_i}{\sum_i F_i}, \quad y^*CoP = \frac{\sum_i F_i y_i}{\sum_i F_i}$$

with $x_i, y_i = \pm 0.5$ corresponding to the physical plate coordinates (± 0.10 m). These dimensionless values were rescaled to metric units (mm) through multiplication by half-side length ($L = 0.10$ m). This normalization ensures that the CoP/CLD equations remain equivalent to those of [23,24], despite geometry reduction.

Each module was recalibrated during its final mount.

CoreMeter automatically applied per-channel calibration constants (a, b) and bias correction. Bench verification showed $R^2 \geq 0.998$, $RMSE \leq 0.7$ N, cross-axis $< 5\%$ FS, and module-level CoP (CLD) error < 3 mm, confirming equivalence to original WBB performance.

No additional in-field calibration was performed between trials. Before each testing session, the seat and foot modules were inspected to ensure stable mounting and verified for zero-load baselines. Bench checks conducted immediately before and after the full testing session showed negligible drift (≤ 0.7 N and < 3 mm CoP shift), corresponding to less than 0.5% of the sensors' operational range. Given this minimal and stable drift, no temperature- or mounting-related correction was required during the experimental protocol.

Signal conditioning. Raw strain-gauge voltages were first demeaned per trial and converted to force using the per-channel calibration $F_i = a_i V_i + b_i$ (Table S1). Force channels were zero-phase low-pass filtered (4th-order Butterworth, 5 Hz) to attenuate high-frequency noise. The triaxial accelerometer (ADXL330) longitudinal axis was zero-phase low-pass filtered (4th-order Butterworth, 10 Hz). A mains notch filter was not required because spectra showed negligible $50/60$ Hz contamination under low-pass constraints.

Module resultant and CoP/CLD. For each 20×20 cm module (seat/foot), the resultant force was computed as follows:

$$F = \sum_{i=1}^4 F_i$$

The module-level Center of Pressure/Load Distribution (CoP/CLD) was obtained via the weighted centroid:

$$x^* = \frac{\sum_i F_i x_i}{\sum_i F_i}, y^* = \frac{\sum_i F_i y_i}{\sum_i F_i}$$

with normalized coordinates $x_i, y_i \in \{-0.5, +0.5\}$ corresponding to physical ± 0.10 m (CoreMeter™ adimensionalization). CoP/CLD time series were numerically differentiated with a Savitzky–Golay differentiator (frame 11 samples, poly order 2) to obtain planar velocities, then low-pass 5 Hz as above to suppress differentiation noise. These steps are implemented identically for seat and foot modules.

Reliability and validation.

Previous studies have demonstrated good–excellent accuracy and reliability of this device compared with laboratory-grade force plates, reporting force uncertainty ± 9.1 N, CoP uncertainty ± 4.1 mm, and ICC = 0.66–0.94 [23–25]. These findings are consistent with our own calibration results and support the confidence of force, displacement, and energy estimates obtained with this system. One example of individual data from the accelerometer is denoted in Supplementary Figure S2.

Manufacturer, model, and specification sheets.

The strain-gauge modules were implemented using a Nintendo Wii Balance Board (RVL-021, Nintendo Co., Ltd., Kyoto, Japan) hosting four uniaxial strain-gauge load cells per module (seat/foot). Specification sheets and device documentation for the RVL-021 module and the ADXL330 accelerometer are provided in Supplementary Table S2. For completeness, empirical effective sensitivity (V/N) derived from our calibration is reported per channel in Table S1 together with linearity, RMSE, and bias metrics.

Calibration procedure and results (bias, linearity, RMSE).

Each load-cell channel was calibrated with a multi-point linear protocol (≥ 5 static loads with certified masses) following Leach et al.; per-channel calibration curves were fit as $V = a \cdot F + b$ (V in Volt, F in Newton). For each channel we report slope as (V/N), intercept b (V), R^2 (linearity), RMSE (N) from cross-validated fits, and bias (N) calculated as the mean of the offcuts ($\hat{F} - F$) on calibration points. Per-channel results are summarized in Supplementary Table S1 (Seat C1–C4; Foot F1–F4); Supplementary Figure S3 shows the V–F curves and the residuals. At the system level, the CoP solution improved from -10.5 to -0.05% error after calibration (bench check), which is consistent with high linearity and sensitivity.

Per-sensor timestamp synchronization and packet loss.

Bluetooth HID streams (seat/foot/IMU) were timestamped on host arrival using a monotonic system clock, and then time-aligned by linear interpolation to a common axis and resampled at 100 Hz prior to zero-lag low-pass filtering (5 Hz). Stream integrity was verified by scanning inter-arrival intervals and cumulative sample counts; no missing packets or desynchronization events were detected in the analyzed trials. Diagnostics are reported in Supplementary Table S3 (mean Δt , SD Δt , max gap, packet loss %, drift over 500 m per stream), and a representative sampling timeline is shown in Supplementary Figure S4.

2.4. Phase Coordination Index Calculation

The coordination between right to left paddling was measured with PCI [26] using the single stroke time and stroke cycle time (the stroke cycle time is composed of two single stroke times). First, the Phi value (in degrees) was calculated (Equation (1)) for each stroke cycle I , as follows:

$$Phi(i) = \frac{\text{Single stroke time} \left(LL_{\text{short-aerial phase}} \right)}{\text{Stroke time} \left(LL_{\text{long-aerial phase}} \right)} \times 360^\circ \quad (1)$$

Then, the bilateral accuracy (in %) was calculated as follows:

$$Accuracy = \frac{|Phi - 180|}{180} \times 100^\circ \quad (2)$$

The bilateral variability (in %) was determined in Equation (3):

$$Variability = \frac{Phi_{SD}}{Phi_{Mean}} \times 100 \quad (3)$$

Finally, PCI (in %) was calculated in Equation (4), as follows:

$$PCI = Accuracy + Variability \quad (4)$$

Symmetry index calculation.

Bilateral Asymmetry (BASY) was evaluated using Robinson's proposal [27]:

$$Symmetry\ index = 100 \times |X_r - X_l| / 0.5(X_r + X_l) \quad (5)$$

2.5. Signal Conditioning, Filtering, and Stroke-Cycle Segmentation

Raw strain-gauge voltages were first demeaned per trial and converted to force using the per-channel calibration equation $F_i = a_i V_i + b_i$ (see Table S1). The four force channels from each module were then combined to compute the resultant force $F = \sum_i F_i$. Force signals were zero-phase low-pass filtered using a fourth-order Butterworth filter at 5 Hz to attenuate high-frequency noise, which was negligible beyond the paddling frequency band. The triaxial accelerometer (ADXL330) longitudinal axis was processed using a fourth-order Butterworth low-pass filter at 10 Hz, removing transient artifacts but preserving stroke-level dynamics. Spectral checks confirmed that no 50/60 Hz mains noise was present, making a notch filter unnecessary. The module-level Center of Pressure/Load Distribution (CoP/CLD) was obtained via the weighted centroid of the four calibrated forces:

$$x_{CLD} = \frac{\sum_i F_i x_i}{\sum_i F_i}, y_{CLD} = \frac{\sum_i F_i y_i}{\sum_i F_i},$$

where $x_i, y_i \in \{-0.5, +0.5\}$ correspond to normalized coordinates (± 0.10 m physical distance). CoP/CLD traces were numerically differentiated using a Savitzky–Golay differentiator (frame length 11 samples, polynomial order 2) to obtain planar velocities. The resulting signals were low-pass filtered again at 5 Hz to reduce differentiation noise.

Stroke-cycle segmentation was based on combined criteria from longitudinal acceleration and foot resultant force. Local acceleration peaks (minimum distance ≥ 0.4 s, prominence ≥ 0.5 SD) defined cycle boundaries, while stroke onset was identified as the first frame where the foot resultant exceeded 5 N above baseline for ≥ 80 ms, and offset as the final frame below this threshold before the next acceleration peak. This hybrid criterion ensured robust segmentation at all cadences (60, 80, 100 strokes·min⁻¹). Cycles failing these criteria (<2%) were flagged and excluded. Work and mechanical energy were estimated at each interface (seat, foot) as follows:

$$W_{mod} = \int F(t) |v_{CLD,\parallel}(t)| dt$$

where $v_{CLD,\parallel}$ is the CLD velocity component projected along the kayak's longitudinal axis. Mechanical energy was derived as the integral of F^2 over time, and normalized by stroke duration, forming an effort index. All computed variables were z-scored prior to PCA and analyzed through linear mixed-effects models as described in Section 2.6.

2.6. Mechanical Work and Transmission Efficiency

The force and displacement data were processed in a custom algorithm in LabVIEW software (v. 16, National Instruments, Austin, TX, USA). The instantaneous human mechanical work was considered to be the product of instantaneous force and displacement. The sum of all positive values of this product during the rowing cycle was considered as positive mechanical work. Average values were calculated from all paddling cycles during the test. The mechanical work of the kayak was defined by estimating the wave, pressure, and friction drag forces, based on data from [28], as follows. The drag equations proposed by Gomes et al. [28] were adopted because they were experimentally validated on sprint kayak hulls at race-relevant speeds. These power-law models accurately describe the velocity dependence of wave, friction, and pressure drag for slender displacement craft such as K1 kayaks, ensuring biomechanical consistency with previous studies.

Force and displacement signals from both modules (seat and footrest; Section 2.3) were projected along the kayak's longitudinal axis before integration, ensuring biomechanical consistency between human mechanical work (input) and boat mechanical work (output).

$$\text{Wave drag (N)} = 0.06 \times \text{speed}^3 \times 0.07 \quad (6)$$

$$\text{Friction drag (N)} = 2.96 \times \text{speed}^1 \times 1.77 \quad (7)$$

$$\text{Pressure drag (N)} = 0.75 \times \text{speed}^1 \times 1.96 \quad (8)$$

The drag forces were multiplied by displacement to reach mechanical work. The displacements were determined by the triaxial accelerometer. The three immediate sources of energy used for the mechanical work of the kayak were summed, resulting in boat mechanical work (BExW, Table 1). Both human and boat mechanical work are expressed in kJ. Furthermore, the transmission efficiency was calculated as the ratio of the boat mechanical work (output) to the human mechanical work (HExW, input, Table 1) in percentage terms [29].

Table 1. Measured variables with acronym and description.

Variable	Acronym	Notes/Description
Acceleration ($\text{m} \cdot \text{s}^{-2}$)	ACC	Longitudinal acceleration by accelerometer (Analog Devices ADXL330, Wilmington, NC, USA).
Time (s)	TIME	Total time required to complete the 500 m, measured using a digital stopwatch (Seiko® S141).
Speed ($\text{m} \cdot \text{s}^{-1}$)	V	Average speed calculated as distance divided by time; the standard distance was 500 m.
Frequency ($\text{stroke} \cdot \text{min}^{-1}$)	FREQ	Stroke frequency: 60, 80, and 100 strokes $\cdot \text{min}^{-1}$.
Weekly training (h)	HRWEEK	Total weekly training hours.
Transmission efficiency (%)	TE	Percentage efficiency indicator, representing how much of the athlete's generated force or energy is effectively transferred to the paddle/kayak. Formula: $\text{TE}(\%) = \text{Output/Input} \times 100$.
Human mechanical work (kJ)	HExW	External mechanical work done by the athlete, excluding internal losses. Estimated as $\text{HExW} = F \times d$, where F is force on the paddle, and d is distance covered.
Boat mechanical work (kJ)	BExW	External mechanical work done on the boat, computed from wave drag, friction drag, and pressure drag and the displacements were determined using a triaxial accelerometer.
Foot 2D Wcom ($\text{J} \cdot \text{kg}^{-1} \cdot \text{m}^{-1}$)	F2D	Estimates 2D mechanical work at the foot level.
Foot vy ($\text{m} \cdot \text{s}^{-1}$)	FAP	Instantaneous velocity (2D antero-posterior and medio-lateral) of the foot's center of pressure (COP) over time.

Table 1. Cont.

Variable	Acronym	Notes/Description
Foot 2D Pcom (J)	F2P	Two-dimensional antero-posterior and medio-lateral COP position on foot over time. Firstly, used to calculate its instantaneous velocity (v [m/s]). Then v was put into the mechanical kinetic energy (J per stroke) (E_k) equation: $E_k = \frac{1}{2} m \cdot v^2$, where m as subject's mass.
Stroke frequency variability	SDA100FARPM	The standard deviation of the average cycle-to-cycle intervals over 100 cycles of accelerometry frequency.
Stroke frequency variability	SDA100FPRPM	The standard deviation of the average cycle-to-cycle intervals over 100 cycles of foot sensors frequency.
Stroke frequency variability	SDA100FSRPM	The standard deviation of the average cycle-to-cycle intervals over 100 cycles of seat sensors frequency.
Power variability	SDA100EP	The standard deviation of the average cycle-to-cycle intervals over 100 cycles of foot energy.
Power variability	SDA100ES	The standard deviation of the average cycle-to-cycle intervals over 100 cycles of seat energy.
Seat 2D Wcom ($J \cdot kg^{-1} \cdot m^{-1}$)	S2D	Two-dimensional mechanical work at the seat level.
Seat v_y ($m \cdot s^{-1}$)	SAP	Instantaneous seat velocity from antero-posterior and medio-lateral COP data.
Seat 2D Pcom (J)	S2DP	Mechanical kinetic energy at the seat, using $E_k = \frac{1}{2} m v^2$, where m is the athlete's mass.
Paddle Factor (% sec)	PF	Ratio of stroke cycle time spent in the propulsion phase, i.e., 100 (Equation (9)).
Phase Coordination Index (%)	PCI	Index measuring bilateral coordination of paddling using phase variability and accuracy [26].
Bilateral Asymmetry (%)	BASY	Index based on Robinson's method to quantify asymmetry between right and left limbs [27].

2.7. Paddle Factor

The paddle duty factor, as well as for walking and running approaches, is determined as a fraction of the stroke cycle time at which one propulsion phase is completed (%).

$$\text{Paddle factor} = 100 \times \text{propulsion time} \div \text{stroke cycle time} \quad (9)$$

2.8. Time

The time to complete each 500 m trial was recorded using a handheld digital stop-watch (Seiko® S141, Tokyo, Japan). Kayak velocity was then calculated using the formula: speed = distance/time, where the distance was fixed at 500 m for all trials.

2.8.1. Statistical Analysis

To aid readers who are less familiar with multivariate statistics, we briefly summarize the analytical approach. Because many biomechanical variables were correlated, we first used Principal Component Analysis (PCA) to group them into a smaller set of summary scores (components) describing mechanical work, mechanical energy, variability, and acceleration. We then examined how these components and selected variables changed with stroke frequency using linear mixed-effects models, which account for the repeated-measures design (each athlete tested at all three cadences). Full technical details and R code are provided in the Supplementary Materials.

Principal Component Analysis (PCA) was performed on standardized (z-scored) biomechanical variables listed in Table 1. Sampling adequacy ($KMO = 0.74$) and Bartlett's test of sphericity ($\chi^2 = 312.8$, $df = 105$, $p < 0.001$) confirmed the suitability of the dataset for PCA. Four components were extracted, explaining 76% of the total variance (29%, 26%, 12%, and 9%) and labeled Mechanical Work, Mechanical Energy, Variability, and Acceleration.

Component retention followed standard criteria: (i) eigenvalues > 1 (Kaiser criterion); (ii) a clear elbow at the fourth component in the scree plot; and (iii) a prespecified cumulative variance threshold ($\geq 70\%$) together with interpretability of the loading pattern. No rotation was applied because the components were already clearly interpretable.

To evaluate the effect of stroke frequency (60, 80, 100 strokes·min⁻¹) on the four PCA components and on the biomechanical outcomes reported in Table 2, linear mixed-effects (LME) models were applied. This approach is appropriate for repeated-measures designs, as it accounts for both fixed effects (e.g., Frequency) and random effects (e.g., participant variability), offering greater statistical power and flexibility in handling missing data [30,31]. Statistical analyses were performed in R [32] using the packages lme4 [31], lmerTest [33], and emmeans. All PCA, LME, and bootstrap procedures were run using a fixed random seed (set.seed) to ensure full reproducibility. The same seed is included in Supplementary Materials.

Table 2. Kinetic/kinematic, phase coordination index, and mechanical work at different paddle frequencies.

Variables (Units)	Paddle Frequencies (Strokes·min ⁻¹)			ANOVA	
	60	80	100	F-Test (DF)	p-Value
SDA100FARPM (strokes·min ⁻¹)	1.50 ± 0.24	0.88 ± 0.23	1.03 ± 0.23	2.48 (2, 22.53)	0.106
SDA100ES (strokes·min ⁻¹)	0.92 ± 0.34 ‡	1.03 ± 0.33	1.40 ± 0.33	3.87 (2, 22.05)	0.036
FAP (m·s ⁻¹)	0.12 ± 0.01 ††	0.15 ± 0.01 *	0.18 ± 0.01	42.37 (2, 22.03)	<0.0001
S2D (J·kg ⁻¹ ·m ⁻¹)	0.12 ± 0.04	0.15 ± 0.04	0.16 ± 0.04	2.90 (2, 22.04)	0.076
SAP (m·s ⁻¹)	0.11 ± 0.02 ‡	0.13 ± 0.02 *	0.16 ± 0.02	16.03 (2, 22.03)	<0.0001
S2DP (J)	1.57 ± 0.78 ‡	2.12 ± 0.77	3.14 ± 0.76	4.30 (2, 22.10)	0.0265
HEXW (kJ)	46.1 ± 9.59 ‡	60.5 ± 9.40	71.1 ± 9.32	5.17 (2, 22.14)	0.0144
PCI (%)	3.32 ± 1.80 ‡	2.34 ± 0.60	2.78 ± 0.91	2.13 (2, 22.00)	0.143
SDA100EP (strokes·min ⁻¹)	1.50 ± 0.47 ††	2.80 ± 0.46	3.22 ± 0.46	19.88 (2, 22.07)	<0.0001
F2D (J·kg·m ⁻¹)	0.32 ± 0.05 ††	0.43 ± 0.05	0.47 ± 0.05	35.56 (2, 22.02)	<0.0001
F2P (J)	2.21 ± 0.69 ††	3.84 ± 0.68 *	5.16 ± 0.68	34.82 (2, 22.05)	<0.0001
PF (% sec)	0.18 ± 0.01 ††	0.19 ± 0.01 *	0.22 ± 0.01	53.34 (2, 22.10)	<0.0001
BEXW (kJ)	18.5 ± 0.49 ††	21.6 ± 0.47 *	24.6 ± 0.46	72.54 (2, 22.28)	<0.0001
BASY (%)	6.54 ± 0.79	4.71 ± 0.75	5.41 ± 0.73	1.58 (2, 22.91)	0.226
SDA100FSRPM (strokes·min ⁻¹)	1.48 ± 0.26	1.03 ± 0.25	1.21 ± 0.24	0.79 (2, 23.16)	0.465
ACC (m·s ⁻²)	0.04 ± 0.004	0.03 ± 0.004 *	0.04 ± 0.003	3.75 (2, 22.34)	0.039

Note: All data are expressed as mean ± SD. Tests in Table 2 are LME F-tests for the fixed effect of Frequency (Participant random intercept; Satterthwaite df via lmerTest), unless otherwise indicated. Fractional df indicate LME Satterthwaite approximations. Tukey-adjusted pairwise contrasts are reported; the false discovery rate was controlled at $q = 0.05$ (Benjamini–Hochberg). Significant differences are denoted with $p < 0.05$ between the different paddle frequencies (60–80, 60–100, 80–100 are denoted as “†”, “††” and “*”, respectively).

2.8.2. LME Model Specifications

Stroke frequency was entered as a categorical within-subject factor with three levels (60, 80, 100 strokes·min⁻¹; reference level = 60 strokes·min⁻¹). For each dependent variable y (each PCA component and each biomechanical outcome in Table 2), we fitted a within-subject linear mixed-effects model of the form:

$$y_{ij} = \beta_0 + \beta_1 \cdot \text{Freq80}_j + \beta_2 \cdot \text{Freq100}_j + u_{0i} + \varepsilon_{ij},$$

where i indexes participants ($i = 1, \dots, 12$) and j indexes frequency conditions ($j = 1, 2, 3$). Participant-specific random intercepts u_{0i} were assumed to follow a normal distribution $N(0, \sigma_u^2)$, and residual errors $\varepsilon_{ij} \sim N(0, \sigma^2)$ with homogeneous variance and independence across participants. Models including by-participant random slopes for Frequency (i.e., $(1 + \text{Frequency} \mid \text{Participant})$) were explored but led to singular fits and did not change the fixed-effect estimates; therefore, we retained the parsimonious random-intercept structure, in line with recommendations for small repeated-measures samples [30,31].

Likelihood-ratio χ^2 tests for the fixed effect of Frequency were obtained by comparing the full model (including Frequency) with a nested model without Frequency, both fitted by maximum likelihood. For the results reported in Table 2, the same models were refitted with restricted maximum likelihood, and F-tests with Satterthwaite degrees of freedom were computed using the *lmerTest* package, yielding fractional df.

For each LME model, estimated marginal means (EMMs) with 95% confidence intervals were obtained for the three frequency levels (60, 80, 100 strokes·min⁻¹) using the *emmeans* package (v. 1.10.5; Iowa City, IA, USA) in R. Standardized effect sizes (partial η^2 and Cohen's f) and model fit indices (Nakagawa's marginal and conditional R^2) were computed using the *effect size* and *performance* packages in R. These indices, together with the EMMs $\pm$ 95% CI, are reported in Supplementary Table S4. The mean number of valid stroke cycles per participant $\times$ frequency condition is provided in Supplementary Table S4 (Panel A).

Pairwise contrasts among frequencies were estimated using the *emmeans* package with Tukey adjustment, while false-discovery-rate control (Benjamini–Hochberg) was applied across exploratory variable-level outcomes. Thus, the χ^2 , F , and t statistics reported in the results sections all derive from the same underlying LMEs. The correlations between the four PCA components and external indicators (PCI, HRWEEK, TE) were computed using Pearson's r (*cor.test* in R). For each correlation, uncertainty was quantified using non-parametric percentile bootstrap 95% confidence intervals (2000 resamples). We report r , the bootstrap 95% CI, the corresponding t -statistic with degrees of freedom ($df = 34$), and the exact two-tailed p value. To account for multiple testing across the 12 correlations examined (4 components $\times$ 3 external indicators), p values were adjusted using the Benjamini–Hochberg false discovery rate (FDR) procedure with $q = 0.05$. Both raw and FDR-adjusted p values (q) are reported in Supplementary Table S5.

2.8.3. Preliminary Checks

Assumptions of normality and homogeneity of variance were verified before performing inferential analyses. The Shapiro–Wilk and Levene's tests were applied to each variable, confirming that data distributions did not significantly deviate from normality and variances were homogeneous ($p > 0.05$). Residuals from LMEs were visually inspected (Q–Q and residual–fitted plots) to confirm normality and homoscedasticity. Outliers (>3 SD from the mean) were examined case-by-case, and sensitivity analyses confirmed the robustness of the results.

2.8.4. Multiplicity Control

For the four prespecified PCA components (primary outcomes), omnibus p values were adjusted across components using the Holm–Bonferroni procedure. For variable-level exploratory analyses (Table 2), pairwise contrasts among frequencies (60–80, 60–100, 80–100) were Tukey-adjusted (*emmeans*), and the false discovery rate (Benjamini–Hochberg) was controlled at $q = 0.05$ across variables. We report adjusted p values and partial η^2 .

For the correlational analyses (Section 3.3), multiple testing across the 12 component–indicator pairs were controlled using the Benjamini–Hochberg FDR procedure ($q = 0.05$).

Each observation represented one participant $\times$ frequency condition ($n = 36$) with no missing values. Component extraction followed eigenvalue > 1 , scree plot elbow, and cumulative variance $\geq 70\%$. Parallel analysis confirmed a four-component solution (Supplementary Figure S5). Factor loadings ≥ 0.6 were considered salient [34], providing stable estimates for $n \approx 30$ –50. Loadings below this threshold are reported in Supplementary Table S6.

Sampling adequacy and factorability of the correlation matrix were assessed using the Kaiser–Meyer–Olkin (KMO) index and Bartlett’s test of sphericity. The full Pearson correlation matrix, together with KMO values and Bartlett’s test, is reported in Supplementary Table S7. The scree plot and the results of the parallel analysis used for component retention are shown in Supplementary Figure S5. To evaluate the stability of the PCA solution, we ran a non-parametric bootstrap with 1000 resamples; median loadings and 95% confidence intervals are reported in Supplementary Table S8, confirming the robustness of salient loadings (≥ 0.6) and their signs. The commented R script used to perform PCA and mixed-effects models, together with the standardized data matrix (participant $\times$ frequency conditions), is provided in the Supplementary Materials.

All fifteen biomechanical variables listed in Table 1 were included in the PCA as standardized (z-scored) averages per participant $\times$ frequency condition.

Thus, all valid stroke cycles within each participant $\times$ frequency condition were averaged prior to PCA; no stroke-level cycles were entered into the component extraction.

The retained components, their eigenvalues, and explained variance are summarized in Table 3, where only salient loadings (≥ 0.6) are displayed. Sub-threshold loadings are reported in Supplementary Table S6 for full transparency.

Table 3. Principal Component Analysis (PCA) performed on standardized (z-scored) variables.

	Factor Loadings				Commonalities
	Component 1	Component 2	Component 3	Component 4	
SDA100FARPM	−0.40	0.24	0.61	−0.05	0.59
SDA100ES	0.93	−0.08	−0.03	0.02	0.87
FAP	−0.35	0.77	−0.07	−0.27	0.79
S2D	0.95	−0.07	0.07	0.16	0.93
SAP	0.90	−0.09	−0.22	0.02	0.86
S2DP	0.96	−0.04	−0.04	0.03	0.92
HExW	−0.37	0.57	−0.26	−0.26	0.59
SDA100EP	0.05	0.83	0.29	0.32	0.87
F2D	−0.03	0.83	0.41	0.13	0.87
F2P	−0.16	0.89	0.21	0.16	0.88
PF	0.47	0.54	−0.25	0.07	0.57
BExW	0.26	0.61	−0.56	0.08	0.75
BASY	−0.36	0.07	− 0.50	0.47	0.60
SDA100FSRPM	0.01	0.13	0.63	−0.04	0.41
ACC	0.21	0.13	−0.09	0.87	0.82
Eigenvalue	4.40	3.86	1.82	1.30	
Percentage of variance	29.33	25.73	12.13	8.67	

The table reports eigenvalues, percentage of variance explained, cumulative variance, and salient factor loadings (≥ 0.60). Loadings below this threshold are provided in Supplementary Table S6. Percentages of variance are computed relative to the total variance of the 15 standardized variables (sum of eigenvalues = 15); no rotation was applied. Factor loadings lower than 0.6 were not included in the table.

3. Results

A Principal Component Analysis (PCA) was applied to decompose the data into its underlying factors and reduce the number of temporal and kinematic variables to obtain

protection against the Type I error. No rotation was applied. We selected four components, which accounted for 76% of the variance (29, 26, 12, 9%, respectively). Weights of the kinematic parameters for the first four components are reported in Table 3.

The first four eigenvalues (4.40, 3.86, 1.82, 1.30) exceeded unity and the scree plot showed an elbow at the fourth component; the cumulative variance (76%) met our a priori retention threshold.

The first component includes SDA100ES, S2D, SAP, and S2DP, representing the mechanical work. The second component comprises FAP, HExW, SDA100EP, F2D, F2P, PF, BExW, and represents the mechanical energy. The third component includes BASY, SDA100FPRPM, and SDA100FSRPM, representing the variability component. Finally, the fourth component includes ACC, and it represents the acceleration component.

3.1. Commentary on Principal Component Analysis (PCA)

Principal Component Analysis (PCA) enabled the synthesis of complex data related to paddling, identifying four main components that represent kinematic and physiological variables (Table 3). The violin plots (Figure 2) illustrate the distribution of each component in relation to three paddling cadences (60, 80, and 100 strokes·min⁻¹), highlighting how these affect technique and movement efficiency.

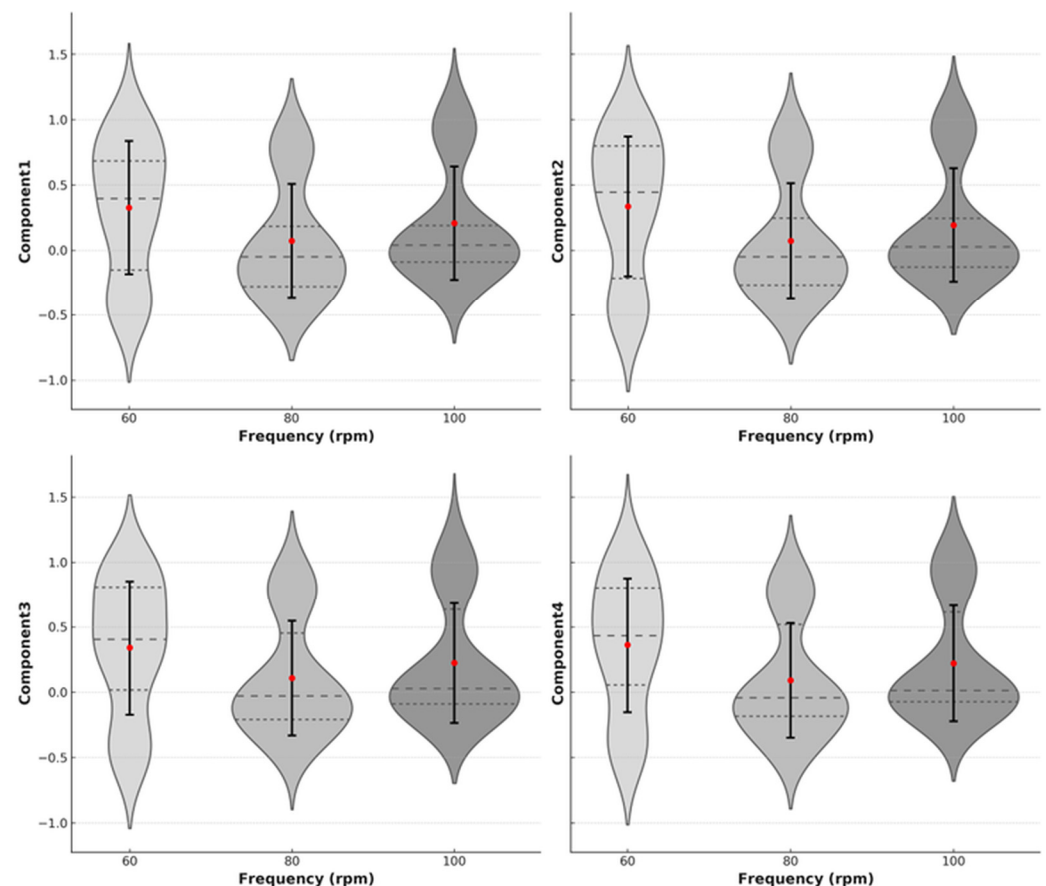


Figure 2. Violin plots showing the distribution of the first four principal components across three paddling cadences (60, 80, and 100 strokes·min⁻¹), highlighting the influence of stroke frequency on technique and movement efficiency. The red dots represent the mean values for each condition. The internal horizontal dashed lines indicate the quartiles (25th percentile, median, and 75th percentile). The shading intensity differentiates the paddling cadences: light gray (60 strokes·min⁻¹), medium gray (80 strokes·min⁻¹), and dark gray (100 strokes·min⁻¹).

Each plot highlights the following:

- The shape of the violin represents the density of values; a wider shape indicates a higher concentration, whereas a narrower shape signifies a more uniform distribution.
- Error bars, positioned at the center of the violin, indicate the mean (central point) and standard deviation (bar length). Shorter bars reflect greater consistency in the data, while longer bars indicate higher variability.

To contextualize the PCA-derived patterns reported in Figure 2, we provide an illustrative summary of how the stroke cycle was temporally distributed across the three imposed cadences. Figure 3 shows the mean proportion of the recovery and propulsive phases derived from the Paddle Factor values at 60, 80, and 100 strokes·min⁻¹.

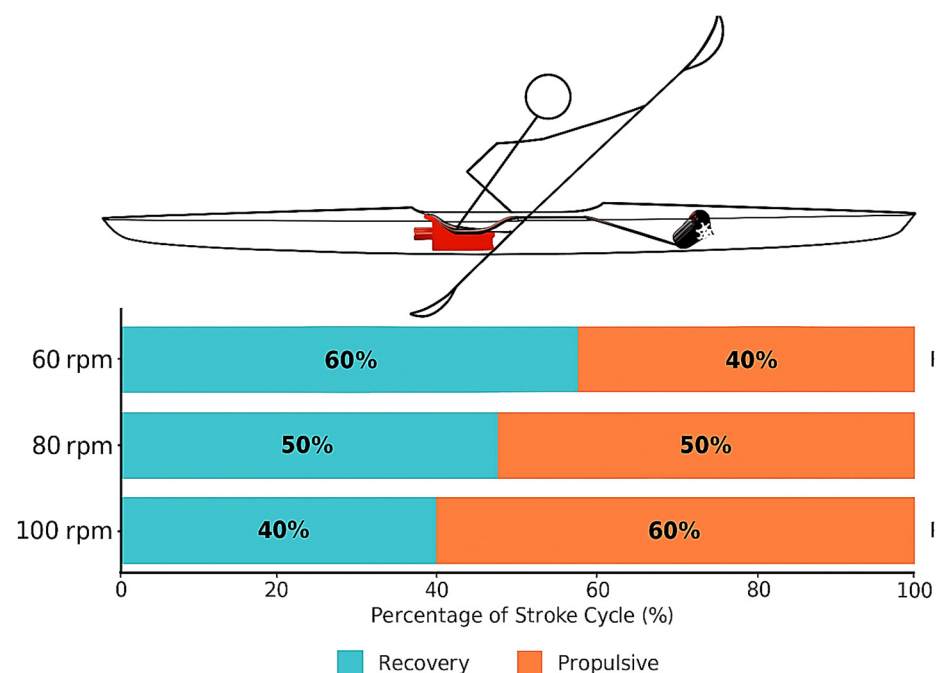


Figure 3. Distribution of propulsive and recovery phases across stroke cadences. **Top:** schematic representation of the experimental setup and stroke technique in the K1 kayak. **Bottom:** stacked horizontal bars showing the relative duration of the recovery (cyan) and propulsive (orange) phases for each imposed cadence (60, 80, 100 strokes·min⁻¹). The proportions were derived from the mean Paddle Factor (PF) values observed at each cadence (PF = 0.39 ± 0.05 at 60 strokes·min⁻¹, 0.50 ± 0.04 at 80, and 0.59 ± 0.06 at 100), corresponding approximately to 40, 50, and 60% of the stroke cycle, respectively. This schematic links the statistical patterns reported in Figure 2 and Table 2 to concrete movement strategies, illustrating how increasing cadence shifts the balance between recovery and propulsive phases.

3.2. Summary of Observations

- Component 1: At lower cadences (60 strokes·min⁻¹), variability is greater, and the mean is lower. Higher cadences (80, 100 strokes·min⁻¹) show greater stability, suggesting that this component is related to efficiency or technical stability.
- Component 2: The distribution is more concentrated, and the mean is higher at 80 strokes·min⁻¹, indicating that, in this acute trial, this intermediate cadence was associated with relatively greater power application and technical consistency when compared with 60 and 100 strokes·min⁻¹.
- Component 3: At 80 strokes·min⁻¹, values are more uniform and the mean is higher, signaling better technical control. At 60 strokes·min⁻¹, greater variability is observed, indicating difficulties in maintaining a smooth motion.

- Component 4: At 60 strokes·min⁻¹, the distribution is more concentrated, suggesting greater control at lower cadences. However, at 100 strokes·min⁻¹, the wider error bar indicates greater instability in force application.

In this small sample of elite U23 kayakers, the intermediate cadence of 80 strokes·min⁻¹ appeared to offer a pragmatic compromise between stability, power, and technical consistency, whereas 60 strokes·min⁻¹ was characterized by greater variability and 100 strokes·min⁻¹ by indications of technical difficulty and instability. However, these patterns were not uniformly supported by all inferential tests (e.g., pairwise differences between 60 vs. 80 and 80 vs. 100 were often non-significant), and the study was not designed to identify an individualized “optimal” cadence or to evaluate longitudinal training adaptations. Accordingly, these observations should be interpreted as descriptive and hypothesis-generating rather than as prescriptive guidance for training. Any practical application of a specific stroke-rate range should be confirmed by larger, longitudinal, and randomized studies.

Mean and standard deviation of each component as a function of Frequency are reported in Table 2. The Mechanical Work ($\chi^2 = 17.10, p < 0.001$) and the Mechanical Energy ($\chi^2 = 53.10, p < 0.001$) tend to increase as a function of Frequency. The Variability component showed a significant interaction with Frequency ($\chi^2 = 16.78, p < 0.001$), with significant decrease between 60 vs. 100 ($t = 4.78, p < 0.001$), but neither 60 vs. 80 ($t = 2.22, p = 0.09$) nor 80 vs. 100 ($t = 2.49, p < 0.05$) results were significant. The Acceleration component did not show any interaction with Frequency ($\chi^2 = 4.95, p = 0.08$).

From a biomechanical perspective, the absence of a clear effect of stroke frequency on the Acceleration component is noteworthy. A plausible explanation is that, within our fixed-distance and imposed-frequency protocol, variations in interface work and coordination were partially absorbed by the combined inertial mass of the athlete–boat system and by hydrodynamic dissipation, resulting in relatively smooth longitudinal acceleration profiles across all three cadences. In addition, the single hull-mounted accelerometer and conservative low-pass filtering adopted in this study were optimized for robustness rather than for detecting small, rapid fluctuations, which may have limited sensitivity to subtle differences in acceleration. Future studies employing higher-resolution multi-sensor configurations could better clarify how frequency-dependent changes in coordination translate into boat acceleration.

For readability, Table 2 reports LME F-tests for the effect of Frequency; fractional degrees of freedom reflect Satterthwaite approximations.

Beyond reporting p values, we computed effect sizes (partial η^2 and Cohen’s f) for all omnibus tests. Given the within-subject design (3 levels) with $n = 12$, we also performed a sensitivity analysis ($\alpha = 0.05$) indicating that the study had $\approx 80\%$ power to detect effects around $f \approx 0.45$ (partial $\eta^2 \approx 0.17$), assuming a typical within-subject correlation of 0.6. This threshold is exceeded by the majority of biomechanical variables (see Section 3), whereas PCI lies close to this boundary.

Observed effect sizes (partial η^2 , approximated by the marginal R^2) were large for key variables, particularly BExW ($\eta p^2 \approx 0.75$) and PF ($\eta p^2 \approx 0.57$), and small-to-moderate for other biomechanical outcomes such as FAP ($\eta p^2 \approx 0.23$) and HExW ($\eta p^2 \approx 0.10$). PCI also showed a small-to-moderate effect size ($\eta p^2 \approx 0.11$), consistent with its non-significant omnibus test given the study’s sensitivity threshold.

The full set of estimated marginal means (EMMs $\pm 95\%$ CI) for each stroke frequency, together with standardized effect sizes and model fit indices (marginal and conditional R^2), is reported in Supplementary Table S4. The pattern of EMMs confirmed the same direction of changes observed in Table 2 (e.g., higher Mechanical Work, Propulsive Force,

and Paddle Fraction at faster cadences), supporting the robustness and internal consistency of the LME estimates.

The main findings for the PCA components remained significant after Holm–Bonferroni adjustment; exploratory variable-level inferences were based on Tukey-adjusted contrasts, with FDR control across variables.

Analysis of variance (ANOVA) was also applied to the time variable to evaluate the impact of paddle frequency on overall performance. Given that the distance was fixed, average velocity was derived from time values to provide an additional index of performance.

3.3. Correlation Analysis

Pearson correlations between the four PCA components and external indicators (PCI, weekly training hours—HRWEEK, and transmission efficiency—TE) are summarized below and fully reported in Supplementary Table S5, which includes 95% bootstrap confidence intervals, degrees of freedom ($df = 34$), exact p values, and FDR-adjusted q values.

3.3.1. PCI

The Mechanical Work component showed a moderate negative correlation with PCI ($r = -0.37$, $t(34) = -2.35$, $p = 0.022$, 95% CI $[-0.63; -0.07]$, $q = 0.066$), whereas the Acceleration component was positively correlated ($r = 0.39$, $t(34) = 2.44$, $p = 0.010$, 95% CI $[0.08; 0.63]$, $q = 0.066$). The Mechanical Energy ($r = -0.16$, $t(34) = -0.95$, $p = 0.344$, $q = 0.575$) and Variability components ($r = -0.28$, $t(34) = -1.74$, $p = 0.089$, $q = 0.178$) did not reach significance after FDR correction. Although some associations reached statistical significance after FDR correction, their magnitude was weak-to-moderate ($|r| \approx 0.3$ – 0.4) and characterized by relatively wide confidence intervals. Therefore, these relationships should be considered tentative and exploratory rather than evidence of strong causal links between training volume, transmission efficiency, and mechanical components.

3.3.2. HRWEEK

The Mechanical Work component was positively correlated with weekly training hours ($r = 0.45$, $t(34) = 2.93$, $p = 0.005$, 95% CI $[0.15; 0.68]$, $q = 0.020$), whereas Mechanical Energy ($r = -0.41$, $t(34) = -2.66$, $p = 0.011$, 95% CI $[-0.65; -0.09]$, $q = 0.029$) and the Variability component ($r = -0.42$, $t(34) = -2.73$, $p = 0.009$, 95% CI $[-0.67; -0.12]$, $q = 0.027$) showed negative correlations. The Acceleration component was small and non-significant ($r = 0.08$, $t(34) = 0.42$, $p = 0.639$, $q = 0.710$).

3.3.3. TE

The Mechanical Work component displayed a positive correlation with transmission efficiency ($r = 0.34$, $t(34) = 2.12$, $p = 0.040$, 95% CI $[0.03; 0.59]$, $q = 0.080$), whereas the Variability component was negatively correlated ($r = -0.48$, $t(34) = -3.22$, $p = 0.002$, 95% CI $[-0.70; -0.16]$, $q = 0.012$). The Mechanical Energy ($r = -0.29$, $t(34) = -1.79$, $p = 0.080$, $q = 0.160$) and Acceleration ($r = -0.05$, $t(34) = -0.28$, $p = 0.774$, $q = 0.774$) components were not significantly correlated with TE.

After controlling for multiple testing across the 12 correlations (four components $\times$ three indicators) using the Benjamini–Hochberg false discovery rate procedure ($q = 0.05$), only the negative correlations between Variability and both HRWEEK and TE remained significant. Given the modest sample size ($n = 12$ athletes; 36 observations), these correlations should be interpreted as exploratory and hypothesis-generating. Bootstrap confidence intervals reported in Supplementary Table S5 provide a transparent quantification of uncertainty.

3.3.4. Kinematic Parameters Across Paddle Frequencies

Analysis of variance (ANOVA) showed significant differences for several kinematic parameters across frequencies ($p < 0.05$). In general, parameters such as Force Application Point (FAP), Stroke Average Power (SAP), and Force to Distance (F2D) all increased with higher stroke frequency, aligning with the PCA results (Table 2).

4. Discussion

This study investigated the effects of different paddle frequencies (60, 80, and 100 strokes·min⁻¹) on coordination, motor control, and paddling variability in well-trained kayak athletes. Our findings provide valuable insights into the biomechanical and physiological adaptations that occur during kayaking at various intensities, with implications for training strategies and performance optimization.

4.1. Interpreting the “Negative Mechanical Energy–Experience” Association

At first glance, the negative correlation between the Mechanical Energy component and weekly training hours may appear counterintuitive. Because no metabolic or electromyographic variables were collected, any discussion of underlying physiological mechanisms must be considered speculative. However, within our fixed-distance and imposed-frequency setting, greater experience plausibly reflects improved stroke economy. More trained paddlers are able to stabilize the trunk–boat system and reduce non-propulsive oscillations, thereby lowering segmental kinetic energy while maintaining (or increasing) boat-directed work. This interpretation aligns with the pattern reported in the Results section, where greater training experience was associated with higher Mechanical Work and lower Variability, which together suggest enhanced transmission efficiency rather than reduced effort. It should be noted, however, that this interpretation applies to the controlled on-water conditions used in this study (competition lake, calm water, fixed distance, imposed stroke frequencies). Further work should verify whether the same trend holds in free-paddling or competition environments, where energy redistribution may depend on fatigue, pacing strategy, and hydrodynamic variability.

The results demonstrate significant changes in Mechanical Work and energy across different paddle frequencies. These findings align with previous research on cyclic activities [35], which has shown that increases in movement frequency are associated with higher energy expenditure and Mechanical Work [36]. In kayaking, the observed increase in Mechanical Work and energy with higher paddle frequencies can be attributed to the greater force production and power output required to maintain a faster stroke rate [36].

The presence of a positive correlation between Mechanical Work and weekly training hours suggests that a more experienced athlete may be better equipped to handle the increased workload associated with higher paddle frequencies [16,37]. This pattern is consistent with physiological and neuromuscular adaptations described in the broader endurance-training literature (e.g., muscle fiber recruitment, motor unit behavior, and metabolic efficiency [38]). However, we did not record metabolic or electromyographic data in the present study; therefore, these mechanisms should be regarded as a possible explanatory framework rather than as direct evidence from our dataset.

These methodological refinements, including the CoreMeter dual-module configuration (20 × 20 cm seat + foot), the adimensional CoP scaling, and recalibration of all load cells, are fully consistent with established validation studies of the Wii Balance Board [23,24], confirming good-to-excellent reliability and concurrent validity with laboratory-grade force plates.

On the other hand, it is interesting that mechanical energy showed a negative correlation with the number of weekly training hours. At face value, this pattern might appear

counterintuitive. One *possible* interpretation, in line with the concept of movement economy described in other endurance sports [10,36,39], is that more experienced athletes tend to reduce non-propulsive mechanical fluctuations while maintaining boat-directed work. Such an organization of effort could favor energetic efficiency over longer distances [40]. Importantly, we did not collect direct metabolic measures (e.g., oxygen consumption) in the present study, so this “economy”-based explanation remains speculative and should be viewed as a hypothesis for future investigation rather than a conclusion supported by our data.

The variability component exhibited a significant interaction with paddle frequency, with a notable decrease between 60 and 100 strokes·min^{−1}. This reduction in variability at higher frequencies aligns with the concept of dynamic systems theory in motor control [41,42], which posits that increased task constraints can lead to more stable movement patterns. In the context of kayaking, the higher paddle frequency may act as a constraint that promotes a more consistent and efficient stroke technique [43]. The negative correlation between the variability component and both weekly training hours and transmission efficiency further supports the notion that experienced athletes develop more stable and efficient movement patterns [17].

From a dynamical-systems perspective, movement variability should not be viewed merely as error or noise, but rather as an inherent feature of skilled motor behavior. We therefore distinguish between *functional variability* and *noise*. Functional variability refers to structured fluctuations that reflect adaptive exploration of coordinative solutions under task constraints, whereas noise denotes unsystematic trial-to-trial deviations that are not explained by the task dynamics.

In our dataset, cadence-dependent changes in variability—larger at 60 and 100 strokes·min^{−1} and reduced at 80 strokes·min^{−1}, where mechanical and coordination indicators were most stable—are consistent with *functional variability*. Conversely, the within-condition dispersion captured by the LME residuals can be interpreted as *noise*. The relative contribution of the fixed effect of cadence versus residual variance thus provides a quantitative indication of how much of the variability is structured by task constraints rather than random fluctuations.

This interpretation supports the view that skilled paddlers exploit functional variability to stabilize performance under changing mechanical demands, while minimizing noise that would otherwise degrade efficiency.

4.2. Novelty of PCI Applications in Canoeing

To our knowledge, this study represents the first application of the Phase Coordination Index (PCI) in canoeing and kayaking. Previous research on PCI has mainly focused on bimanual or locomotor coordination tasks, such as cycling or gait rhythm analysis [44]. By adapting PCI to the cyclical paddling pattern, we provide a quantitative, time-based index of interlimb and intra-cycle coordination stability, capturing subtle timing fluctuations across stroke frequencies. This methodological innovation fills a gap in canoeing biomechanics literature and offers a novel framework for assessing motor control efficiency and technical consistency in elite paddlers.

4.3. Potential Fatigue at the Highest Cadence (100 Strokes·min^{−1})

Although cadence order was randomized and 10 min passive recovery was provided between trials, a residual fatigue effect at 100 strokes·min^{−1} cannot be ruled out. This may contribute to the greater instability observed at the extreme cadence and should be interpreted as a “stress-test” of coordination rather than steady-state performance. Future studies should include direct fatigue indices (e.g., RPE, heart rate, blood lactate) and

manipulate recovery durations to quantify the specific impact of fatigue at very high stroke frequencies.

This finding is consistent with research in other cyclic sports, where elite athletes demonstrate reduced variability in key performance parameters compared to their less experienced counterparts [45]. However, it is important to note that some degree of variability is beneficial for motor learning and adaptation. The observed variability patterns across different paddle frequencies may represent an optimal balance between movement consistency and adaptability, allowing kayakers to maintain performance while adjusting to changing environmental conditions or fatigue [1].

The Phase Coordination Index (PCI) showed a negative correlation with mechanical work, indicating that higher work output is associated with improved bilateral coordination [35,46]. This finding highlights the importance of synchronized upper limb movements in kayaking performance [12]. The relationship between PCI and Mechanical Work suggests that as athletes increase their paddle frequency and power output, they also enhance their ability to coordinate left and right paddle strokes effectively [9]. The positive correlation between the acceleration component and PCI highlights the complex interplay between movement speed and coordination. As acceleration increases, maintaining precise coordination becomes more challenging, potentially leading to slight asymmetries or timing variations between paddle strokes. This observation aligns with previous research [47] in other bilateral activities, such as running, where increased speed can lead to greater fluctuations in interlimb coordination. The analysis of bilateral asymmetry (BASY) revealed insights into the symmetry of force application and movement patterns. The inclusion of BASY in the variability component of our Principal Component Analysis suggests that asymmetry contributes to overall movement variability in kayaking. This finding highlights the importance of developing balanced strength and technique on both sides of the body to optimize performance and reduce injury risk [48].

From an applied perspective, bilateral coordination and asymmetry metrics such as PCI and BASY may be relevant for injury prevention as well as for performance. In kayaking, persistent asymmetries in force application and timing can lead to uneven loading of the shoulder girdle, spine, and trunk musculature, particularly when combined with high chronic training volumes and abrupt workload spikes [16–19]. Although our cross-sectional design does not allow us to establish causal links with injury, the low-to-moderate BASY values observed in this cohort (~4–6%) suggest that elite kayakers can tolerate a certain degree of asymmetry during short race-like bouts. However, progressively increasing asymmetry or consistently elevated BASY values during periods of intensified training could signal maladaptive loading patterns and warrant technical or conditioning interventions (e.g., targeted unilateral strength work and drills emphasizing the non-dominant side). Future longitudinal studies should explicitly test whether athletes who exhibit larger or worsening bilateral asymmetries are at greater risk of overuse complaints at the shoulder, elbow, or lumbar spine.

The transmission efficiency (TE) showed a positive correlation with mechanical work, indicating that higher work output is associated with improved energy transfer from the athlete to the boat. This relationship underscores the importance of technique optimization in kayaking, where efficient force application and body positioning can significantly impact performance [19,47]. The negative correlation between TE and the variability component suggests that more consistent movement patterns contribute to better energy transmission. This finding aligns with research in other aquatic sports, such as rowing, where reduced variability in key technical parameters is associated with improved efficiency and performance [49]. The analysis of paddle factor (PF) provides insights into the temporal aspects of the paddle stroke cycle. The inclusion of PF in the mechanical energy component of

our Principal Component Analysis indicates its relevance to overall energy expenditure and work output [19]. Optimizing the ratio of propulsive phase to recovery phase can contribute to improved efficiency and sustained performance over longer distances [50].

Our study also showed that the theoretical model closely approximated actual performance times and speeds, supporting the accuracy of this prediction approach [51]. This model, which links metabolic power requirement and maximal metabolic power to performance time, has been successfully applied to other forms of locomotion and may conceptually be extended to kayaking, pending direct validation [52]. The ability to predict performance with such accuracy has significant implications for training and competition strategies. Moreover, the strong correlation between theoretical and actual performance times suggests that the underlying physiological and biomechanical principles governing kayaking performance are well-captured by our model. This provides a solid foundation for future research into optimizing kayaking technique and training methodologies [52].

4.4. Limitations and Future Research

While this study provides valuable insights into kayaking biomechanics and motor control, several limitations should be acknowledged. The sample size, although representative of elite kayakers, was relatively small, and may have limited the generalizability of our findings. Additionally, our study focused on a single bout of paddling at different frequencies, and longitudinal investigations examining the effects of prolonged training at various paddle frequencies could provide further insights into long-term adaptations and performance improvements. Although the testing setup reproduced realistic stroke mechanics, hydrodynamic interactions in open water may further influence coordination and energy transmission; thus, the validity is high for stroke biomechanics but limited for environmental variability.

Moreover, stroke frequencies were imposed using an auditory metronome. While this approach ensured strict standardization of cadence across trials, it also introduced an artificial constraint that may have affected paddlers' natural coordination patterns. Consequently, extrapolation of the present findings to fully self-selected race conditions should be made with caution, and future studies should directly compare metronome-paced and self-selected stroke frequencies to assess the impact of this constraint on coordination dynamics.

Taken together, these design and sampling constraints mean that our data cannot establish an "optimal" stroke frequency or support prescriptive training programs; instead, they identify candidate patterns that warrant confirmation in larger, longitudinal and randomized studies.

Future research directions should include investigating the relationship between paddle frequency and physiological parameters such as oxygen consumption and muscle activation patterns, in order to test explicitly the tentative "economy"-based mechanisms we discuss in relation to training experience, as well as exploring the impact of different kayak designs and paddle configurations on biomechanical efficiency, examining the transfer of skills between on-water and ergometer-based training, investigating cognitive factors in kayaking performance, and developing sport-specific measures of coordination and variability tailored to kayaking [1,53].

Although the sample size was relatively small ($n = 12$), it was composed of well-trained, homogeneous elite kayakers, which minimized inter-individual variability and provided sufficient statistical power for within-subject comparisons. Nevertheless, the limited sample size constrains generalizability beyond elite male kayakers with similar characteristics.

4.5. Practical Implications and Recommendations

Within the limits of a small, homogeneous sample and an acute single-session design, any practical implications derived from these findings should be regarded as tentative. In this group of elite U23 kayakers, the intermediate cadence around 80 strokes·min⁻¹ was associated with comparatively favorable coordination and mechanical profiles; however, these patterns must be interpreted in relation to the observed effect sizes and within-subject variability. In particular, cadence explained a large proportion of variance in key mechanical indicators (e.g., Paddle Factor: $\eta^2 = 0.57$; marginal $R^2 = 0.57$), whereas coordination-related metrics exhibited smaller-to-moderate effects alongside substantial inter- and intra-individual dispersion. Accordingly, the apparent advantage of an intermediate cadence does not indicate a universal or optimal training prescription, but rather identifies a condition in which mechanical output and coordination demands were relatively balanced for some athletes under controlled conditions.

From an applied perspective, coaches and athletes might use these observations as a starting point for individualized experimentation rather than as prescriptive guidance. Exploratory testing sessions could be used to characterize each athlete's mechanical and coordinative responses across a spectrum of stroke frequencies, paying particular attention to how stability, variability, and efficiency metrics change with cadence. Such data may assist in hypothesis-driven refinement of training design but should not yet inform formal programming or periodization.

Future applied work may explore how variable-cadence drills and biomechanical feedback tools (e.g., video analysis, accelerometers, strain-gauge systems, and other wearable sensor technologies [54]) can enhance technical awareness and adaptability. These approaches could eventually support individualized monitoring of parameters such as Force Application Point and Stroke Average Power, but their efficacy should first be validated in longitudinal or intervention studies.

Overall, the present results highlight the potential of integrating quantitative coordination metrics (e.g., PCA components, PCI) into performance monitoring as a complementary indicator of technical quality, while avoiding prescriptive interpretation until stronger longitudinal evidence becomes available.

5. Conclusions

Our study characterizes associations between stroke frequency and coordination/ biomechanics in elite U23 male kayakers under real water conditions. While ~80 strokes·min⁻¹ emerged as a candidate cadence with comparatively favorable coordination metrics, this does not imply causation or prescriptive training guidance. The findings are preliminary and hypothesis-generating. Future research should confirm these patterns using larger samples, longitudinal designs, and randomized or within-subject training interventions, and include physiological/fatigue markers to evaluate transfer to performance.

These results therefore apply primarily to young elite male kayakers, and caution should be used when generalizing the results to other populations or conditions.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/biomechanics6010002/s1>. Table S1. Per-channel calibration results (Seat C1–C4; Foot F1–F4). Reported coefficients: a (V/N), b (V), R^2 , RMSE (N), Bias (N), and Max non-linearity (%FS). Table S2. Adapted datasheet (RVL-021 modules + ADXL330 accelerometer). Table S3. Telemetry diagnostics (Seat, Foot, IMU): nominal fs (Hz), mean Δt (ms), SD Δt (ms), max gap (ms), packet loss (%), drift (ms/500 m). Table S4. Linear mixed-effects (LMEs) model summaries for biomechanical outcomes in Panel A and B. Panel A shows the mean number of valid stroke cycles per participant $\times$ frequency condition. Panel B. EMM, 95% CI, effect sizes and R^2 for LME models. Table S5. Pearson correlations between the four PCA components and external indicators

(PCI, weekly training hours, transmission efficiency). The table reports correlation coefficients (r), 95% bootstrap confidence intervals, test statistics (t , $df = 34$), exact two-tailed p values, and FDR-adjusted q values (Benjamini–Hochberg). Table S6. Sub-threshold and cross-loading variables from the PCA solution (four components, unrotated, 76% cumulative variance). Loadings ≥ 0.60 are reported in Table 3 (main text). This table reports all remaining loadings for transparency, together with communalities and interpretive notes. Table S7. Pearson correlation matrix (r), variable-specific Kaiser–Meyer–Olkin (KMO) indices, and Bartlett’s test of sphericity for the 15 variables entered into PCA. Table S8. Bootstrap stability of PCA loadings: median loading and 95% confidence intervals over 1000 resamples for each variable and component. Bold values indicate stable salient loadings (≥ 0.6) across bootstrap samples. Figure S1. Module geometry and coordinate layout for the 20×20 cm instrumented plates. The four load-cell channels (C1–C4) are positioned at the corners ($\pm 0.10, \pm 0.10$ m), with the coordinate origin located at the module center (0, 0). This configuration is used for CoP/CLD computation and normalization in the CoreMeter software. Sensor positions correspond to channel labels shown in the figure. Figure S2. The curves of accelerometry as a function of time represent individual participant data at 60 (blue), 80 (orange), and 100 (gray) strokes $\cdot \text{min}^{-1}$. Figure S3. Calibration curves (Voltage vs. Force) and residual plots for each load-cell channel (Seat C1–C4; Foot F1–F4). Figure S3. Calibration curves (Voltage vs. Force) and residual plots for each load-cell channel of the instrumented kayak seat (C1–C4) and footrest (F1–F4). Solid lines represent the fitted linear model ($V = a \cdot F + b$) as reported in Supplementary Table S1. Points show observed voltages with simulated noise consistent with the reported RMSE values. Residual plots confirm excellent linearity and low dispersion across the full operational range. Figure S4. Sampling timeline and alignment procedure: example of Bluetooth HID inter-arrival intervals (pre- and post-resampling to 100 Hz). Figure S4. Sampling timeline and alignment procedure for the instrumented kayak system. Panel A shows raw Bluetooth HID inter-arrival intervals (Δt) for seat, foot, and IMU streams over a representative 500-sample window, illustrating small timing jitter around the nominal 10 ms period and occasional gaps up to ~ 15 ms, consistent with the diagnostics reported in Supplementary Table S3. Panel B shows the same streams after resampling and alignment to a common 100 Hz timeline, resulting in a stable effective sampling interval ($\Delta t \approx 10$ ms) for all devices. Figure S5. Scree plot of observed eigenvalues and results of the parallel analysis for the 15-variable PCA. The intersection between the curves confirms the four-component solution retained in the study, explaining 76% of the total variance.

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