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From 6,000 m to 2,000 m: A Field-Based Model to Predict Rowing Ergometer Performance in Female National-Selection Athletes

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Abstract

Rowing selection and monitoring rely on 2,000-m ergometer time, yet repeated maximal 2,000-m trials are physically and logistically costly, and laboratory maximal-oxygen-uptake testing is rarely feasible across a national programme. This study aimed to predict 2,000-m ergometer time from tests already administered in the Indonesian National Rowing Selection (SELEKNAS). Using verified records from 22 female national-selection rowers, the average power and stroke rate of the 6,000-m, 1-minute, and 150-m ergometer tests were entered into a forward stepwise multiple regression, and all model assumptions were examined. Mean 6,000-m power was the dominant predictor, explaining 72.6% of the variance in 2,000-m time; adding 1-minute stroke rate raised the total to 79.5% (adjusted $R^2 = 0.773$; standard error of the estimate = 5.07 s; $p < 0.001$), with normally distributed residuals, no multicollinearity (VIF = 1.00), and independent residuals. The model predicted 90.9% of athletes' times to within 10 s. A routinely collected field test can therefore estimate 2,000-m performance without additional maximal trials or laboratory testing, offering coaches and national selectors a practical, low-cost tool for talent screening and performance monitoring in female rowers.

1. Introduction

Rowing occupies a strategic position in Indonesia's pursuit of medals at multi-sport events such as the SEA Games and the Asian Games, and the identification and development of athletes on the basis of objective performance data has consequently become a priority for the national federation. Within this process, the rowing ergometer (Concept2) has been adopted as an international standard for assessing a rower's physical capacity because it isolates propulsive work from the water, weather, and boat-handling factors that are difficult to control during on-water measurement (Borges et al., 2025). The 2000 m distance is the reference event for both indoor and on-water competition, so 2000 m ergometer time is routinely treated as the primary criterion of performance during athlete selection, including the periodic Indonesian National Rowing Selection (SELEKNAS).

In practice, the SELEKNAS physical-testing battery extends well beyond the 2000 m trial. Athletes also complete a 6000 m test that indexes aerobic endurance, a 1 min all-out test that reflects anaerobic capacity and power endurance, and a 150 m test that captures alactic sprint power; together these efforts profile the range of physiological qualities the event demands. Performing a maximal 2000 m test at every evaluation, however, requires substantial physical and psychological readiness and can induce cumulative fatigue that disrupts subsequent tests or training scheduled on the same day. This burden creates a clear need for a model that can estimate 2000 m performance from tests that are already collected within the standard protocol, without repeatedly imposing an additional maximal 2000 m effort.

Physiologically, maximal oxygen uptake (VO~2max~) has long been reported as the single strongest predictor of 2000 m rowing performance in both male and female rowers (Cosgrove et al., 1999; Riechman et al., 2002). Two recent systematic reviews reinforce this conclusion: Borges et al. (2025)

reported that VO~2max ~ and peak power output from incremental tests are the most consistent correlates of 2000 m ergometer time (r = 0.83–0.99), whereas Kilbey et al. (2025) identified the power produced at a fixed blood-lactate concentration as a further strong correlate. Direct VO~2max~ assessment nonetheless requires expired-gas analysis and costly spirometry, which is difficult to apply routinely in a national selection that screens many athletes drawn from regions with limited laboratory infrastructure. This constraint has motivated the development of prediction models built from ergometer and field tests that rely only on the performance monitor already integrated in the Concept2.

Several such models have been proposed. In female rowers, a 30 s sprint combined with laboratory VO~2max~ explained a very high proportion of the variance in 2000 m time (Riechman et al., 2002). Short all-out efforts have proved especially informative: 20 s and 60 s tests correlate strongly with 2000 m time (r = − 0.952 and − 0.930, respectively; Cerasola et al., 2022), and 60 s mean power combined with anthropometric and VO~2max~ variables predicts 2000 m performance in national-level young rowers (Cerasola et al., 2020). Comparable evidence exists for a 100 m maximal test in youth rowers (da Silva et al., 2021), a modified Wingate test that accounts for most of the variance in 1500 m performance among adolescent rowers (Maciejewski et al., 2016), and a combination of functional anaerobic power, strength, and anthropometry (Akça, 2014). Most of these models, however, rely on a single short anaerobic test paired with laboratory VO~2max ~ or anthropometric measures, and were developed largely in European, American, and Brazilian samples.

Evidence from Indonesia remains comparatively sparse and does not address the specific tests used in national selection. Existing local work has examined the contribution of anthropometry and muscle strength to 2000 m achievement (Wahyuningsih & Raharjo, 2015) or the combined role of aerobic, anaerobic, and muscle-power capacity in general (Nurjaya et al., 2019), without isolating the joint predictive value of the 6000 m, 1 min, and 150 m tests. To date, no study has derived a 2000 m prediction equation from precisely this triad of tests, even though it constitutes the routine protocol of the Indonesian national programme. Addressing this gap is practically important, because coaches and selection panels need estimation tools grounded in data that are already gathered, so that 2000 m performance can be projected without adding maximal test load or requiring VO~2max~ testing that cannot be delivered uniformly across the country. The three tests are also complementary in principle: the prolonged 6000 m effort serves as a field proxy for aerobic capacity, whereas the 1 min and 150 m tests index the anaerobic and alactic power that shape the start and finishing phases of a 2000 m race.

Accordingly, the present study pursues two objectives. First, it examines the relationships between the power, time or distance, and stroke-rate outputs of the 6000 m, 1 min, and 150 m tests and 2000 m ergometer time. Second, it develops a stepwise multiple regression model to predict 2000 m performance from these test variables in female athletes competing in the 2020 Indonesian National Rowing Selection. By translating routinely collected test data into a validated prediction equation, the study aims to provide coaches and national selectors with a practical, low-cost tool for evaluating and projecting athletes' 2000 m potential more efficiently.

2. Materials and Methods

2.1. Study design

This study employed a correlational–predictive design with a cross-sectional approach, based on a secondary analysis of physical-test records obtained during the 2020 Indonesian National Rowing Selection (SELEKNAS). A predictive design was appropriate because the aim was to model a criterion outcome (2000 m ergometer time) from a set of concurrently measured test variables rather than to infer causation. Because all measurements were collected within a single, centrally administered selection event, every athlete completed an identical test battery under the same equipment, environmental, and scheduling conditions, which reduces between-session sources of error. Analysing routinely collected selection data also reflects the applied context in which the resulting model is intended to operate, namely the estimation of 2000 m performance from tests that national programmes already administer. The overall study design and analytical workflow are summarized in Fig. 1. All records were de-identified before analysis.

The study was conducted in accordance with the Declaration of Helsinki. Ethical approval was granted by the Research Ethics Committee of the Sport Science Laboratory, Faculty of Physical Education and Health, Universitas Pendidikan Indonesia (approval number 048/UN40.F4/EC/SSL/2026), and written informed consent was obtained from all participants.

2.2. Participants

The sample comprised 34 female rowers who participated in the 2020 SELEKNAS and completed the full test battery. Eligibility required a valid, complete set of records for all four ergometer tests; athletes with a missing or invalid trial on any test were excluded. Because the athletes had already been selected into the national programme, the sample constitutes a homogeneous, high-performance criterion group, which is appropriate for developing a prediction model intended specifically for this population. Participant characteristics are presented in Table 1.

Table 1
Participant characteristics (n = 34).

Variable	Mean ± SD	n
Age (years)	20.88 ± 3.48	34
Height (cm)	181.30 ± 5.03	33
Body mass (kg)	76.85 ± 6.58	34
Note. Height was available for 33 of the 34 athletes owing to one missing record.		

2.3. Instrumentation and testing procedures

All tests were performed on a Concept2 rowing ergometer (Concept2 Inc., Morrisville, VT, USA), the device most widely adopted for the standardized assessment of rowing capacity because it removes the water, weather, and boat-handling factors that confound on-water measurement (Cerasola et al., 2022; Borges et al., 2025). Before each test, athletes completed a standardized warm-up under the supervision of the testing team, and the drag-factor/damper setting was fixed according to the SELEKNAS protocol to ensure comparable resistance across athletes. All power, time, distance, pace, and stroke-rate values were logged automatically by the ergometer's Performance Monitor (PM), which minimizes observer-related measurement error.

The battery comprised four maximal tests, each targeting a distinct physiological quality (Fig. 1): (i) a 6000 m test indexing aerobic endurance; (ii) a 1 min all-out test reflecting anaerobic power and power endurance; (iii) a 150 m test capturing alactic sprint power; and (iv) a 2000 m test used as the performance criterion. For each test, the recorded outputs were average power (W), the corresponding completion time (s) or distance covered (m), average pace per 500 m, and stroke rate (strokes·min^{-1}).

2.4. Variables and data reduction

The criterion (dependent) variable was 2000 m completion time (s). The candidate predictors were the average power and the stroke rate from each of the three non-criterion tests (6000 m, 1 min, and 150 m), yielding six candidate predictors. Average power was selected as the primary physiological representation of each test because, on the Concept2, power and average pace per 500 m are algebraically derived from one another and are therefore perfectly collinear; entering both would create statistical redundancy, so pace per 500 m was excluded from the predictor set. Stroke rate was retained as an independent variable representing the technical (rhythm/cadence) aspect of rowing. Anthropometric variables (age, height, body mass) were examined descriptively and correlated with the criterion but were not entered as predictor candidates, following Riechman et al. (2002), so that the model would reflect the physiological test outputs and avoid collinearity between body-size and capacity measures.

2.5. Statistical analysis

Descriptive statistics (mean ± standard deviation, and range where relevant) were computed for all participant and test variables. The bivariate association between each test variable and 2000 m time was quantified using the Pearson product–moment correlation coefficient (r). The six candidate predictors were then entered into a stepwise multiple linear regression with 2000 m time as the dependent variable; the probability threshold for a variable to enter the model was set at $p < 0.05$, and variables not meeting this criterion were excluded from the final equation. Predictive performance was summarized with the coefficient of determination (R^2), the adjusted R^2, and the standard error of the estimate (SEE, in seconds), and the incremental contribution of each retained predictor (ΔR^2) was reported.

The regression assumptions were formally examined: residual normality using the Shapiro–Wilk test, multicollinearity among predictors using the variance inflation factor (VIF), and residual independence

(absence of autocorrelation) using the Durbin–Watson statistic. A stepwise procedure was chosen deliberately to identify the most parsimonious subset of routinely collected predictors, so that the resulting tool would be practical to apply in the field. The regression was fitted on the athletes with complete predictor and criterion records, and anthropometric variables were correlated using pairwise-available data. The final model is reported as an unstandardized prediction equation so that it can be applied directly by practitioners. All analyses were conducted in Python (Python Software Foundation) using the SciPy (Virtanen et al., 2020) and statsmodels (Seabold & Perktold, 2010) libraries, with the significance level set at $\alpha = 0.05$.

3. Results

All 22 athletes completed the full ergometer battery (6000 m, 1 min, 150 m, and 2000 m tests), and every case contributed a complete set of predictor and criterion values; no data were missing for the variables entered into the analysis. The sample comprised 7 lightweight and 15 heavyweight/open-category rowers, with a mean height of 168.36 ± 5.02 cm (range 160.0–183.0) and a mean body mass of 64.17 ± 6.40 kg (range 53.7–77.0). On the criterion test, participants completed the 2000 m distance in a mean time of 474.74 ± 10.65 s (range 456.9–493.9 s), giving a coefficient of variation of approximately 2.2% and confirming that, although the athletes were a homogeneous high-performance group, the criterion retained sufficient spread to support regression modelling.

3.1. Descriptive characteristics of the test battery

Descriptive statistics for all test variables, together with their bivariate correlation with 2000 m time, are presented in Table 2. In the 6000 m test, athletes produced a mean power of 166.55 ± 12.14 W (range 145–187) over a mean completion time of 1539.11 ± 37.24 s, at a mean stroke rate of 24.45 ± 1.01 strokes·min^{-1}. In the 1 min all-out test, mean power reached 346.77 ± 29.55 W and the mean distance covered was 298.82 ± 8.42 m, performed at a substantially higher mean stroke rate of 47.18 ± 3.32 strokes·min^{-1}. The 150 m sprint test elicited the highest mean power of the battery (375.55 ± 37.12 W; range 320–475), completed in 29.36 ± 0.93 s at the highest cadence recorded (53.77 ± 5.31 strokes·min^{-1}). The progressive increase in mean power and stroke rate from the 6000 m test through the 1 min test to the 150 m test is consistent with the intended shift in metabolic emphasis across the battery, from predominantly aerobic to increasingly anaerobic and alactic efforts.

On the criterion test itself, in addition to completion time, athletes produced a mean 2000 m power of 209.95 ± 14.11 W (range 186–235) at a mean stroke rate of 30.82 ± 1.22 strokes·min^{-1} (range 28–33); these criterion-test outputs are reported here for completeness but were not used as predictors, since the predictors were drawn exclusively from the three non-criterion tests.

The relative dispersion of the variables differed markedly. The two long-duration aerobic indices were the most stable across athletes: 6000 m power and 6000 m time showed coefficients of variation of roughly 7.3% and 2.4%, respectively, whereas the short-duration power outputs were more variable (150 m

power ≈ 9.9%; 1 min power ≈ 8.5%). Stroke-rate variables were comparatively narrow in the endurance test (6000 m: ≈ 4.1%) but wider in the sprint test (150 m: ≈ 9.9%), reflecting greater individual variation in cadence strategy during maximal short efforts.

The sample also spanned two competitive weight categories. When examined descriptively by category, the 15 heavyweight/open athletes completed the 2000 m distance faster, on average, than the 7 lightweight athletes (471.4 ± 8.7 s versus 481.9 ± 11.5 s) and produced higher mean 6000 m power (170.1 ± 11.5 W versus 159.0 ± 10.5 W), consistent with their greater body mass (67.8 ± 4.1 kg versus 56.5 ± 1.4 kg). These subgroup values are presented for description only; weight category was not modelled as a predictor.

Table 2
Descriptive statistics of the ergometer test variables and their Pearson correlation with 2000 m time (n = 22).

Test variable	Mean ± SD	Range	r (with 2000 m time)	p
6000 m: power (W)	166.55 ± 12.14	145–187	−.852	< .001
6000 m: time (s)	1539.11 ± 37.24	1479.6–1610.0	+ .852	< .001
6000 m: stroke rate (spm)	24.45 ± 1.01	23–26	−.337	.125
1 min: power (W)	346.77 ± 29.55	291–405	−.684	< .001
1 min: distance (m)	298.82 ± 8.42	282–315	−.691	< .001
1 min: stroke rate (spm)	47.18 ± 3.32	41–53	+ .247	.267
150 m: power (W)	375.55 ± 37.12	320–475	−.639	.001
150 m: time (s)	29.36 ± 0.93	27.1–30.9	+ .678	< .001
150 m: stroke rate (spm)	53.77 ± 5.31	45–66	+ .063	.781
2000 m: time (s) (criterion)	474.74 ± 10.65	456.9–493.9	—	—

Note. spm = strokes per minute. Correlation coefficients follow APA convention (no leading zero). A negative correlation between a power variable and 2000 m time indicates that higher power is associated with a faster (shorter) 2000 m time.

3.2. Bivariate associations with 2000 m performance

The strongest bivariate correlates of 2000 m time were the two aerobic indices derived from the 6000 m test. Mean 6000 m power was strongly and negatively associated with 2000 m time ($r = -.852$, $p < .001$), indicating that athletes generating greater sustained aerobic power completed the 2000 m distance faster; the equivalent time-based index (6000 m completion time) showed a correlation of identical

magnitude in the opposite direction ($r = +.852$, $p < .001$), as expected given that power and time on the same test are inverse expressions of the same performance.

The anaerobic and alactic indices formed a second, moderately strong tier of correlates. In the 1 min test, both mean power ($r = -.684$, $p < .001$) and distance covered ($r = -.691$, $p < .001$) were significantly associated with 2000 m time. In the 150 m test, mean power ($r = -.639$, $p = .001$) and completion time ($r = +.678$, $p < .001$) were likewise significant. Thus, every power- and time/distance-based output across the three non-criterion tests correlated significantly with 2000 m performance, with the aerobic 6000 m indices showing the largest coefficients and the shorter anaerobic/alactic indices showing moderate coefficients.

In contrast, the three stroke-rate variables were weak and, with one exception approaching but not reaching the second tier, non-significant. The 6000 m stroke rate showed a weak, non-significant negative correlation with 2000 m time ($r = -.337$, $p = .125$), the 1 min stroke rate a weak positive correlation ($r = +.247$, $p = .267$), and the 150 m stroke rate essentially no association ($r = +.063$, $p = .781$). This pattern indicates that, at the bivariate level, cadence contributed little to explaining differences in 2000 m performance relative to the power and time/distance outputs.

Consistent with the analysis plan, the anthropometric variables were correlated with 2000 m time for descriptive purposes but were not entered as predictors. Standing height was essentially unrelated to 2000 m time ($r = -.001$, $p = .998$), and body mass showed only a weak, non-significant negative association ($r = -.385$, $p = .077$), the direction of which reflects the modest tendency for heavier athletes to record faster times noted above. The absence of any significant anthropometric correlate reinforces the decision to construct the prediction model from the physiological test outputs rather than from body-size variables.

3.3. Stepwise regression model for predicting 2000 m time

To identify the most parsimonious combination of routinely collected predictors, the six candidate variables (the power and stroke rate of the 6000 m, 1 min, and 150 m tests) were entered into a forward stepwise multiple linear regression with 2000 m time as the dependent variable and an entry criterion of $p < .05$. The procedure retained two predictors and is summarised in Table 3.

In the first step, mean 6000 m power entered the model as the single strongest predictor and accounted for 72.6% of the variance in 2000 m time ($R^2 = .726$, adjusted $R^2 = .713$, SEE = 5.71 s, $p < .001$). In the second step, the 1 min stroke rate entered the model and contributed a significant additional 6.8% of explained variance ($\Delta R^2 = .068$, entry $p = .021$), raising the total to 79.5% ($R^2 = .795$, adjusted $R^2 = .773$, SEE = 5.07 s). The overall model was statistically significant, $F(2, 19) = 36.77$, $p < .001$, and the reduction in the standard error of the estimate from 5.71 s to 5.07 s indicates a meaningful improvement in predictive precision when the cadence term was added.

No further variable met the $p < .05$ entry criterion once these two predictors were in the model. The next most competitive candidate, 1 min mean power, fell just short of the threshold (entry $p = .058$), followed

by 150 m power (p = .262), 150 m stroke rate (p = .300), and 6000 m stroke rate (p = .498). The remaining power and time variables, although significant as bivariate correlates, therefore did not add unique predictive information beyond that already captured by 6000 m power and 1 min stroke rate, most plausibly because their performance-relevant variance overlapped with that of the retained aerobic-power term.

Table 3
Summary of the forward stepwise regression model for predicting 2000 m time (n = 22).

Step	Predictor(s) in the model	R^2	Adjusted R^2	SEE (s)	ΔR^2	p
1	Power 6000 m	.726	.713	5.71	.726	< .001
2	Power 6000 m + Stroke rate 1 min	.795	.773	5.07	.068	< .001

Note. SEE = standard error of the estimate; ΔR^2 = increment in explained variance at each step. Entry criterion p < .05.

The unstandardised coefficients of the final two-predictor model are reported in Table 4. Both predictors were statistically significant: mean 6000 m power (b = − 0.752 s·W⁻¹, 95% CI [− 0.942, − 0.561], p < .001) and 1 min stroke rate (b = + 0.839 s·spm⁻¹, 95% CI [0.141, 1.538], p = .021). The standardised coefficients confirmed that 6000 m power was by far the dominant predictor (β = −.857) relative to 1 min stroke rate (β = +.261). The resulting prediction equation is:

$$\text{2000 m time (s)} = 560.300 - 0.752 \times \text{Power}_{6000\,\square}\ \text{(W)} + 0.839 \times \text{StrokeRate}_{1\,\square\square}\ \text{(spm)}$$

Interpreted in applied terms, the equation indicates that each additional 1 W of mean 6000 m power is associated with an estimated 0.75 s reduction in 2000 m time, holding cadence constant, whereas each additional 1 stroke·min⁻¹ in the 1 min test is associated with an estimated 0.84 s increase in 2000 m time, holding aerobic power constant.

Table 4
Coefficients of the final regression model predicting 2000 m time (n = 22).

Predictor	b	SE	95% CI	β	t	p	VIF
Constant	560.300	21.727	[514.82, 605.78]	—	25.79	< .001	—
Power 6000 m (W)	−0.752	0.091	[− 0.942, − 0.561]	−.857	−8.24	< .001	1.00
Stroke rate 1 min (spm)	+ 0.839	0.334	[0.141, 1.538]	+ .261	+ 2.52	.021	1.00

Note. b = unstandardised coefficient; β = standardised coefficient; CI = confidence interval; VIF = variance inflation factor.

3.4. Model diagnostics and assumption testing

The assumptions underlying the multiple regression were formally examined and satisfied. The residuals were normally distributed, as confirmed by a non-significant Shapiro–Wilk test ($W = 0.965$, $p = .607$), indicating no departure from normality. Multicollinearity was negligible: the variance inflation factor for both predictors was 1.00, and the two predictors were essentially uncorrelated with each other ($r = .016$), which is consistent with their capturing distinct dimensions of performance, sustained aerobic power on the one hand and short-effort cadence on the other. Residual independence was supported by a Durbin–Watson statistic of 1.62, within the conventionally acceptable range around 2 and indicating no problematic autocorrelation of residuals.

The distribution of residuals against predicted values is shown in Fig. 2B and revealed no systematic pattern, funnel shape, or curvature, supporting the assumptions of linearity and homoscedasticity. The negligible multicollinearity is particularly relevant to the stability of the model: because 6000 m power and 1 min stroke rate contributed independent information, their regression coefficients can be interpreted without the inflation of standard errors that typically accompanies correlated predictors.

3.5. Predictive accuracy of the model

The correspondence between the 2000 m times predicted by the final model and the athletes' actual times is displayed in Fig. 2A, in which the data points cluster closely around the identity line ($y = x$). The correlation between predicted and actual 2000 m times was high ($r = .891$), consistent with the model's coefficient of determination ($R^2 = .795$).

The absolute accuracy of the model was also quantified. The mean absolute error of prediction was 3.76 s and the root-mean-square error was 4.72 s, both small relative to the observed range of 2000 m times (approximately 37 s across the sample). The largest single prediction error was 10.66 s. In practical terms, 77.3% of the athletes' 2000 m times were predicted to within ± 5 s of their actual time, and 90.9% were predicted to within ± 10 s. Taken together, the two routinely collected predictors, mean 6000 m power and 1 min stroke rate accounted for approximately four-fifths of the between-athlete variance in 2000 m performance and yielded predictions with an average error of under 4 s.

4. Discussion

This study set out to predict 2000 m rowing-ergometer time from tests already embedded in the Indonesian national selection protocol, thereby avoiding both a repeated maximal 2000 m trial and laboratory VO~2max~ testing. In female national-selection rowers, mean 6000 m power and 1 min stroke rate together explained 79.5% of the variance in 2000 m time, with 6000 m power acting as the dominant predictor (72.6% alone) and the model meeting all regression assumptions. The following sections interpret these findings against the literature on the determinants and prediction of 2000 m rowing performance.

4.1. Aerobic power as the dominant predictor

The pre-eminence of 6000 m power is consistent with the long-standing view that aerobic capacity is the principal physiological determinant of 2000 m rowing performance. Maximal oxygen uptake and aerobically anchored power output have repeatedly emerged as the strongest single correlates of 2000 m time (Cosgrove et al., 1999; Riechman et al., 2002; Ingham et al., 2002; Nevill et al., 2011; Smith & Hopkins, 2012), a conclusion reaffirmed by recent systematic reviews reporting VO~2max ~ and peak power output as the most consistent correlates across the literature (Borges et al., 2025) and identifying lactate-threshold power as a further robust index (Kilbey et al., 2025). The 6000 m test, although it does not measure gas exchange directly, is a prolonged near-maximal effort of roughly 25 min that is heavily dependent on oxidative metabolism; its mean power therefore functions as an accessible field proxy for aerobic capacity, in line with earlier work relating sustained ergometer power and endurance capacity to rowing performance (Mikulic, 2009; Mäestu et al., 2005; Secher, 1993). That a single field-derived aerobic index accounted for nearly three-quarters of the variance in 2000 m time underscores the central role of aerobic power even within a homogeneous, already-selected group of athletes.

4.2. Comparison with existing prediction models

The explained variance obtained here (R^2 = .795) is competitive with published prediction models, particularly given that it was achieved without any laboratory measurement. It is nonetheless lower than the R^2 = .96 reported by Riechman et al. (2002) in female rowers, whose model combined a 30 s sprint with directly measured VO~2max~. This gap is most plausibly attributable to the use of a field proxy (6000 m power) rather than gas-exchange VO~2max~, which captures oxidative efficiency more precisely than average power in a self-paced field effort. Models that incorporate additional physical domains have likewise reported higher ceilings for example, functional anaerobic power, strength, and anthropometry combined (Akça, 2014), or a 100 m maximal test combined with body mass in youth rowers (da Silva et al., 2021), the latter obtained in a very small, homogeneous sample and therefore prone to inflated coefficients. Conversely, single-test field models tend to explain less variance than the present two-predictor equation: in NCAA Division I female rowers, the best single predictor (a 60 s maximal test) explained 61.1% of 2000 m variance (DeLeo et al., 2026), and short all-out tests of 20–60 s show strong but single-index associations with 2000 m time (Cerasola et al., 2020, 2022; Maciejewski et al., 2016). Field-based batteries emphasising critical and peak power (Holmes et al., 2020), load–velocity and strength-power profiling (Bourdin et al., 2004; Jacobs & Schumann, 2025), and anthropometric–strength determinants in traditional rowing (Sebastia-Amat et al., 2020) reinforce the same conclusion reached in the Indonesian context by Nurjaya et al. (2019): aerobic capacity combined with a secondary power or technical index provides the most efficient prediction of rowing performance.

4.3. The secondary predictor and the role of anaerobic and technical variables

The entry of 1 min stroke rate as the second predictor, adding 6.8% of explained variance, is noteworthy. The anaerobic and alactic power indices (1 min power, 1 min distance, 150 m power, and 150 m time)

were all significant bivariate correlates of 2000 m time (r = − .639 to − .691), consistent with evidence that short-duration power contributes meaningfully to 2000 m performance (Bourdin et al., 2004; Maciejewski et al., 2016; Cerasola et al., 2022; da Silva et al., 2021). However, none of these power indices added unique variance once 6000 m power was in the model, most plausibly because their performance-relevant information overlapped with the dominant aerobic-power term, an overlap also reported in the Indonesian national programme, where aerobic and muscular power jointly outperformed anaerobic capacity assessed in isolation (Nurjaya et al., 2019). What remained was a cadence term: 1 min stroke rate, which carried information statistically independent of aerobic power (inter-predictor r = .016). Because stroke rate reflects the rhythm and technical strategy of rowing rather than work capacity per se (Shimoda et al., 2009; Kramer et al., 1994), its positive coefficient, higher 1 min cadence associated with slower 2000 m time at a given aerobic power should be interpreted cautiously; it may index a less economical high-rate strategy rather than a performance benefit, and it should be regarded as a statistical rather than a causal contributor. Notably, this cadence-based second predictor differs from power-based secondary predictors reported in some female samples, a divergence that is itself consistent with the possibility of sex- and sample-specific model structures.

4.4. Sex-specific considerations and anthropometry

Because the present model was derived exclusively in female athletes, it contributes to an area that remains under-represented in the literature: Borges et al. (2025) noted that roughly 72% of participants in prior studies were male, cautioning against extrapolating male-derived findings to women. Female and male rowers differ in the physiological and anthropometric bases of performance (Yoshiga & Higuchi, 2003), and female-specific prediction work is only recently accumulating (Holmes et al., 2020; DeLeo et al., 2026). Within this female sample, anthropometric variables were weak, non-significant correlates of 2000 m time (height r = − .001; body mass r = − .385), and body size was deliberately excluded from the model following Riechman et al. (2002). This pattern is expected within a selected, relatively homogeneous squad, where physiological capacity discriminates performance more than body size, even though anthropometry is an established determinant across broader and more heterogeneous cohorts (Kramer et al., 1994; Sebastia-Amat et al., 2020; Wahyuningsih & Raharjo, 2015). The modest, non-significant tendency for heavier (heavyweight-category) athletes to record faster times is consistent with the mass advantage documented in open-category rowing, but the effect did not reach significance in this small sample.

4.5. Practical applications

The practical value of the model lies in its accessibility. Because the 6000 m and 1 min tests are already administered within the national selection battery, coaches can estimate an athlete's 2000 m potential without imposing an additional maximal 2000 m trial or requiring gas-exchange VO~2max~ testing that is difficult to deliver uniformly across regions. Such field-based, low-cost monitoring tools are precisely what applied reviews of rowing assessment have advocated (Smith & Hopkins, 2012), and they complement the profiling approaches increasingly used in national programmes (Jacobs & Schumann, 2025). Where laboratory access exists, the field proxy can be supplemented by direct aerobic or

threshold measures to refine estimation (Kilbey et al., 2025; Holmes et al., 2020), but the present equation offers a defensible first-line screening and monitoring tool grounded in data that are already collected.

4.6. Strengths, limitations, and future directions

A key strength of this study is that it was built entirely on verified, routinely collected competition-selection data, analysed with a transparent and reproducible pipeline, and that the final model satisfied the assumptions of normality, non-collinearity, and residual independence. Several limitations must nonetheless temper interpretation. First, the sample was small (n = 22) and drawn from a single selection event, which limits statistical power and the stability of stepwise variable selection; the reported R^2 and standard error of the estimate are in-sample values and are therefore likely optimistic, since no external or cross-validation was performed. Second, the model is sex-specific and should not be assumed to transfer to male rowers without re-derivation. Third, 6000 m power is a field proxy rather than a direct measure of VO~2max~, and participant age was not recorded in the available dataset, precluding age-adjusted analysis. Future work should cross-validate the equation on larger, independent female cohorts, ideally across multiple selection years; compare the field proxy against directly measured VO~2max~, critical power, and lactate-threshold indices (Holmes et al., 2020; Kilbey et al., 2025); and extend the modelling to male athletes and to longitudinal monitoring so that the equation's predictive validity and responsiveness to training can be established. Pending such validation, the present findings should be regarded as a robust but preliminary, sample-specific prediction model for female national-selection rowers.

5. Conclusion

This study developed a practical equation to predict 2000 m rowing-ergometer time from tests already embedded in the Indonesian national selection battery. In female national-selection rowers, mean 6000 m power together with 1 min stroke rate explained 79.5% of the variance in 2000 m time, with average 6000 m power acting as the dominant predictor; the model satisfied all regression assumptions and predicted most athletes' times to within a few seconds. Aerobic power, captured here through a routine field test rather than laboratory gas analysis, thus remains the central determinant of 2000 m performance in this population.

The principal contribution of the study is practical. Because both predictors are drawn from tests that national programmes already administer, coaches and selection panels can estimate an athlete's 2000 m potential without imposing an additional maximal 2000 m trial or requiring VO~2max~ testing that is difficult to deliver uniformly across regions. The resulting equation offers a low-cost, accessible tool for talent screening and performance monitoring, grounded in data that are collected as a matter of routine.

These findings should nonetheless be regarded as preliminary and sample-specific. They were derived from a small, single-sex cohort at one selection event and were not externally cross-validated, so the reported accuracy is likely optimistic. Confirmation in larger, independent female cohorts, and extension

to female athletes and to longitudinal monitoring is needed before the equation informs selection decisions. Pending such validation, it provides a robust, evidence-based starting point for efficient, field-based evaluation of rowing performance.

Declarations

Ethics approval and consent to participate

Ethical approval was granted by the Research Ethics Committee of the Sport Science Laboratory, Faculty of Physical Education and Health, Universitas Pendidikan Indonesia (Komite Etik Penelitian Laboratorium Sport Science FPOK UPI), under Ethical Approval No. 048/UN40.F4/EC/SSL/2026. The approval was issued on 8 March 2026 and is valid until 8 March 2027. The ethical approval certificate covers the research protocol involving 22 elite female national rowing athletes and specifies participant-protection procedures, including written informed consent, pre-test medical screening, data anonymization, and athlete health/welfare protocols. The study was conducted in accordance with the principles of the Declaration of Helsinki. Written informed consent to participate was obtained from all participants.

Consent for publication

Not applicable. The manuscript contains no individually identifiable information or individual-level data that could reasonably identify the participants.

Competing interests

The authors declare that they have no competing interests relevant to the content of this article.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used an AI-based language-editing tool solely to improve the grammatical accuracy, sentence structure, clarity, and readability of the English language. The tool was not used to generate, analyse, interpret, or modify the research data, statistical results, scientific conclusions, or references. All scientific content, methodological decisions, statistical analyses, interpretations, and final manuscript content were reviewed and verified by the authors, who take full responsibility for the content of the publication.

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Author Contribution

Dede Rohmat Nurjaya (D.R.N.) and Burhan Hambali (B.H.) contributed to the conceptualization and study design. Dede Rohmat Nurjaya (D.R.N.), Burhan Hambali (B.H.), Akhmad Mar'i Muyassar (A.M.M.), and Aviron Azizah Fasya (A.A.F.) contributed to data curation and interpretation of the findings. Dede Rohmat Nurjaya (D.R.N.) conducted the statistical analysis and drafted the manuscript. Akhmad Mar'i Muyassar (A.M.M.) and Aviron Azizah Fasya (A.A.F.) contributed to the literature review, data interpretation, and manuscript development. Burhan Hambali (B.H.) provided methodological supervision and critical intellectual input. All authors critically reviewed and revised the manuscript, approved the final version, and agreed to be accountable for all aspects of the work.

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Availability of data and materials

The de-identified dataset analysed during the current study is available from the corresponding author on reasonable request and subject to permission from the Indonesian Rowing Federation (PB PODSI). The analysis code used to reproduce the reported statistical analyses is also available from the corresponding author on reasonable request.

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Figures

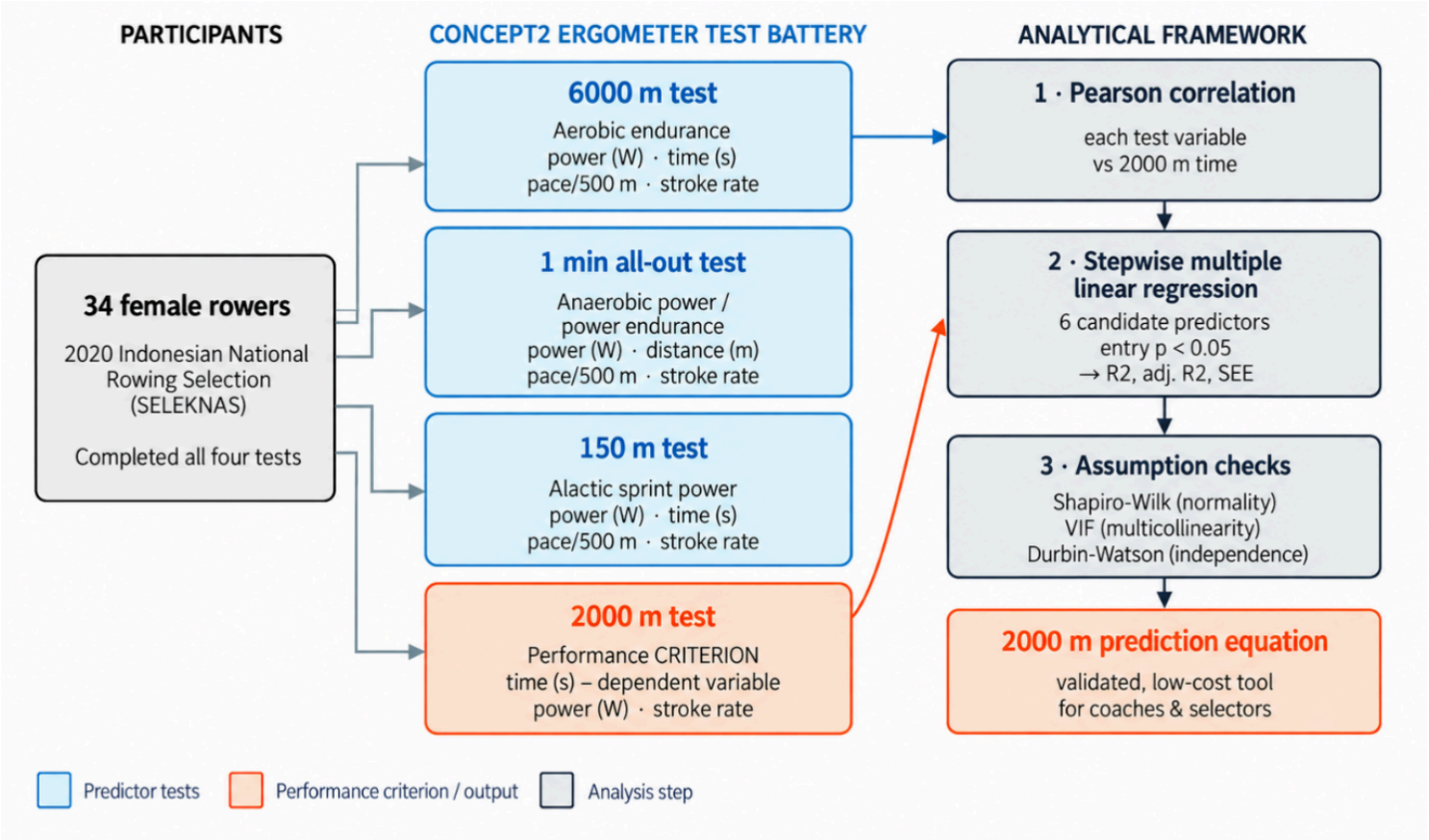


Figure 1

Overview of the study design: the SELEKNAS Concept2 test battery, the variables extracted from each test, and the analytical framework used to predict 2000 m performance.

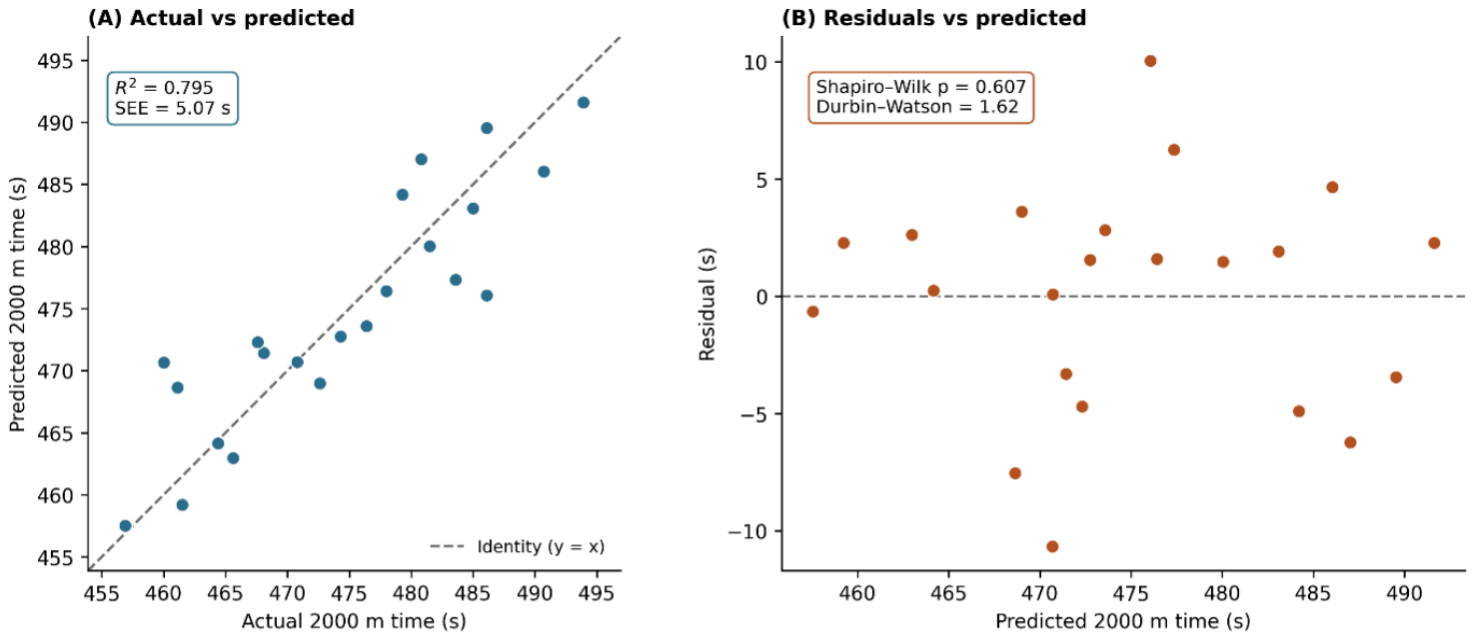


Figure 2

Model performance for predicting 2000 m ergometer time. (A) Predicted versus actual 2000 m time with the identity line (y = x); (B) residuals versus predicted values.