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The Modified 3-Minute All-Out Test Parameters as Predictors of 50-, 100-, and 200-m Front Crawl Official Performance in Trained Swimmers

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Abstract

Di Gennaro, S, Panascì, M, Apollaro, G, Fassone, M, Puce, L, Ruggeri, P, and Faelli, E. The modified 3-minute all-out test parameters as predictors of 50-, 100-, and 200-m front crawl official performance in trained swimmers. *J Strength Cond Res* XX(X): 000–000, 2026—In this study, we investigated (a) the relationship between the modified 3-minute all-out test ($3mAO_{mod}$) parameters and swimming official performance in 50-, 100-, and 200-m front crawl; (b) the predictive accuracy of critical speed (CS) model; (c) the predictive linear regression (MLR) models incorporating CS, curvature constant (D′) or anaerobic speed reserve (ASR), and anthropometry. Twenty-three young swimmers (mean ± *SD*: age = 17.5 ± 1.9 years, mass = 61.8 ± 7.2 kg, height 1.79 ± 0.08 m) performed the $3mAO_{mod}$ and, within 6 weeks, competed in 50-, 100-, and 200-m official races. The relationships between $3mAO_{mod}$ parameters and race times were examined using Pearson's and Spearman's correlation. Race times were predicted using the CS model and MLR, including CS, D′, or ASR, sex, age, height, and body mass. Mean absolute error (*MAE*) and paired sample t-tests with Bonferroni corrections were used to compare actual and predicted results. Significance was set at $p \leq 0.05$. The correlation between CS and race time increased with the increase in race distance ($r = -0.491$ to -0.698) while the correlation between D′ and ASR with race time decreased with the increase in race distance (rho = −0.628 to −0.347 and −0.574 to −0.274, respectively). The CS model underestimates race times in the 50- and 200-m races ($p \leq 0.001$, $MAE = \pm 3.33$ and ±5.06 seconds, respectively), but not in the 100-m race ($p = 0.070$, $MAE = \pm 1.72$ seconds). Predictions from MLRs were not significantly different from actual performance in all events ($p = 0.999$, ± 0.41 seconds $< MAE < \pm 3.56$ seconds). The $3mAO_{mod}$ parameters are related to 50-, 100-, and 200-m performance, supporting their physiologic rationale and, when applied to the developed MLRs, can predict performance with higher accuracy than the CS model, and in a user-friendly manner.

Key Words: swimming, modeling, critical speed, anaerobic speed reserve, curvature constant

Introduction

The speed (or power)–duration relationship is widely used across various endurance sports to describe the link between the speed and the time for which that intensity can be sustained (13). This relationship follows a hyperbolic-like pattern, tending toward an asymptote at intensities close to the maximal lactate steady state (16). This pattern can be described by several models, such as the power law model, the anaerobic power reserve model, or the critical speed (CS) model (10,13,28). The latter, in particular, is one of the most used and it allows the estimation of (a) CS, defined as the theoretical maximal intensity that can be sustained indefinitely and where physiological parameters such as oxygen uptake, lactate, and phosphocreatine can still stabilize; (b) the so-called curvature constant (D′), which represents the distance an athlete can perform beyond CS, often interpreted as measure of anaerobic work capacity (14). In swimming contexts, considering the greater challenges in performing gas exchange and lactate analysis to delineate the physiologic thresholds, the CS model, despite being indirect, offers a valid and feasible assessment of the boundary between the heavy and severe intensity domains and allows an accurate performance prediction (14).

A significant limitation of this model is that it requires the athlete to perform multiple maximal trials for various distances to estimate CS and D'. This practice is highly invasive within an athlete's training program. To overcome this problem, the so-called 3-minute all-out test was introduced, first in cycling, then in running, and, more recently, also in swimming, where it can be applied in a 25-m pool using a modified, intermittent-based version ($3mAO_{mod}$) (21). This test enables the estimation of CS and D′ with high precision compared with the standard approach, with a duration of approximately 4 minutes. In addition, the $3mAO_{mod}$ allows the determination of peak velocity (21) and, consequently, a recently introduced easy-to-use proxy of anaerobic characteristics, namely the anaerobic speed reserve (ASR) (28). The ASR was originally defined as the difference between the maximal sprinting speed and the speed associated with maximal oxygen uptake (vVO_2max) (28). However, some studies suggest that using CS to define the lower boundary provides a parameter more related to D′ than the original approach, and it is also

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strongly related to exercise tolerance within the severe and extreme intensity domains (8,11,18). Although ASR has been extensively studied in running and cycling (28), evidence in swimming is still limited. To date, the relationship between ASR and D' in swimming has been investigated in only one study. The researchers observed a strong correlation between them (8), suggesting ASR as a straightforward and practical parameter for both race time prediction and exercise intensity prescription (8). But it is still unclear whether this parameter can be used as an alternative to D′ for swimming performance prediction.

Moreover, the validity of the 3-minute all-out test has also been contested, with evidence suggesting it overestimates both performance and the true maximal metabolic steady state across cycling and running (3,25). Nevertheless, CS (alone or in combination with D′) can accurately predict longer performances such as 400-m front crawl (33). However, predictive accuracy for shorter distances spanning 50–200 m remains unknown. Therefore, given this ongoing debate, coupled with the scarcity of data validating the $3mAO_{mod}$ performance prediction accuracy in swimming, we investigated the relationships between the $3mAO_{mod}$-derived parameters and 50-, 100-, and 200-m front crawl official race times, and we evaluated the predictive ability of the CS model. In addition, integrating the critical influence of anthropometry in swimming performance (19), and the parallelism between ASR and D′, we also developed linear equations incorporating CS, D′, or ASR, and anthropometric variables for predicting race times across the 50-, 100-, and 200-m front-crawl distances.

Methods

Experimental Approach to the Problem

One week after a previous familiarization with the test, all subjects completed the $3mAO_{mod}$ in a 25-m pool at the same time of the day (±1h) in an indoor swimming pool with a water temperature of 27° C. The test was performed 1 week before the summer competition season. Anthropometric assessment in terms of barefoot subjects' stature and body mass was also collected (Seca 217, Vogel and Halke, Hamburg, Germany). Then, in the next 6 weeks, subjects competed in 3 official front crawl events (50, 100, and 200-m) held in a 50-m swimming pool. Race times were recorded and used for correlation analyses and predictive modeling of performance.

Subjects

An a priori power analysis was performed using G*Power (version 3.1.9.7; Heinrich Heine University, Düsseldorf, Germany) to estimate the required sample size. Based on data from a previous study investigating the predictive ability of the 3-minute all-out test in cycling performance (25), a point-biserial correlation (*t*-test family) with an effect size of $r = 0.60$, $\alpha = 0.05$, and statistical power = 0.80 was used. The calculations indicated a minimum sample size of 21 subjects.

Twenty-three young trained swimmers (13 females and 10 males) were recruited (males: median [minimum, maximum] age = 19 [16, 20] years; mean ± *SD*, mass = 64.6 ± 8.2 kg: height 1.74 ± 0.08 m; females: age = 17.4 ± 1.4 years, mass = 59.3 ± 5.3 kg; height = 1.66 ± 0.06 m) (20). The FINA points were calculated by the Federation Internationale de Natation (FINA) software (Software 2009 by GeoLogix) (FINA points 100-m front crawl for males: 495 ± 75; for females 515 ± 91). All subjects regularly trained 4–5 sessions per week during the last year. None of them reported muscular or orthopedic injuries or health problems in the previous 6 months. To standardize testing conditions, subjects were instructed to abstain from food and caffeine consumption in the 3–4 hours preceding the test and not exercise in the previous 24 hours (31). All subjects received a detailed explanation of the study's objectives and procedures and provided their written informed consent (and when minors, also that of their parents). The research adhered to the Declaration of Helsinki, with prior approval from the local ethics committee (University of Genoa, approval n° 2024/62).

Procedures

The Modified 3-Minute All-Out Test. Before the $3mAO_{mod}$ test, swimmers completed a 10-minute low-intensity warm-up, including activation drills. Then, they engaged in a 5-minute passive rest before starting the $3mAO_{mod}$. The test was conducted according to the protocol outlined by Mitchell et al. (21). Subjects performed 12 all-out 25-m repetitions interspersed by 5 seconds of passive rest. Athletes were instructed to attempt to surpass their personal best time for each 25-m segment. The time for each segment was measured by a member of the research team, who is also a swimming coach with ≥20 years of experience in the field, using a handheld stopwatch (3 × 300 m Stopwatch, Finis).

Data Analysis. Critical speed and D′ were determined according to Mitchell et al. (21). The mean speed for each 25-m segment was calculated, and subsequently, nonlinear regression analysis was performed to fit an exponential decay model to the relationship between the speed of each pool ($S_{(t)}$) and the cumulative time (t) across the entire $3mAO_{mod}$: $S_{(t)} = A \cdot e^{-bt} + c$.

A and b represent weighting factors, and c is the model's asymptote. Critical speed was defined as the average speed achieved during the 2 slowest 25-m segments within the final 4 repetitions of the $3mAO_{mod}$.

D' was calculated as follow: $(t_1 \cdot S_1) - (CS \cdot t_1) + (\int_{t_{12}}^{t_1} A \cdot e^{-bt} + c) - CS$.

Here, t_1 is the time to complete the first 25 m, and t_{12} is the time taken to complete all 12 segments. All fitting procedures were performed using MATLAB R2023b (The MathWorks Inc., Natick, MA). The race times predictions using the CS model have been calculated by solving the 2-parameter using D′ and CS obtained from the $3mAO_{mod}$ as follows:

$$t = \frac{Race_{dist} - D'}{CS}$$

where t is the estimated time and race $Race_{dist}$ is the distance of the race (i.e., 50, 100, or 200-m). The ASR has been calculated as the difference between the peak velocity (first pool mean velocity) and the CS (4,18).

50-, 100-, 200-Meter Front Crawl Official Races. Within 6 weeks after the $3mAO_{mod}$ test, the subjects conducted 50-, 100-, and 200-m front crawl official races in a standard 50-m pool. Before the races, swimmers performed 15 minutes of warm-up, consisting of 5 minutes of dryland drills followed by 5 minutes of low-intensity swimming, to conclude with 5 minutes at their preferred pace, including brief sprints of 2–3 seconds (24). From the end of the warm-up to the start of the competition, there was a time lag spanning from 10 to 30 minutes. The race time has been subsequently collected from the Italian swimming federation website (https://www.federnuoto.it/).

Statistical Analyses

The Shapiro–Wilk test was applied to assess the distribution of the variables. Descriptive statistics for normally distributed variables are presented as mean ± *SD*, while for those not normally distributed, as medians with range [minimum, maximum]. The coefficient of variation and the intraclass correlation coefficient (ICC) were calculated to assess the reliability of the 3mAO$_{mod}$ parameters compared with the familiarization session (17). Pearson correlation coefficients (r) were calculated to determine relationships among variables. Correlation coefficients of >|0.1|, >|0.3|, >|0.5|, and >|0.7| were considered small, moderate, large, and very large (15). Height, ASR, and D′ violated normality assumptions; consequently, Spearman's correlation was applied. Multiple linear regression (MLR) analysis was applied to predict 50-, 100-, and 200-m performance using CS, D', sex (female = 1; male = 0), age, body mass, and body height as independent variables (MLR$_{D'}$). Considering the practical challenges of determining D′ in the field, a further MLR analysis was conducted using ASR instead of D' (MLR$_{ASR}$). To assess the potential for multicollinearity, we calculated the Variance Inflation Factor for all independent variables, confirming that no value exceeded the threshold of 10 (2). We also performed a variance decomposition analysis, which confirmed that no 2 variables exhibited a variance proportion above 0.9 for any given dimension (2,12). Together with the R^2, the adjusted R^2 (*adj* R^2) has been calculated to account for the number of predictors. Standard error of estimation (*SEE*) and mean absolute error (*MAE*) were calculated to evaluate the prediction accuracy of the models. A paired sample *t*-test with Bonferroni corrections was used to compare the actual and predicted results. Mean bias and 95% limits of agreement are presented in the Bland–Altman plots to graphically show the differences between predicted and actual race times. Statistical significance was set at $\alpha = 0.05$ (2-tailed). Finally, to examine proportional bias, correlation analyses between bias and actual race times and 3mAO$_{mod}$ parameters were performed. All statistical analyses were performed using IBM SPSS Statistics for Windows, version 26.0 (IBM Corp., Armonk, NY).

Results

The mean CS was 1.45 ± 0.10 m·s^{-1}, the median D′ was 15.57 [5.73, 29.92] m, and ASR was 0.32 [0.20, 0.41] m·s^{-1}. There was no sex difference in 100 m FINA points (males: 495 ± 74 vs. females: 515 ± 91, $p = 0.670$). Nevertheless, males presented higher CS (1.51 ± 0.07 vs. 1.39 ± 0.09 m·s^{-1}, $p = 0.002$), peak velocity (1.90 ± 0.08 vs. 1.67 ± 0.09 m·s^{-1}, $p < 0.001$), D' (17.60 ± 7.34 vs. 11.66 ± 4.98 m, $p = 0.044$), and ASR (0.39 ± 0.12 vs. 0.28 ± 0.07 m·s^{-1}, $p = 0.025$) than females. Coefficient of variation for CS, peak velocity, ASR, and D′ was 1.85, 1.08, 12.18, and 14.24%, respectively; while ICC was 0.864, 0.974, 0.809, and 0.870. Correlation analyses among race times, performance parameters, and anthropometry are given in Table 1. In addition, sex-specific correlations are illustrated in the matrices shown in Figure 1.

Significant correlations between actual race times and those predicted by the CS model were observed (50-m: $r = 0.858$, $p < 0.001$, *SEE* = 4.570 seconds, *MAE* = 3.328 seconds, *MAE* (%) = 12.50; 100-m: $r = 0.940$, $p < 0.001$, *SEE* = 2.371 seconds, *MAE* = 1.722 seconds, *MAE* (%) = 2.96; 200-m: $r = 0.844$, $p < 0.001$, *SEE* = 6.887 seconds, *MAE* = 5.058 seconds, *MAE* (%) = 3.75). However, these predictions are significantly lower than the actual race times for 50-m ($p < 0.001$) and 200-m ($p = 0.001$) but not for 100-m ($p = 0.070$).

Table 1

Correlation coefficients among race times, 3mAO$_{mod}$ parameters, and anthropometry.*†

	Pb50	Pb100	Pb200	CS	D'	ASR
CS						
r	−0.491	−0.680	−0.698			
p	0.017	<0.001	<0.001			
D'						
rho	−0.628	−0.472	−0.347	−0.153		
p	0.001	0.023	0.105	0.485		
ASR						
rho	−0.574	−0.467	−0.274	−0.274	0.818	
p	0.004	0.025	0.206	0.738	<0.001	
Age						
r	−0.504	−0.315	−0.188	−0.265	0.626‡	0.436‡
p	0.014	0.143	0.390	0.223	0.001	0.038
Body mass						
r	0.077	0.011	−0.147	0.059	−0.727‡	−0.528‡
p	0.727	0.961	0.503	0.789	<0.001	0.010
Body height						
rho	−0.779	−0.718	−0.706	0.382	0.608	0.431
p	<0.001	<0.001	0.001	0.125	0.002	0.040

*CS = critical speed; D′ = distance performed above CS; ASR = anaerobic speed reserve.
†Pb50, Pb100, and Pb200 are front crawl race times in 50-, 100-, and 200-m, respectively.
‡Indicates that Spearman correlation was applied.

The MLR$_{D'}$ provides the following equations:

- 50-m race time = 61.846 − 15.726 × CS − 0.195 × D' + 0.69 × sex − 0.379 × age + 0.002 × mass − 1.31 × height ($R^2 = 0.924$, *adj* $R^2 = 0.895$; $p < 0.001$, *SEE* = 0.672 seconds, *MAE* = 0.412 seconds, *MAE* (%) = 1.49);
- 100-m 1race time = 131.492–42.849 × CS – 0.46 × D' + 1.443 × sex – 0.533 × age – 3.575 × height ($R^2 = 0.943$, *adj* $R^2 = 0.920$. $p < 0.001$. *SEE* = 1.277 seconds, *MAE* = 0.867 seconds, *MAE* (%) = 1.48);
- 200-m race time = 308.866 – 104.822 × CS – 0.967 × D' + 7.035 × sex – 0.611 × age – 0.011 × mass – 1.374 × height ($R^2 = 0.796$, *adj* $R^2 = 0.720$. $p < 0.001$, *SEE* = 5.552 seconds, *MAE* = 3.295 seconds, *MAE* (%) = 2.48).

No significant difference appears between actual and MLR$_{D'}$ predicted race times (50-m: $p = 0.999$; 100-m: $p = 0.999$; 200-m: $p = 0.999$).

The MLR$_{ASR}$ provides the following equations:

- 50-m race time = 68.46 – 14.26 × CS – 9.687 × ASR + 0.857 × sex – 0.402 × age + 0.002 × mass – 6.039 × height ($R^2 = 0.924$, *adj* $R^2 = 0.895$. $p < 0.001$, *SEE* = 0.673 seconds, *MAE* = 0.475 seconds, *MAE* (%) = 1.71);
- 100-m race time = 146.786 – 38.553 × CS – 21.442 × ASR + 1.639 × sex – 0.596 × age +0.001 × mass – 8.254 × height ($R^2 = 0.928$, *adj* $R^2 = 0.901$. $p < 0.001$, *SEE* = 1.419 seconds, *MAE* = 0.937 seconds, *MAE* (%) = 1.56);
- 200-m race time = 339.121 – 90.292 × CS – 35.912 × ASR + 6.153 × sex – 0.802 × age – 0.009 × mass – 30.673 × height ($R^2 = 0.755$, *adj* $R^2 = 0.663$. $p < 0.001$, *SEE* = 6.089 seconds, *MAE* = 3.564 seconds, *MAE* (%) = 2.64).

There was no significant difference between actual and MLR$_{ASR}$ predicted race times (50-m: $p = 0.999$; 100-m: $p = 0.999$; 200-m: $p = 0.999$).

The relationships between predicted and actual race times and Bland–Altman plots are shown in Figures 2 and 3.

Average actual and predicted race times are presented in Table 2.

Exploratory sex-specific MLRs have been conducted and presented in Table 3.

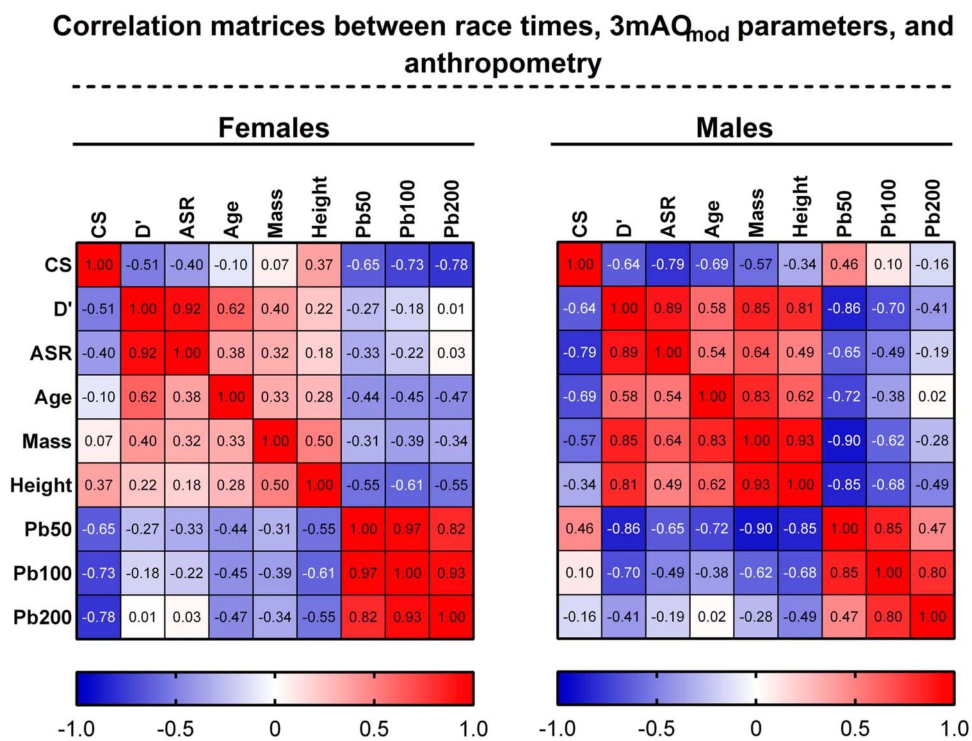

Figure 1. Correlation matrices divided by sex between 3mAO$_{mod}$ parameters, anthropometry, and performance variables. Abbreviations: 3mAO$_{mod}$, modified 3-minute all-out test; CS = critical speed; D′ = distance above CS; ASR = anaerobic speed reserve; Pb50, Pb100, and Pb200 are the official race times of 50, 100, and 200 m front crawl races, respectively. In the female (n = 13) analyses, only $r < -0.55$ or >0.55 are statistically significant; in the male (n = 10) analyses, only $r < -0.64$ or >0.64 are statistically significant.

A proportional bias emerged among the CS model-predicted race times and relative bias. Figure 4 shows the parameters significantly related to the bias.

Discussion

In this study, we investigated the relationships between the 3mAO$_{mod}$ parameters (CS, D′, ASR) and race times in 50-, 100-, and 200-m front crawls. In addition, we evaluated the CS model's predictive accuracy using the 3mAO$_{mod}$ parameters and developed linear equations, also incorporating anthropometric measurements to predict race times. The first finding of our study relates to the relationships between the 3mAO$_{mod}$ parameters and race times. In particular, an inverse relationship was observed between D′ and race times in the 50- and 100-m events. Interestingly, and supporting the anaerobic underpinning meaning of D′, this relationship tended to weaken as race distance increased, becoming nonsignificant in the 200-m event. Notwithstanding literature on the physiologic meaning of D' is contradictory. In fact, some studies have observed correlations between D′ and anaerobic indices such as blood lactate concentration or maximal accumulated oxygen deficit (14,23,34), while others found inconsistent results (9,30). This inconsistency may be because of a (partial) lack of physiologic significance of this variable, a high variability of its measurement because of the high difficulty of repeating maximal trials, or both (21,26). Nevertheless, our results show that athletes with higher D' values exhibit superior performance in shorter events such as 50- and 100-m front crawl, thus indirectly suggesting D′ as an anaerobic index. Interestingly, when the data were analyzed separately by sex, D' was significantly associated with performance only in males, not in females. Although the inferential power of this finding is limited by the reduced sample size after splitting, it suggests potential sex-specific physiologic determinants of performance, even within the same event (e.g., 50, 100, or 200 m). This could be partly attributable to the shorter absolute race times in males than in females when matched for relative performance (using FINA points). Similarly to D′, ASR showed a large correlation with 50-m performance, which gradually diminishes with increasing race distance and becomes nonsignificant in the 200-m event. Accordingly, Buchheit et al. (6) observed that athletes with a higher ASR experience less metabolic stress at a given speed. Then, normalizing intensity for $\dot{V}O_2max$, athletes with higher ASR demonstrate greater exercise tolerance, particularly during efforts lasting less than 5 minutes (4,11). Moreover, we observed a very large relationship between ASR and D′ that is equally preserved even when stratifying the results by sex.

Potential explanations for this relationship include both mechanical and mathematical factors. From a mechanical standpoint, both parameters reflect the reserve of velocity or distance that an athlete can still swim beyond a certain threshold (28). It is worth noting that the speed–duration relationship in swimming differs from the power–duration relationship in disciplines such as cycling (29,30). This divergence arises because the energetic cost of locomotion in swimming is highly influenced by the water's drag resistance. This drag force increases quadratically with velocity, exponentially elevating the metabolic cost (30,35). Consequently, interpreting work capacity and power output above critical speed in swimming presents a greater challenge, because these measures are influenced by the distinct environment. From a mathematical perspective, the relationship between ASR and D′ could be partially explained by the fact that ASR is

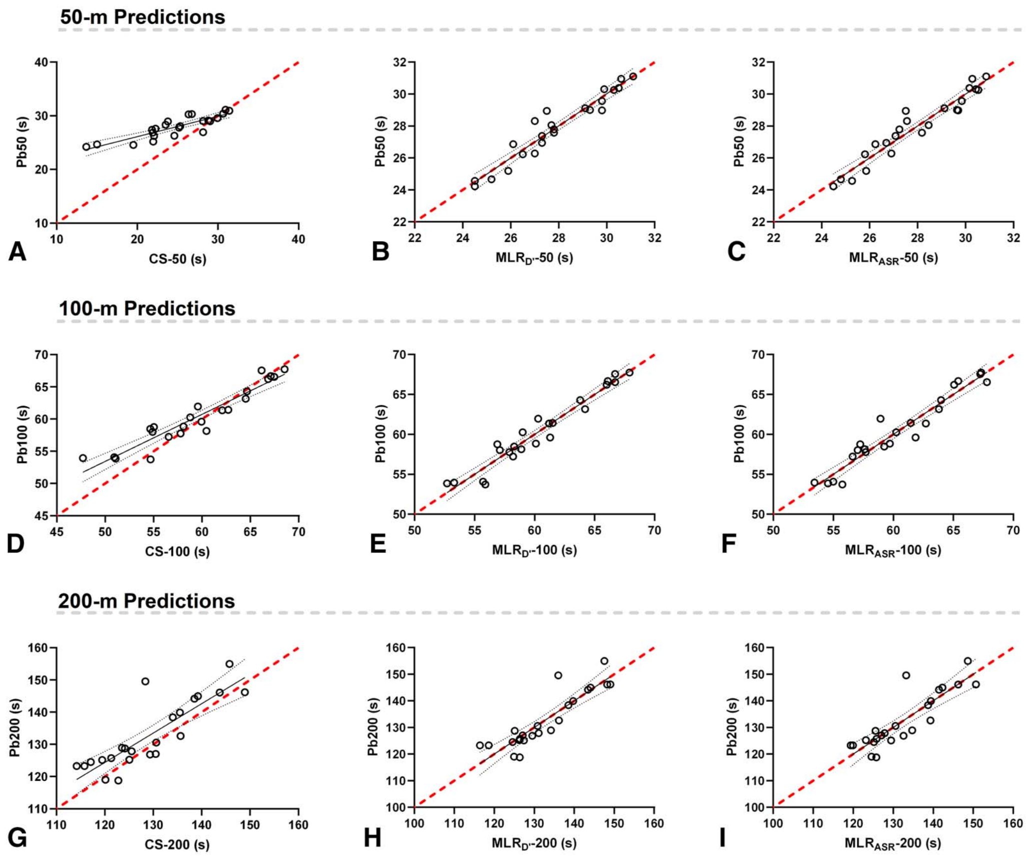

Figure 2. Predicted versus actual race time. The red dashed line is the identity line (R = 1). Pb50, Pb100, Pb200, front crawl race time in 50-, 100-, and 200-m, respectively. CS-50, CS-100, and CS-200 are the race times predicted by the critical speed model. MLR$_{D'}$-50, MLR$_{D'}$-100, and MLR$_{D'}$-200 are the race times predicted by the multiple linear regressions (MLR) using D' (distance performed above CS) as anaerobic marker. MLR$_{ASR}$-50, MLR$_{ASR}$-100, and MLR$_{ASR}$-200 are the race times predicted by MLR using the anaerobic speed reserve as anaerobic marker.

inherently incorporated into the equation for calculating D' (21). Moreover, when analyzing this relationship by sex, a pattern similar to that of D' emerged: ASR was positively associated with performance in males only and solely in the 50-m front crawl. Even though it should be noted that these findings warrant caution because of the reduced sample size resulting from the stratification by sex. Concerning CS, a moderate-to-large relationship across all distances has been observed. Contrary to the D′, the strength of this correlation increased as the duration of the race increased. This pattern further supports the physiologic rationale behind this parameter. Numerous previous studies have highlighted the importance of a high CS in sustaining prolonged high-intensity exercise before the onset of fatigue (9,16). This association is likely attributed to the strong correlation between CS and other physiologic indicators of endurance performance, such as the maximal lactate steady state and respiratory compensation point (16). An intriguing finding was the moderate correlation between CS and 50-m performance. The average 50-m race time was 27.94 seconds, so considering that the cardiodynamic and primary phases of the oxygen kinetic typically last between 1 and 2 minutes, the energy contribution for a 50-m race is mainly supplied by anaerobic lactic and alactic pathways (1). Therefore, although CS is correlated with 50-m race times, this does not necessarily imply a direct causal relationship. In fact, performance in this event is largely determined by technical skills and movement efficiency (29). However, to achieve high levels of movement economy and propulsive capacity, it is necessary to perform a high training volume, especially at low intensities, to learn and improve the movement without the detrimental effects of fatigue (29). This volume of low-intensity training could induce a concurrent improvement in aerobic power and technical skills, which led us to find this positive relationship between CS and 50-m performance (22). A further interesting result emerged from the sex-stratified analysis. CS was positively associated with performance, but in this case, in females only. Taken together with the previous finding that D' was associated with performance only in males, these results might suggest again the distinct metabolic and physiologic demands of the same event on male and female swimmers.

The second aim of this study was to evaluate the predictive accuracy of the CS model applying the 3mAO$_{mod}$ parameters. Our findings indicate a systematic underestimation of race times across all distances. Specifically, we observed underestimations of ~10, ~1.4, and ~2.7%, respectively, in 50-,100-, and 200-m race times, thus suggesting this model is inaccurate for predicting such short-duration events, especially the 50-m front crawl. Although the reasons are not entirely clear, some hypotheses can be proposed. First, the CS model was initially developed to explain performance for a duration spanning from 2 to 30 minutes, therefore, largely outside the time domain of the 50 m (13). Second, CS and D′, derived from the 3mAO$_{mod}$, were validated against the traditional 2-parameter model (21). Previous research reported that this model tends to overestimate performance in events lasting less than 2 minutes (27,32). Conversely, the 3-

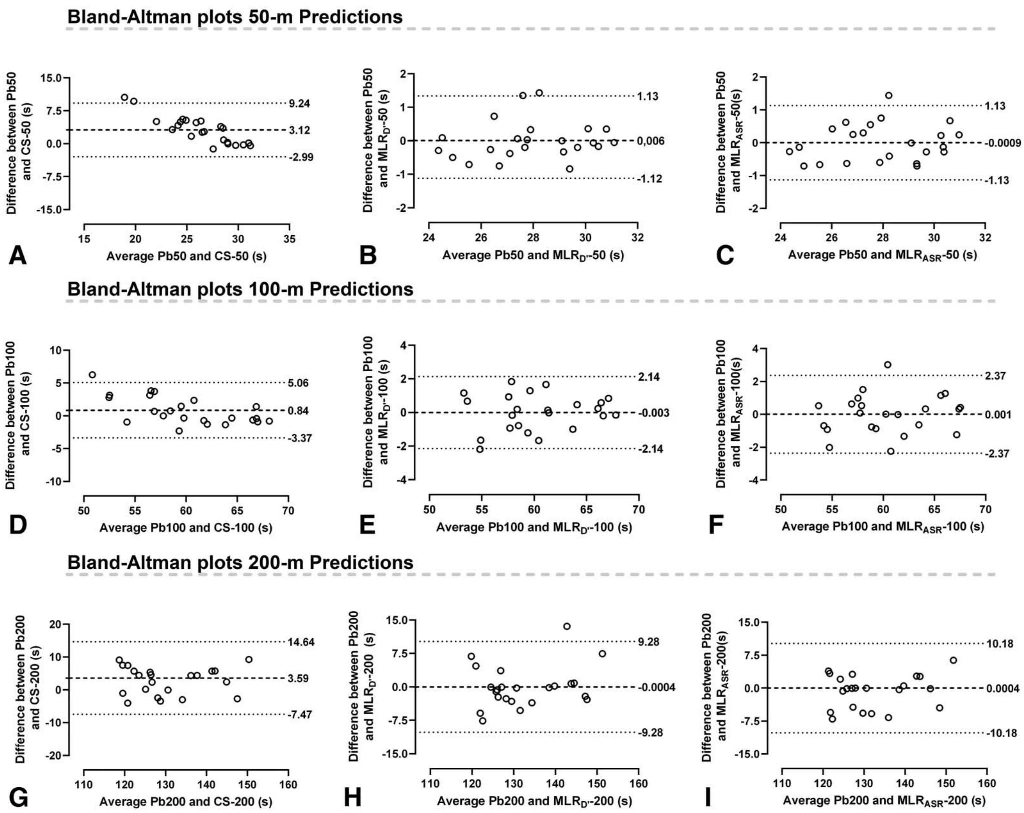

Figure 3. Bland–Altman plots of predicted vs actual race times. The dashed black line is the mean bias and the dotted lines are the 95% confidence intervals. Pb50, Pb100, Pb200, front crawl race time in 50-, 100-, and 200-m, respectively. CS-50, CS-100, CS-200 are the race times predicted by the critical speed model; MLR$_{D'}$-50, MLR$_{D'}$-100, and MLR$_{D'}$-200 are the race times predicted by the multiple linear regressions (MLR) using D' (distance performed above CS) as anaerobic marker. MLR$_{ASR}$-50, MLR$_{ASR}$-100, and MLR$_{ASR}$-200 are the race times predicted by MLR using the anaerobic speed reserve as anaerobic marker. CS = critical speed.

parameter model, which incorporates a *k*-factor representing a hypothetical maximum power output, has been shown to provide more accurate predictions for events lasting approximately 30 seconds (27,32). Considering that the 50-m performance is more power limited rather than capacity limited, the 2-parameter CS model applied in this study may not accurately predict performance.

Moreover, from the Bland–Altman plots, proportional bias emerged. Indeed, a strong inverse relationship was observed between race time and prediction error for both the 50-m and 100-m events. This indicates that the 2-parameter CS model becomes less accurate as the race times decrease. Then, a significant positive correlation was found between D′ and prediction error for both the 50-m and 100-m events, suggesting that D' may be a primary source of error in these predictions.

Table 2

Average actual and predicted race times.*

Race	Actual	CS model	MLR$_{D'}$	MLR$_{ASR}$
50-m (s)	27.94 ± 2.08	24.82 ± 4.74‡	27.94 ± 2.00	27.94 ± 2.00
100-m (s)	60.42 ± 4.52	59.58 ± 5.86	60.42 ± 4.39	60.42 ± 4.36
200-m (s)	132.69 ± 10.49	129.10 ± 9.75†	132.69 ± 9.36	132.69 ± 9.11

*CS = critical speed; MLR$_{D'}$ = multiple linear regression (MLR) using the curvature constant (D′) and anaerobic index; MLR$_{ASR}$ = MLR using the anaerobic speed reserve (ASR).
†$p < 0.01$.
‡$p < 0.001$; significantly different from the actual race time.

Although a definitive explanation for this relationship is challenging, several factors could be considered. First, D′ estimated by the 3mAO$_{mod}$ shows moderate-to-large uncertainty compared with the traditional D′ estimation and is the result of an intermittent all-out test, which may overestimate the curvature constant because of the 5-second recovery after each pool (21). Second, the physiologic significance of D′ has been widely debated. Although some researchers view this variable as synonymous with anaerobic work capacity, others contest this interpretation (14,30). For instance, Weyand and Bundle (7) highlighted that during all-out efforts such as the 3mAO$_{mod}$, the power decrements (and thus also the area under the curve) may be more associated with the progressive skeletal muscle force impairment rather than the depletion of the finite anaerobic work capacity.

The third aim of this study was to develop linear equations incorporating the CS, D′, or ASR and anthropometric measures to predict race time. Both multiple regression models demonstrated high accuracy. Specifically, MLR$_{D'}$ explained 92% of the variance for 50- and 100-m events and 80% for 200-m events. Similarly, MLR$_{ASR}$ explained 92, 93, and 76% of the variance for 50-, 100-, and 200-m events, respectively. In addition, Bland–Altman analysis revealed no significant bias, indicating high model accuracy. Like the CS model, accuracy decreased for the 200-m event, possibly because of subjects' unfamiliarity with this distance. The improved accuracy of the MLR$_{D'}$ and MLR$_{ASR}$ models compared with the CS model can

Table 3

Multiple linear regression models divided by sex.*

			Beta coefficients						Results						
Model	Race	Sex	β0	β1	β2	β3	β4	β5	R^2	$_{adj}R^2$	*p*	Predicted (s)	SEE (s)	*MAE* (s)	*MAE* (%)
MLR$_{D'}$	Pb50	F	58,26	−18.80	−0.2598	−0.0895	0.0410	−0.493	0.924	0.869	<0.001	28,73	0.548	0.349	1.202
		M	55,80	−12.44	−0.2204	−0.4441	0.0290	−0.398	0.901	0.777	<0.050	26,49	0.747	0.424	1.600
	Pb100	F	140,50	−42.48	−0.4419	−0.4637	0.0074	−3.211	0.970	0.949	<0.001	63,14	0.780	0.476	0.755
		M	145,40	−44.34	−0.6961	−1.3760	0.5793	−12.850	0.830	0.618	0.106	56,96	1.591	0.992	1.741
	Pb200	F	340,00	−93.72	−0.2763	−3.0080	−0.1059	−6.029	0.938	0.894	<0.001	135,98	2.772	1.773	1.291
		M	423,20	−76.81	−1.4830	−3.0000	2.7830	−161.500	0.628	0.164	0.396	126,64	7.171	4.308	3.403
MLR$_{ASR}$	Pb50	F	62,81	−15.64	−14.500	−0.360	0.0263	−1.907	0.931	0.881	<0.001	29,06	0.524	0.351	1.208
		M	63,11	−9.77	−6.389	−0.233	−0.0613	−6.490	0.857	0.678	0.077	26,49	0.904	0.551	2.079
	Pb100	F	148,20	−37.30	−25.260	−0.919	−0.0163	−5.477	0.9797	0.965	<0.001	63,06	0.651	0.445	0.705
		M	182,00	−41.35	−24.530	−0.872	0.3909	−36.130	0.742	0.420	0.220	56,91	1.940	1.222	2.145
	Pb200	F	344,80	−90.32	−15.300	−3.297	−0.1218	−7.561	0.939	0.895	<0.001	137,45	2.777	1.775	1.292
		M	522,00	−78.76	−58.890	−2.174	2.5290	−217.300	0.618	0.141	0.413	126,54	7.225	4.313	3.407

*MLR$_{D'}$ and MLR$_{ASR}$ are the multiple linear regression model using critical speed (CS), distance above CS (D′), or anaerobic speed reserve (ASR) (respectively), age, body mass, and height; Pb50, Pb100, and Pb200 are the front crawl races in 50-, 100-, and 200-m, respectively; β0 is the intercept of the model; β1, β2, β3, β4, β5 are the beta coefficients that have to be multiplied to CS ($m\cdot s^{-1}$), D′(m) or ASR ($m\cdot s^{-1}$), age (years), body mass (kg), and height (m); *SEE* = standard error of estimation; *MAE* = mean absolute error.

be attributed to 2 primary factors. First, the inclusion of anthropometric parameters provided additional information correlated with athlete performance (5,19,35). In fact, the present study showed a strong correlation between height and race performance across all 3 distances. These findings are consistent with previous studies that have observed a positive association between race time and anthropometric factors, such as height and arm span, in both adolescent and adult swimmers (35). Second, the regression equations were specific to the study sample. This is because the beta coefficients, generated by the regression procedures, are strictly determined to generate the model with the lowest estimated standard error for the actual race times. Finally, the exploratory sex-stratified MLRs also yielded models with low prediction errors. However, the small sample size relative to the number of predictors frequently resulted in statistically insignificant coefficients of determination. Although these findings are promising, they necessitate further investigation to validate the models' predictive accuracy and to substantiate the proposed sex-based differences in the physiologic demands of the swimming events studied herein.

It should be noted that this study does have some potential limitations: (a) the MLR equations provide excellent results but have been tested only against the same data used to build the same equations, therefore, further investigation is needed to assess their external validity; (b) the 3mAO$_{mod}$, although provides validated CS and D′, does not take into account the swimming turning phase, limiting his ecological validity; (c) in female swimmers, it was not possible to set up the preliminary test during the same phase of the menstrual cycle; (d) the use of a handheld stopwatch for data collection, while appropriate for the scope of this study, is a potential source of measurement error. Consequently, despite the good-to-excellent reliability observed, the results may possess a lower degree of precision than those obtained with automated timing systems (e.g., photocells), which may have influenced the findings.

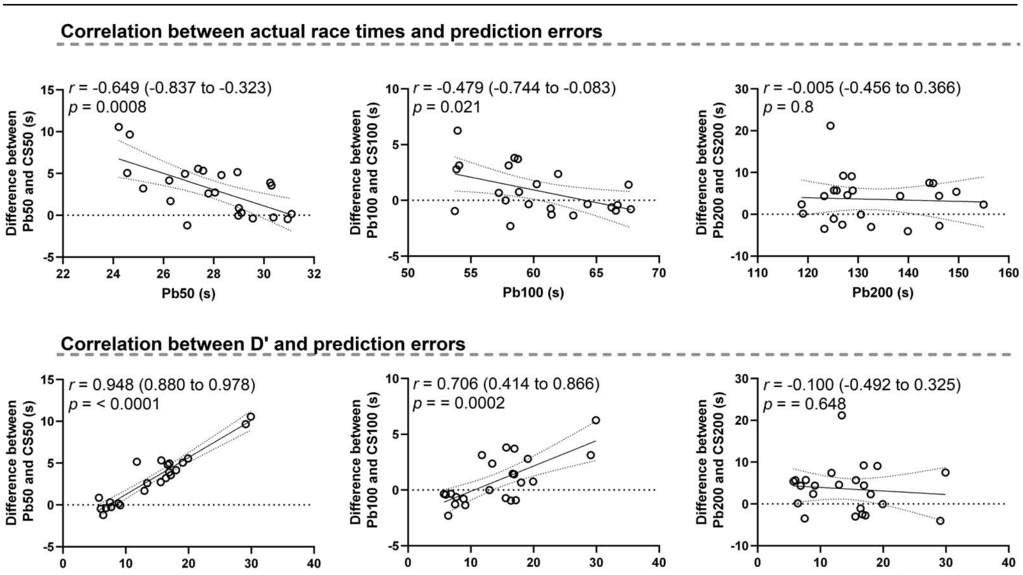

Figure 4. Proportional bias examination of the critical speed model predicted results. CS = critical speed; D′ = distance performed above CS. Pb50, Pb100, and Pb200, front crawl race times in 50-, 100-, and 200-m, respectively. CS-50, CS-100, and CS-200 are the race times predicted by the critical speed model.

Practical Applications

Our findings indicate the $3mAO_{mod}$ test as a practical and easy-to-administer tool for evaluating both aerobic (CS) and anaerobic (D′, ASR) characteristics in swimmers in less than 4 minutes, and when used to resolve the CS model, can predict race times >100 m front crawl performance, but not the 50-m one. Instead, the MLR equations developed can accurately predict all front crawl distances investigated. In addition, the application of the ASR within the equations, while avoiding the mathematical complexity of D′ calculation, retains comparable predictive accuracy, making it a practical alternative for performance prediction in field settings.

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