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Human Kinetics
ORIGINAL INVESTIGATION

Interaction of Kinematic, Kinetic, and Energetic Predictors of Young Swimmers' Speed

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Purpose: The aim of this study was to assess the interaction of kinematic, kinetic, and energetic variables as speed predictors in adolescent swimmers in the front-crawl stroke. ***Design:*** Ten boys (mean age [SD] = 16.4 [0.7] y) and 13 girls (mean age [SD] = 14.9 [0.9] y) were assessed. ***Methods:*** The swimming performance indicator was a 25-m sprint. A set of kinematic, kinetic (hydrodynamic and propulsion), and energetic variables was established as a key predictor of swimming performance. Multilevel software was used to model the maximum swimming speed. ***Results:*** The final model identified time (estimate = –0.008, $P = .044$), stroke frequency (estimate = 0.718, $P < .001$), active drag coefficient (estimate = –0.330, $P = .004$), lactate concentration (estimate = 0.019, $P < .001$), and critical speed (estimate = –0.150, $P = .035$) as significant predictors. Therefore, the interaction of kinematic, hydrodynamic, and energetic variables seems to be the main predictor of speed in adolescent swimmers. ***Conclusions:*** Coaches and practitioners should be aware that improvements in isolated variables may not translate into faster swimming speed. A multilevel evaluation may be required for a more effective assessment of the prediction of swimming speed based on several key variables rather than a single analysis.

Keywords: swimming, speed determinants, modeling, human physical conditioning, physical education and training

Competitive swimming is a time-based sport wherein athletes who complete a given distance in the shortest time perform best. Not surprisingly, one of the focuses of research in swimming is to identify the main determinants of swimming speed, particularly in sprint events,[1] front crawl being the fastest stroke.[2]

The literature on swimming research provides solid evidence about the multifactorial phenomenon that characterizes swimming speed, regardless of the swimming stroke.[1,3] Studies reported that swimming speed is strongly determined by anthropometrics (body dimensions)[4,5] and biomechanics (stroke kinematics[6] and hydrodynamics—propulsion[1] and drag[7]). Energetic variables such as critical speed[8] (aerobic contributor) and blood markers[6] (anaerobic contributor) are swimming speed predictors. Notwithstanding, research on swimming indicates that swimming speed is more dependent on the interaction between several variables from different scientific domains than on variables from a single domain.[1,3] Such reasoning occurs due to the potential interaction between the several determinants of swimming performance. That is, there may be a standard approach for the performance improvement, but different paths may be established based on the athletes' characteristics.[9] Thus, trivial or small improvements in one variable can trigger a change in the interaction between the other variables that compose the overall system. This pattern of interconnected relationships can eventually influence swimming speed and competitive performance.

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In youth swimming, anthropometry and biomechanics play a major role in predicting swimming speed or its key determinants.[10] Studies have shown that the interaction between variables related to anthropometry, kinematics, efficiency, and motor control determines swimming speed.[11,12] However, there is less evidence about these prediction models or key determinants containing energetic variables in young swimmers. In adult/elite swimmers, energetics was shown to play a key role in sprint speed (100 m freestyle) wherein the performance of faster swimmers is associated with greater oxygen consumption and aerobic power.[13] As for young swimmers, it was observed that sprint speed was significantly correlated to swimming speed at maximum oxygen uptake and ventilatory thresholds.[14] Moreover, physiological variables, particularly blood lactate concentration, were essential contributors to the final model.[6]

Nevertheless, more evidence can be found on the relationship between energetics and performance but for longer distances than sprint events. For instance, Zacca et al[15] observed that biomechanics plays a major role on young swimmers' performance. Energetics also plays an important yet less significant role. Nonetheless, these findings were collected in 400-m middle-distance freestyle swimmers.[15] Therefore, research is still needed on the influence and importance of energetic contributors to sprint speed, especially when interacting with other key determinants.

The aim of this study was to identify the main determinants of swimming speed in young swimmers in front crawl stroke based on the interaction of kinematic, kinetic (hydrodynamic and propulsion), and energetic variables. It was hypothesized that swimming speed would be determined by an interaction of several variables related to kinematic, hydrodynamic, propulsion, and energetic determinants. Moreover, variables related to swimming technique would have the greatest contribution.

Methods

Subjects

Twenty-three swimmers (10 boys: age = 16.4 [0.7] y; body mass = 70.4 [6.0] kg; height = 1.77 [0.06] m; arm span = 1.84 [0.10] m, Fédération Internationale de Natation [FINA] points = 581.8 [57.9] in the 100-m freestyle event–short course meter swimming pool; 13 girls: age = 14.9 [0.9] y, body mass = 57.2 [6.3] kg; height = 1.63 [0.07] m; arm span = 1.67 [0.07] m; FINA points = 616.0 [79.8] in the 100 m freestyle event–short course meter swimming pool) were selected from a national squad, which included swimmers participating in international youth championships, national record holders, and national age-group champions (Tier 3 athletes).[16] Parents or guardians signed an informed consent form. All procedures were in accordance with the Declaration of Helsinki regarding human research, and the Polytechnic Ethics Review Board approved the research design.

Research Design

For the in-water testing, swimmers were evaluated over 2 days to ensure their full recovery between tests. The tests took place in a 25-m indoor swimming pool (water temperature: 27.5 °C, air temperature: 26.0 °C, and relative humidity: 67%). On each test day, the swimmers performed a standardized 1000-m warm-up prior to data collection.[17] On the first day, they performed three 25-m all-out trials in front crawl with a push-off start, and the fastest one was used for analysis. During the test, a set of kinematic, hydrodynamic, propulsion, and energetic variables was measured. On the second day, swimmers performed a 50-m and a 400-m front-crawl test with a push-off start at race pace.[15] In the 400-m trial, the average speed of each swimmer was recorded every 50 m. There was a 4-hour interval between trials. Figure 1 presents a flowchart of the tests performed and variables measured.

Kinematics

For the all-out testing, the string of a mechanical apparatus (SpeedRT, APLab) was attached to the swimmers' waist.[18] The speedometer calculated the displacement and speed of the swimmer at a rate of 100 Hz. Afterward, the speed–time data were imported into a signal processing software (AcqKnowledge, version 3.9.0, Biopac Systems). The signals were handled with Butterworth fourth-order low-pass filter (cut-off: 5 Hz). A video camera (Sony FDR-X3000) recorded the swimmers in the sagittal plane to identify the entry and exit of the hand and was synchronized with the speed–time data.

The following kinematic variables were collected during 3 consecutive stroke cycles over the middle 10 m to neglect the push-off effect. Swimming speed (v, m/s) was obtained from the speed–time curve. The stroke frequency (SF, Hz) was calculated by the number of cycles per unit of time (based on the footage recorded) from the time it took to complete one full cycle ($f = 1/P$; where P is the period) and afterward converted to Hz. The intracyclic variation of swimming speed (dv, %) was computed as being the coefficient of variation (CV): CV = mean/1SD × 100.

Hydrodynamics

The active drag coefficient (C_{Da}, dimensionless) was computed through the velocity perturbation method.[19] Swimmers performed 2 all-out trials of 25 m in front crawl with a push-off start. One trial consisted of swimming "freely" at maximum speed, and the other one was carried out with swimmers towing a hydrodynamic body (ie, a perturbation device) also at maximum speed.[19] The free-swim data (time between the 11th and the 24th meters) were obtained from the kinematics section. For the trial with the hydrodynamic body, a camera (Sony X3000) was used to record the swimmer's displacement time between the 11th and the 24th meters. Swimming speed was calculated as: $v = d/t$, where v is the swimming speed (in meters per second), d is the distance (in meters), and t is the time (in seconds). The C_{Da} was computed as[19]:

$$C_{Da} = \frac{2 \times D_a}{\rho \times FSA \times v^2}, \quad (1)$$

where C_{Da} is the active drag coefficient (dimensionless), D_a is the active drag (N), ρ is the density of the water (997 kg/m^3), FSA is the frontal surface area (in meters squared), and v is the swimming

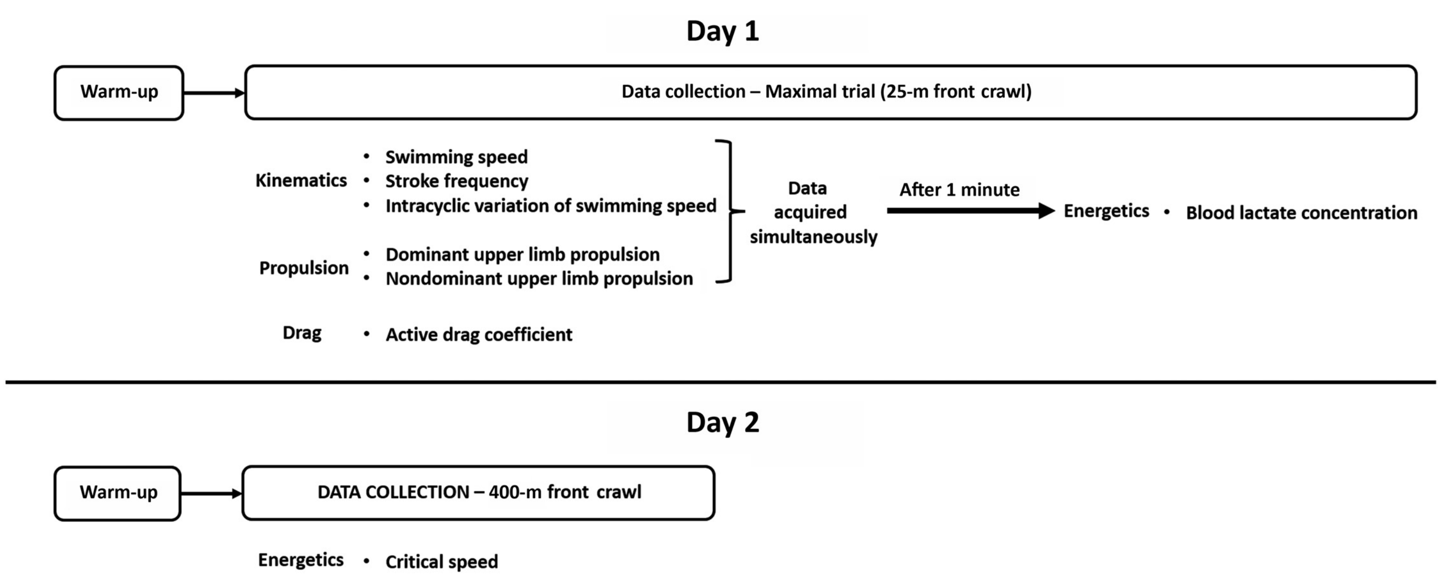

Figure 1 — Flowchart of the tests performed and variables measured.

speed (in meters per second). The FSA was measured by digital photogrammetry with the swimmers being photographed by a digital camera (Alpha 6000, Sony) in the transverse plane (downward view) on land, simulating the aerodynamic position.[20] Afterward, a correction was performed based on the FSA variation during the stroke cycle.[7]

Propulsion

The propulsion data were acquired simultaneously with the kinematics; hence, they refer to the best trial. The Aquanex force data acquisition equipment (Swimming Technology Research) was used to measure thrust (f = 100 Hz).[21] This system was based on sensors that estimated in-water force. These sensors were placed between the third and fourth metacarpals to measure the pressure differential between the palmar and dorsal surfaces. At the beginning of each trial, the swimmers were asked to keep their hands immersed at the waistline for 10 seconds to calibrate the system with the hydrostatic pressure values.[21] The video camera was placed on the side of the swimming pool, recording the swimmers in the transverse plane. The sensors and video output were connected to an A/D converter connected to a laptop on the pool deck running the Aquanex software (Aquanex version 4.2 C1211).[1] Consequently, time–force series were imported into a signal processing software (AcqKnowledge version 3.9.0, Biopac Systems). The signals were handled with Butterworth fourth-order low-pass filter (cut-off: 5 Hz). For each dominant and nondominant arm pull, the mean propulsion ($F_{mean\_dominant}$ and $F_{mean\_non\text{-}dominant}$, N) was analyzed.

Energetics

The blood lactate concentration (BLa, mmol/L) was collected in the maximal trial and used as an energetic indicator. Blood samples were collected from the fingertip for BLa concentration analysis with a portable analyzer (LT-1710, Lactate Pro)[22] 1 minute after the maximal trial performed during the kinematics/propulsion measurements. The anaerobic alactic contribution (AnAl, kW) was estimated from the maximum division of phosphocreatine in the contracting muscle[23]:

$$\mathrm{AnAl} = \mathrm{PC_r} \times (1 - e^{-\frac{t}{T}}) \times \mathrm{BM}, \tag{2}$$

where PC_r is the phosphocreatine concentration at rest, t (in seconds) is the exercise time, T (in seconds) is the time constant of the PC_r division at the beginning of the exercise (about 23.4 s) according to Binzoni et al,[24] and BM is the body mass (in kilograms). The AnAl was expressed in kilojoules by assuming an energy equivalent of 0.468 kJ/mM and a phosphate/oxygen ratio of 6.25.[25] Then, the estimate for AnAl was converted to kilowatts.[25]

The critical speed (CS, m/s) was obtained based on the 50-m and 400-m front crawl tests. The CV was calculated based on the 50-m and 400-m individual times using the slope of the simple linear regression model: $d = a \times t + b$, where d is the distance (in meters), a is the slope of the fit line, t is the time taken to cover the distance (in seconds), and b is the y-intercept at the origin of the X-axis (horizontal).[26]

Statistical Analysis

The Shapiro–Wilk test and the Levene test were used to assess the normality and homoscedasticity, respectively. The mean plus 1SD was computed as descriptive statistics.

For the mean data comparison, the student t-test independent samples ($P \le .05$), the mean difference with 95% confidence intervals (95% CI), and the magnitude of the effect size (Cohen d) were computed. This effect size index was interpreted as trivial if: $d < 0.20$; small if: $d < 0.60$; moderate if: $d < 1.20$; large if: $d < 2.00$; very large if: $d < 4.00$; and nearly perfect if: $d \ge 4.00$.

The multilevel hierarchical linear model (HLM) procedure was used to verify the swimming speed predictors. HLM is a particular regression model designed to consider the hierarchical or nested structure of the data. This is a more advanced procedure than the traditional linear regression model that was developed by making certain assumptions about the nature of the dependency structure between the observed responses.[27] A two-level HLM was used to model swimming speed. HLM creates a hierarchical structure such as a "tree," being able to identify variables as predictors of swimming speed. Only independent variables that did not show a multicollinearity effect with swimming speed were tested. At the first level, variables that allowed repeated measures (kinematics and propulsion) were tested as predictors. Time, that is, intercyclic variation from the first to the third measured stroke cycle, was also tested as a predictor. This was done to understand whether swimming speed tended to present a significant decrease or increase over time. At the second level, variables that did not change (C_{Da}, BLa, CV, and AnAl) were tested as predictors. Gender was also tested to understand whether the final model would retain gender as a significant predictor. The final model only included significant predictors. The maximum likelihood estimation was calculated using the HLM7 software.[28]

Results

Table 1 presents the descriptive statistics (mean [1SD]) of all variables measured by gender. Table 2 presents the gender effect for all measured variables. Swimming speed (dependent variable) was the variable with the highest gender effect ($t = -10.911$, $P < .001$, $d = 4.44$). This occurred in most variables. However, nonsignificant gender effects were observed in CS (energetics), dv (kinematics), and $F_{mean\_non\text{-}dominant}$ (propulsion).

Table 3 presents the significant determinants of swimming speed. The final model did not identify gender as a significant predictor when interacting with the other variables. Thus, the interaction is the same for girls and boys. On the other hand, time (ie, intercyclic variation of the measured stroke cycles) was identified as a significant predictor. This meant that, over time, swimming speed tended to decrease. The SF (kinematics), C_{Da} (hydrodynamics), BLa, and CS (energetics) were also identified. With each unit increase in SF (Hz) and BLa (mmol/l), swimming speed increased by 0.718 m/s (95% CI, 0.395 to 1.041, $P < .001$) and 0.019 m/s (95% CI, 0.011 to 0.027, $P < .001$), respectively. By contrast, with each unit increase in C_{Da} (hydrodynamics) and CS (energetics), swimming speed decreased by −0.330 m/s (95% CI, −0.526 to −0.134, $P = .004$) and −0.150 m/s (95% CI, −0.279 to −0.021, $P = .035$), respectively. Altogether, fast sprints were related to faster stroke cadences, more lactate found in the bloodstream, and less drag coefficient and aerobic contribution, regardless of gender. Hence, the combination of kinematics, hydrodynamics, and energetics determined the swimming speed of young swimmers.

Table 1 Descriptive Data of all Variables Assessed by Gender, Mean (SD)

	Males				Females			
Critical speed, m/s	1.40 (0.29)				1.39 (0.06)			
Blood lactate concentration, mmol/L	12.33 (3.25)				7.71 (0.30)			
Anaerobic alactic contribution, kW	0.25 (0.02)				0.19 (0.03)			
Active drag coefficient, dimensionless	0.57 (0.09)				0.73 (0.14)			
	First SC	**Second SC**	**Third SC**	**Average**	**First SC**	**Second SC**	**Third SC**	**Average**
v, m/s	1.64 (0.06)	1.65 (0.09)	1.63 (0.09)	1.64 (0.08)	1.44 (0.06)	1.44 (0.08)	1.43 (0.08)	1.44 (0.07)
dv, %	8.91 (1.44)	8.65 (2.14)	8.72 (2.54)	8.76 (2.02)	7.99 (1.87)	8.12 (2.48)	9.20 (1.63)	8.43 (2.05)
SF, Hz	0.88 (0.05)	0.89 (0.07)	0.88 (0.05)	0.88 (0.06)	0.82 (0.05)	0.81 (0.05)	0.82 (0.04)	0.82 (0.04)
$F_{mean\_dominant}$, N	40.8 (8.2)	40.0 (6.9)	41.8 (5.6)	40.9 (6.8)	34.1 (4.4)	33.4 (4.6)	32.9 (4.7)	33.5 (4.5)
$F_{mean\_nondominant}$, N	37.9 (8.7)	38.6 (6.9)	38.5 (6.4)	38.3 (7.1)	33.0 (5.4)	34.3 (5.6)	32.2 (4.7)	33.2 (5.2)

Abbreviations: SC, stroke cycle; *v*, swim speed; *dv*, intracyclic variation of the swim speed; $F_{mean\_dominant}$, mean propulsion of the dominant upper limb; $F_{mean\_nondominant}$, mean propulsion of the nondominant upper limb; SF, stroke frequency. Note: In-water variables (kinematics and propulsion) include data from the 3 stroke cycles measured.

Table 2 Gender *t*-Test Comparison of all Variables Analyzed

	Mean difference (95 CI)	*t* test	*P*	*d* (descriptor)
Critical speed, m/s	−0.01 (−0.18 to 0.16)	−.11	.912	0.05 (trivial)
Blood lactate concentration, mmol/L	−4.62 (−6.49 to − 2.75)	−5.14	<.001	2.00 (large)
Anaerobic alactic contribution, kW	−0.06 (−0.08 to −0.04)	−5.53	<.001	2.35 (very large)
Active drag coefficient, dimensionless	0.16 (0.05 to 0.26)	3.08	.006	1.36 (large)
v, m/s	−0.22 (−0.26 to −0.18)	−10.91	<.001	4.44 (nearly perfect)
dv, %	−0.33 (−1.74 to 1.09)	−.48	.637	0.20 (moderate)
Stroke frequency, Hz	−0.07 (−0.11 to −0.02)	−3.15	.005	1.18 (moderate)
$F_{mean\_dominant}$, N	−7.39 (−12.11 to − 2.67)	−3.25	.004	1.33 (large)
$F_{mean\_non\text{-}dominant}$, N	−5.16 (−10.37 to 0.06)	−2.06	.052	0.84 (moderate)

Abbreviations: *d*, effect size (Cohen *d*); *dv*, intracyclic variation of the swim speed; $F_{mean\_dominant}$, mean propulsion of the dominant upper limb; $F_{mean\_nondominant}$, mean propulsion of the nondominant upper limb; SF, stroke frequency; *v*, swim speed. Note: For the variables measured during the three consecutive stroke cycles, the average was used for comparison.

Table 3 Fixed Effects of the Final Models Computed With SE and 95 CI

Fixed effect	Estimate (SE)	95 CI	*P*
Time	−0.008 (0.004)	−0.016 to − 0.0002	.044
SF	0.718 (0.165)	0.395 to 1.041	<.001
C_{Da}	−0.330 (0.100)	−0.526 to − 0.134	.004
BLa	0.019 (0.004)	0.011 to 0.027	<.001
Critical speed	−0.150 (0.066)	−0.279 to − 0.021	.035

Abbreviations: BLa, blood lactate concentration; C_{Da}, active drag coefficient; SF, stroke frequency; time, intercyclic variation of the measured stroke cycles.

Discussion

The aim of this study was to identify the main determinants of swimming speed in adolescent swimmers in front crawl stroke based on the interaction of kinematic, hydrodynamic, propulsion, and energetic variables. The main results indicated that swimming speed in young swimmers of both genders was determined by SF (kinematics), C_{Da} (hydrodynamics), BLa, and CS (energetics). This highlights swimming speed as a multifactorial phenomenon dependent on the interaction between variables from different scientific domains. There was no substantial gender effect in modeling 25-m sprint swimming performance, confirming that the model is suitable for male and female young swimmers.

Youth swimming research has been a topic of great importance in the last decade.[6,10,11] For example, talent identification research focuses on identifying swimmers with potential to deliver the best performances in adulthood.[29] A typical experimental approach has involved: (1) determining the variables responsible for the best performances, (2) understanding the development and changes in performance and in these variables, and (3) monitoring these variables to understand their variation and relationship with performance.[10] However, as swimmers engage in heavy workloads and specific training programs at a relatively young age, it is important to assess which determinants may be the best predictors of swimming speed from an early age.[6]

Several studies have analyzed the relationship of different variables from several scientific fields in front crawl sprint speed in young swimmers.[10,12] Overall, the main rationale indicates that swimmers with a wider arm span have a longer stroke length and faster SF, leading to faster swimming speed.[30] Others have observed that larger values of propulsion also lead to faster swimming speeds[31] and that swimmers with better hydrodynamics also present faster swimming speeds.[11] Energetics plays a key role in the sprint speed of young swimmers as well.[6,14] However, less is known about the interactions between variables from all these scientific fields. The model of the present study included BLa, C_{Da}, CS, and SF with an interaction between energetics, hydrodynamics, and kinematics. The assessment of BLa after a maximal trial provides information about the physiological stress of swimmers.[32] The present data show that swimmers with greater BLa after a maximal trial are more likely to present faster swimming speeds. Indeed, these findings support those of a previous study in which swimming performance was positively related to peak lactate values.[33] Although the AnAl did not enter the final model, and short events or trials are dependent on the three metabolic components (aerobic, anaerobic lactic, and AnAl), the AnAl component played an important role.[34] The same positive relationship was observed in the SF. That is, faster SF will lead to faster sprint speeds. The literature shows that the fastest swimmers tend to present the fastest SF in short-distance freestyle events (ie, front-crawl stroke).[11,35] Although propulsion was not included in the final model, it can be stated that propulsion has a direct and positive relationship with SF. It was shown that swimmers who have the fastest SF also have the highest propulsion values.[1]

On the other hand, C_{Da} had a negative relationship with the prediction of swimming speed. The C_{Da} is considered the best indicator of a swimmer's hydrodynamic profile.[8] Swimmers who can promote forward displacement while generating less drag are more likely to achieve faster swimming speeds.[11,12] Like C_{Da}, the CS also had a negative effect on swimmers' speed. The 400-m protocol used in the present study is the most common procedure to assess the swimmers' aerobic profile.[26] It was observed that the fastest swimmers were characterized by having the fastest CS.[35] However, the current data indicate that the CS had a negative effect on swimming speed. This *d–t* relationship is considered a useful tool for defining training intensities and predicting swimming performances.[26] Notwithstanding, the CS test measures the swimmers' aerobic capacity. Thus, based on the present data, it can be argued that swimmers who have a faster CS are more likely to perform better in middle- or long-distance events than in sprints. Indeed, Marinho et al[36] indicated that anaerobic CS (based on 10, 15, 20, and 25 m trials) had a strong relationship with 50-m and 100-m freestyle events (front crawl). Therefore, it can be argued that the CS test can be used with caution when employed as a measurement of assessment in sprint swimming.

As mentioned, time (ie, intercyclic variation of the measured stroke cycles) was considered a swimming speed predictor. This means that swimming speed significantly decreased over the trial. Thus, it is illogical to use averaged variables during a given trial (at least at sprint speeds) because they may not characterize individual stroke cycles. Another great advantage of using this kind of statistical approach is that it allows the use of different variables (ie, those that change and those that do not) and the ability to interact with those variables. Moreover, gender was not included in the final model. Interestingly, the relevant swimming literature provides evidence of gender differences in young swimmers, even at early ages (ie, prepubescent).[12] Thus, it can be considered that gender would be assumed as a predictor of swimming speed. Notwithstanding, when all variables were analyzed separately, most of them revealed significant differences between genders with moderate to nearly perfect effect size (except CS, *dv*, and $F_{mean\_nondominant}$). This result indicates that speed or performance modeling must be done with more efficient statistical software, allowing the input of several variables that facilitate more detailed outputs. Once again, current data highlight that the prediction of swimming speed must not be performed based on the average values of a given trial. Moreover, researchers and practitioners must adopt more efficient statistical procedures than a traditional regression analysis, for example. The use of statistical software that allows the inclusion of variables of different types will provide more accurate information in predicting swimming speed.

Several limitations need to be addressed: (1) This model is only suitable for front crawl sprint speed and for the age group of these swimmers, and (2) more stroke cycles must be analyzed as a time effect was observed (a decrease in swimming speed was observed throughout the trial). Thus, future studies should be conducted to understand this interaction in other age groups and events (strokes and distance).

Practical Applications

Overall, these results indicate that fast sprints in youth swimming of both genders were related to faster stroke cadences (SF), more lactate in the blood stream (BLa), less drag coefficient (C_{Da}), and less aerobic contribution (CS). Therefore, maximum swimming speed was determined by an interaction of kinematic, hydrodynamic, and energetic variables. Although propulsion was not considered a predictor, it has a positive and strong relationship with SF. That is, swimmers who produce greater propulsion are more likely to achieve faster SFs. This interaction did not identify gender as a predictor. Consequently, these results indicate that this model is suitable for young male and female swimmers. Unlike more traditional statistics, multilevel statistical procedures provide deeper information about swimming speed modeling rather than using average values during a swimming trial. Multilevel software allowed access to more detailed information on swimming speed modeling. Therefore, researchers and coaches are advised to use more adequate statistical procedures when using variables from different categories. Moreover, coaches should be aware that trying to improve all swimming determinants simultaneously may not be the best way to improve swimming performance (at least in youth swimming).

Conclusion

Swimming speed in adolescent swimmers was predicted by an interaction of kinematic, hydrodynamic, and energetic variables. Gender was not identified as a predictor, demonstrating that this model is suitable for male and female swimmers. Therefore, fast sprints in both genders were related to the combination of faster stroke cadences, more lactate, and less drag coefficient and aerobic contribution. Multilevel statistical analysis will allow coaches and practitioners to better understand how swimmers behave during swimming strokes and identify key determinants of swimming speed.

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