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40 **Abstract**

41 This study aims to identify stroke regulation profiles and tipping-points in stroke regulation
42 timing during international open water races according to performance level. Twelve elite or
43 world-class swimmers were analyzed during 18 international races. Stroke rate and jerk cost
44 were computed cycle-to-cycle using an Inertial Measurement Unit and regulations profiles
45 fitted using polynomials. We performed two-ways mixed-ANOVA to compare stroke
46 kinematics among race segments and performance groups (G1 -fastest- to G3 -slowest-).
47 Swimmers displayed specific regulation profiles (i.e. J-shape with end-spurt, J-shape without
48 end-spurt and reverse L-shape for stroke rate and U-shape, reverse J-shape and reverse L-shape
49 for jerk cost, for respectively G1, G2 and G3) with significant effect of race segment on stroke
50 kinematics for G1 and G2. We highlighted tipping-points in stroke regulations profiles (TP1
51 and TP2) at respectively 30% and 75% of the race with greater magnitude in G1 than G2. TP1
52 reflects the end of a stroke economy period (0-30%) and TP2 the end of a progressive increase
53 in stroke kinematics (30-75%) towards end-spurt (75-100%). Open water races follow a high-
54 grading dynamics requiring biomechanical regulations along the race. Targeting stroke rate
55 reserve and management of stroke smoothness should be considered during training of open
56 water swimmers.

57 **Keywords:** swimming, endurance, stroke rate, jerk cost, pacing

58 **Introduction**

59 Race analysis in swimming can support the guidance of training and the adjustment of race
60 strategy through provision of feedback to coaches (Barbosa et al., 2021). Several studies
61 including race analysis during official competitions or simulated events using official results
62 and/or video recordings have been previously published (Gonjo & Olstad, 2020). Among them,
63 pacing strategy and stroke mechanics have been shown to have a significant impact on
64 performance. Indeed, open water races during international championships displayed an
65 optimal speed management (Rodríguez & Veiga, 2018) described as a conservative approach.
66 It aims at saving energy at the start and the middle of the race with partial delayed positioning
67 within the leading group and then to considerably increase the pace in the last race section
68 (Saavedra et al., 2018; Baldassarre et al., 2019a; Rodríguez et al., 2021). Swimming paces are
69 then largely similar across performance levels for a great proportion of the race distance and
70 only the fast finish is highly related to race success (Baldassarre et al., 2019a; Rodríguez &
71 Veiga, 2018). Then, successful swimmers can increase their speed up to 9% in the last lap with
72 dramatic end race spurt whereas non-successful athletes maintain or decrease their pace (Veiga
73 et al., 2019). Thus, many open water races are decided by a sprint over the last 300-500 meters
74 (Saavedra et al., 2019a). Despite the identification of successful pacing strategies and
75 performance determinants in previous literature supporting decisive final split, there is a crucial
76 lack of information on regulations timing of stroking mechanisms supporting kinematical
77 explanation. Therefore, the open-water performance should be evaluated with respect to
78 regulations of technical components.

79 However, these kinematical aspects leading to race success remain unclear. Whereas
80 evaluations in the pool previously showed relevant insights such as a decrease in velocity and
81 stroke length associated with a constant stroke rate during a simulated 25km (Invernizzi et al.,
82 2014), few studies investigated regulations of stroke mechanics in open water conditions.
83 Indeed, it has been shown that the stroke rate increases during the last kilometer of a 5km test
84 simulated at race pace (Zacca et al., 2020). Despite the relevance of such findings, the real
85 transferability to in-situ conditions is still questionable and led to limited insights as regards to

86 open water performance. Only one study reported race stroking data during official open water
87 competition. Thus, Rodríguez et al., (2021) showed that stroke rate regulation is a key parameter
88 for open water performance since it directly supports the conservative race strategy. As for
89 pacing, the ability to display a higher stroke rate in the second part of the 10km-race
90 discriminates against the final ranking. However, the study of Rodríguez et al., 2021 relies on
91 intermediate stroke rate data that restrict in-depth comprehension of stroking mechanisms,
92 particularly regarding the regulation timing of stroke kinematics during the race. Apart from
93 stroke frequency, jerk cost has drawn attention as a reflection of a smooth and efficient
94 movement in several activities (Hogan & Sternad, 2009; Hreljac, 2000; Sparrow & Newell,
95 1998). Thus, jerk cost has been recently applied to evaluate swimming technique by quantifying
96 the stroke smoothness during a 50m front crawl (Ganzevles et al., 2019) or to chronically
97 monitor swimmers during a season and track stroke adaptations (Bouvet et al., 2022). Such
98 evaluation may be of great interest during open-water competition to provide useful information
99 regarding movement efficiency and its relation to the pacing. It may provide insights into
100 refined flow and coordination patterns of elite swimmers (Barbosa et al., 2021). From a
101 practical perspective, smooth swimming movements referring to a low jerk cost, are those
102 without abrupt, intermittent and discontinuous changes in accelerations, whereas non-smooth
103 stroke patterns reflect abruptness and erratic discordance. In that sense, smoothness is a
104 universal feature of skilled movement which may be used as a unique window into athletic
105 coordinative proficiency (Kiely et al., 2019). Finally, tracking jerk cost across the race can be
106 a powerful way to quantify the achievement of the successful conservative approach. To do so,
107 embedded measurements are required.

108 In-situ assessment of spatio-temporal parameters and stroke mechanics in open water
109 swimming is largely constrained by several factors (motion on a large outdoor area, mass start
110 configuration, etc) compromising the use of conventional video. To overcome these limitations,
111 Inertial Measurement Units (IMU) have become a relevant solution for swimming monitoring
112 in a real environment over a prolonged period without huge technical and logistical pressure
113 (Mooney et al., 2015; Magalhaes et al, 2015; Guignard et al., 2017). Previous literature using
114 such sensors during pool swimming showed their relevance to automatically quantify valuable
115 spatio-temporal parameters related to stroke characteristics such as lap times, stroke rate and
116 jerk cost (Ganzevles et al., 2019; Bouvet et al., 2022; Ganzevles et al., 2017; Delhaye et al.,
117 2022; Davey et al., 2008). During open water events, accelerometers encapsulated in timing
118 bracelets provided insights regarding average stroke rate by lap as an attempt to analyze stroke
119 regulations during the race (Rodríguez et al., 2021). However, in order to better understand
120 kinematical regulations, there is a need for continuous monitoring of stroke parameters all along
121 the race.

122 The present study aimed at analyzing cycle-to-cycle stroke rate and jerk cost in order to identify
123 both stroke regulation profiles and the specific time-points in stroke regulation timing during
124 international open water races according to performance level.

125 **Methods**

126 *Participants*

127 Twelve members of the open water French national team were involved in the study. According
128 to the nomenclature of McKay et al., 2022 the participants were 4 world-class and 8 elite
129 swimmers (4 women, age: 26.5 ± 5.7 years, height: 173.8 ± 5.2 cm, weight: 64.0 ± 6.1 kg, mean
130 performance on 1500m long course: $16:43.7 \pm 00:20.2$ and 8 men, age: 23.0 ± 3.1 years, height:
131 186.0 ± 6.2 cm, weight: 78.6 ± 7.3 kg, mean performance on 1500m long course:

132 15:24.1±00:17.3). All participants signed an informed consent form in agreement with the
133 French Ethical Committee (approval obtained under reference 2021-A00250-41).

134 *Data collection*

135 Data were collected during two LEN European open water cups (leg 1 and leg 2) including both
136 a 10km race, and 5km race during leg 1. The collected dataset contains 18 races consisting of
137 8 female and 10 male races. More specifically, among the 12 swimmers, 4 swimmers performed
138 both 10km legs (3 females and 1 male). Moreover, among them, 2 of them (1 male and 1
139 female) performed additionally the 5km event. Final and split times were collected from the
140 official result. Lap lengths were 2.50km and 1.66km for leg 1 and leg 2, respectively. In the
141 analysis, each race was divided into four segments (S1 to S4) respectively representing 25% of
142 the final distance.

143 Participants were instrumented with one waterproofed IMU (Xsens DOT, Xsens Technologies
144 B.V, Enschede, The Netherlands). Only the 3D accelerometer data, sampled at 30Hz using a
145 full scale set at 16g, were used. The sensor was placed on the sacrum, then fixed with double-
146 sided tape and secured with waterproof medical adhesive (Tegaderm, 3M, Cergy-Pontoise,
147 France). The IMU described a coordinate system defined with x-axis pointing cranially, y-axis
148 pointing laterally, and z-axis pointing posteriorly (Figure 1).



149

150 **Figure 1.** IMU location on the sacrum of the swimmer.

151

151 *Data processing*

152 Participants were divided into performance groups according to their final ranking. Data were
153 pooled into three balanced groups including 6 races of swimmers from 1st to 7th place (G1 with
154 4 female races and 2 male races), 6 swimmers from 8th to 13th (G2 with 3 female races and 3
155 male races) and 6 swimmers above the 14th place (G3 with 1 female race and 5 male races).
156 G1 included two races of the same female swimmer on separate events (winning the 5km and
157 finishing 7th in one of the 10km leg). G2 included races from two swimmers who competed in
158 both 10km legs (a male swimmer finishing 9th in both legs and a female swimmer finishing 8th
159 on leg 1 and 12th on leg 2).

160 The IMU signals were processed over the entire duration of the race in order to extract cycle-
161 to-cycle stroke rate and jerk cost. Raw accelerations were filtered using a second order
162 Butterworth low-pass filter with a 8Hz cut-off frequency. Cycle beginning and end were
163 identified with a zero-crossing on the mediolateral acceleration filtered with a second-order
164 Butterworth band-pass filter between 0.1 and 1Hz (Ganzevles et al., 2019). The jerk cost was

165 calculated as the average of the squared jerk signal coming from the derivative of the
166 acceleration Euclidean norm following a second-order Butterworth band-pass filter between
167 0.1 and 5Hz (Ganzevles et al., 2019). A low jerk cost refers to a smooth stroke pattern whereas
168 a high jerk cost indicates a jerky stroke pattern.

169 *Statistical analysis*

170 Statistical analyses were conducted using RStudio (Version 1.2.5033, RStudio, Inc., Boston,
171 MA, USA). The level of significance was set at $p < 0.05$. Data were presented as mean \pm standard
172 deviation per race segment and over the entire race, uncertainty of estimates was indicated using
173 95% confidence intervals.

174 In order to compare stroke regulations according to the performance groups, a two-way mixed
175 analysis of variance (ANOVA) was employed to compare the stroke rate and the jerk cost values
176 using race segment as within-subjects factor and performance group as between-subjects factor.
177 We previously assessed the hypothesis of the mixed ANOVA design including: outliers and
178 extreme outliers detection according to the boxplot method, data normality according to
179 Shapiro-Wilk test and variance and covariance homogeneity according to Levene test and Box's
180 M-test. All of these assumptions were satisfied. In case of significant two-way interaction
181 detected, post-hoc tests including simple main effects of each factor at each level of the other
182 were conducted and followed by pairwise comparisons with t-test and Bonferroni correction.
183 In case of non-significant interaction, main effects of each factor on stroke rate and jerk cost,
184 independently of the other, was also investigated and followed up with post-hoc tests. The
185 magnitude of differences was interpreted by effect size using generalized eta-squared (η_g^2) and
186 threshold values of 0.01, 0.06 and 0.14 defining trivial, small, medium and large effects
187 respectively (Cohen, 1988). To assess the relationship between overall stroke rate and jerk cost
188 with finishing positions, Pearson product-moment correlation (r) was employed. The
189 correlation was defined as small ($0.1 < r < 0.3$), moderate ($0.3 < r < 0.5$), large ($0.5 < r < 0.7$), very
190 large ($0.7 < r < 0.9$) and nearly perfect ($r > 0.9$) (Hopkins et al., 2009). In order to evaluate
191 kinematical profiles and tipping-points in stroke regulation timing through stroke rate and jerk
192 cost, time histories of both parameters were investigated. Each time history was time
193 normalized with respect to the final duration. Moreover, stroke rate and jerk cost were
194 normalized to their respective average value in each recording. Finally, kinematical profiles by
195 performance group were fitted using 3rd order polynomials including 95% confidence intervals.
196 The latter allows a classification based on curve shape (McGibbon, 2018; Casado et al., 2020).
197 Tipping-point was defined as a shift in fitted polynomial trend and/or a dissociation of the
198 profile curves of the performance groups. It indicates a discriminant feature in stroke regulation
199 timing.

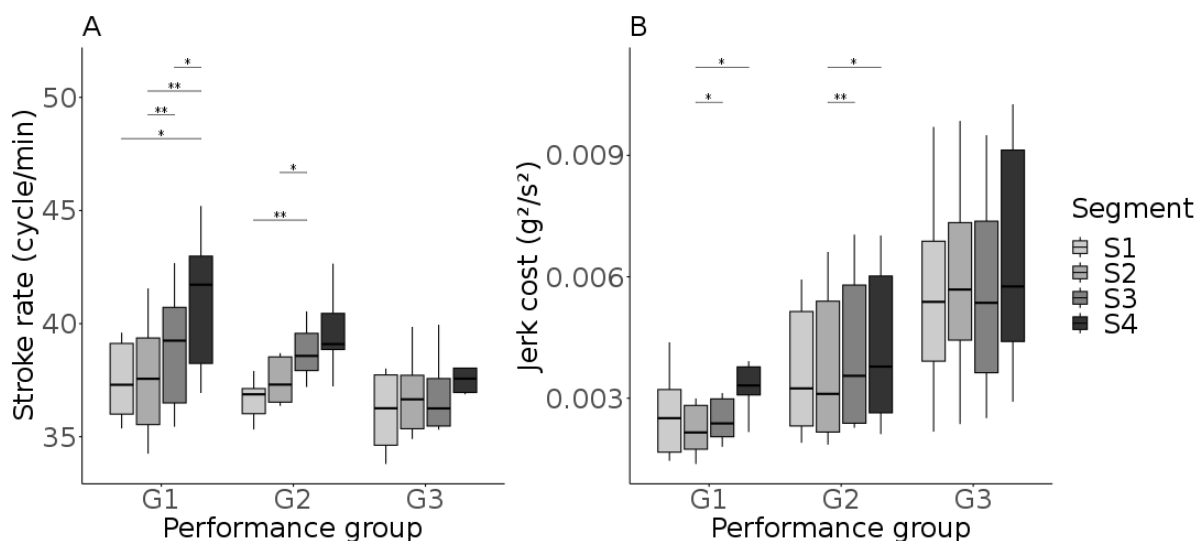
200 **Results**

201 Stroke rate, jerk cost and speed according to race segment and performance group are presented
202 in Table 1.

203 Stroke rate per segment according to the performance group is presented on Figure 2.
204 Statistically significant two-way interactions between performance group and race segment
205 ($F(6.45) = 2.50$, $p = 0.035$, $\eta_g^2 = 0.05$) were highlighted for the stroke rate. More specifically, a
206 statistically significant simple main effect of the race segment was found on the stroke rate for
207 the G1 ($F(3.15) = 21.3$, $p < 0.001$, $\eta_g^2 = 0.24$) and the G2 ($F(3.15) = 14.1$, $p < 0.001$, $\eta_g^2 = 0.46$). For
208 G1, pairwise comparisons for consecutive laps showed a significant stroke rate increase of 6.2%
209 in S4 vs S3 ($p = 0.022$) and of 1.0% in S3 vs S2 ($p = 0.002$). For G2, mean stroke rate was

210 significantly higher of +3.2% in S3 vs S2 ($p=0.013$). Unlike G2, swimmers from G1 were able
 211 to increase the stroke rate from S3 to S4 ($\Delta G1: +2.41 [1.05 ; 3.17] \pm 1.01$ cycles/min, $\Delta G2: +0.70$
 212 $[-0.56 ; 2.31] \pm 1.36$ cycles/min). Moreover, we found a statistically significant main effect of
 213 the race segment ($F(3.45)=31.7$, $p<0.001$, $\eta_g^2= 0.24$) but not of the performance group
 214 ($F(2.15)=1.53$, $p=0.248$, $\eta_g^2= 0.15$) on the stroke rate according to the mixed model. All
 215 pairwise comparisons were significant for the segments with a higher stroke rate for the latest
 216 segments except between S1 and S2 ($p=0.071$). Regarding performance group pairwise
 217 comparisons, only G1 presented a higher overall stroke rate than G3 of 5.4% ($p=0.014$).

218 Jerk cost per segment according to the performance group is presented on Figure 2. No
 219 significant two-way interactions were found between performance group and race segment for
 220 the jerk cost ($F(6.45)=1.848$, $p=0.111$, $\eta_g^2= 0.01$). A significant simple main effect of the race
 221 segment was detected for G1 ($F(1.6)=11.3$, $p=0.039$, $\eta_g^2= 0.15$) and G2 ($F(3.15)=8.61$,
 222 $p=0.003$, $\eta_g^2= 0.02$). Pairwise comparisons for consecutive laps revealed a significantly higher
 223 jerk cost of respectively +8.85% and +11.4% for G1 and G2 in S3 vs S2 (for G1: $p=0.011$ and
 224 for G2: $p=0.006$). Between S1 and S2, swimmers from G1 showed more ability to reduce jerk
 225 cost compared to G2, ($\Delta G1: -0.09 [-0.37 ; 0.19] \pm 0.39 \times 10^{-3} \text{ g}^2/\text{s}^2$, $\Delta G2: +0.10 [-0.25 .$
 226 $0.45] \pm 0.56 \times 10^{-3} \text{ g}^2/\text{s}^2$), while demonstrating capability to increase it more importantly between
 227 S3 and S4 ($\Delta G1: +0.72 [0.27 ; 1.69] \pm 0.68 \times 10^{-3} \text{ g}^2/\text{s}^2$, $\Delta G2: -0.02 [-0.13 ; 0.39] \pm 0.25 \times 10^{-3}$
 228 g^2/s^2). A statistically significant main effect of the race segment ($F(3.45)=15.284$, $p<0.001$, $\eta_g^2=$
 229 0.01) but not the performance group ($F(2.15)=3.159$, $p=0.072$, $\eta_g^2= 0.29$) was found on the jerk
 230 cost according to the mixed model. Pairwise comparisons indicated a higher jerk cost between
 231 S4 (4.45 ± 2.33) and all other race segments (vs. S1: 4.05 ± 2.23 , $p=0.002$; vs. S2: 4.18 ± 2.41 ,
 232 $p=0.002$; vs S3: 4.08 ± 2.20 , $p=0.007$). Regarding performance group pairwise comparisons, G1
 233 presented a lower overall jerk cost than G2 ($p=0.006$) and G3 ($p<0.001$) as well as G2 vs G3
 234 ($p=0.005$).



235
 236 **Figure 2.** Mean stroke rate evolution per race segment according to the performance group
 237 (A) and mean jerk cost evolutions per segment according to the performance group. * $p<0.05$,
 238 ** $p<0.01$, *** $p<0.001$.

239 **Table 1.** Means \pm SD and 95% confidence intervals of average and race segment speed (m/s), stroke rate (cycle/min) and jerk cost ($\times 10^{-3}$ g²/s²)
 240 for the three performance groups. * Indicates a swimming pace statistically lower than that of the previous performance group. ° Indicates a stroke
 241 rate statistically lower than that of the previous performance groups. # Indicates a jerk cost statistically higher than that of the previous performance
 242 group.
 243

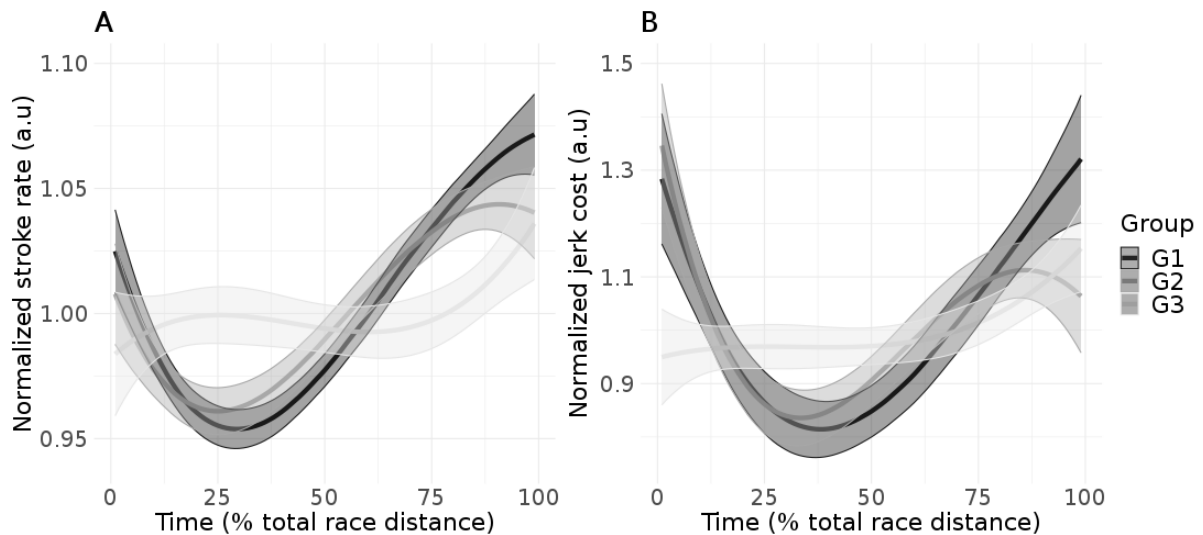
		Average on the race	Segment 1 (0-25%)	Segment 2 (26-50%)	Segment 3 (51-75%)	Segment 4 (76-100%)
Group 1	Stroke Rate (cycle/min)	38.8[37.8;39.7] \pm 2.84	37.8 [36.3;39.2] \pm 1.97	38.1[36.1;40.0] \pm 2.69	38.5 [35.8;41.1] \pm 2.87	40.9[38.5;43.3] \pm 3.09
	Jerk cost ($\times 10^{-3}$ g ² /s ²)	2.91[2.47;3.34] \pm 1.28	2.69[1.90;3.50] \pm 1.16	2.60[1.73;3.47] \pm 1.22	2.83[1.81;3.86] \pm 1.10	3.56[2.35;4.77] \pm 1.57
	Speed (m/s)	1.43[1.36;1.51] \pm 0.14	1.40[1.17;1.63] \pm 0.14	1.41[1.18;1.64] \pm 0.15	1.44[1.19;1.69] \pm 0.16	1.48[1.23;1.74] \pm 0.16
Group 2	Stroke Rate (cycle/min)	37.9[37.4;38.4] \pm 1.68	36.7[36.0;37.3] \pm 1.02	37.5[36.7;38.2] \pm 1.16	38.7[37.7;39.7] \pm 1.15	39.4[38.1;40.7] \pm 1.86
	Jerk cost ($\times 10^{-3}$ g ² /s ²) #	3.93[3.36;4.51] \pm 1.85	3.68[2.7;4.6] \pm 1.67	3.78[2.51;5.05] \pm 2.00	4.21 [2.51;5.91] \pm 2.04	4.19 [2.80;5.57] \pm 1.94
	Speed (m/s)	1.37[1.33;1.41] \pm 0.07	1.35[1.23;1.47] \pm 0.08	1.36[1.24;1.47] \pm 0.07	1.37[1.26;1.49] \pm 0.07	1.41[1.27;1.54] \pm 0.09
Group 3	Stroke Rate (cycle/min) °	36.8[36.2;37.4] \pm 1.74	36.1[34.9;37.3] \pm 1.84	36.8 [36.0 ; 37.4] \pm 1.86	37.0[35.4;38.6] \pm 1.70 °	37.8[36.9;38.8] \pm 1.02 °
	Jerk cost ($\times 10^{-3}$ g ² /s ²) #	5.68[4.83;6.54] \pm 2.61	5.57[3.9;7.2] \pm 2.58 #	5.92 [4.29 ; 7.54] \pm 2.56 #	5.19[2.6;7.8] \pm 2.77	5.97[3.1;8.8] \pm 3.10
	Speed (m/s) *	1.29[1.27;1.31] \pm 0.02	1.27[1.01;1.45] \pm 0.02 *	1.31[1.17;1.45] \pm 0.02	1.30[1.05;1.54] \pm 0.03	1.29[1.29;1.30] \pm 0.00 *

245 Correlation results between stroke rate or jerk cost and final rankings are presented on Table 2.
 246 Except for swimmers from G3 that showed a significant moderate positive correlation of stroke
 247 rate with final rank, all groups presented a significant small negative correlation of the stroke
 248 rate with the final ranking. The jerk cost was significantly correlated with negative large
 249 association to final ranking for G1 whereas the opposite behavior is observed for G2 and G3
 250 which presented a significant moderate positive correlation.

251 **Table 2.** Pearson linear simple correlation (r) and 95% confidence intervals between
 252 kinematical parameters (stroke rate (cycle/min) and jerk cost ($\times 10^{-3} \text{ g}^2/\text{s}^2$)) with the final race
 253 rank for all the swimmers and the three performance groups on the overall race. Significant
 254 correlation is indicated as follows: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
 255

	Stroke rate	Jerk cost
Group 1	-0.22 [-0.51 ; 0.12]	-0.51 [-0.72 ; -0.21] **
Group 2	-0.24 [-0.51 ; 0.07]	0.49 [0.21 ; 0.69] **
Group 3	0.47 [0.18 ; 0.69] **	0.45 [0.15 ; 0.67] **
All swimmers	-0.20 [-0.37 ; -0.02] *	0.57 [0.44 ; 0.68] ***

256 Time histories for stroke rate and jerk cost are presented in Figure 3. Stroke parameters followed
 257 a specific pattern in each performance group. G1 swimmers displayed a J-shaped with end-
 258 spurt curve for stroke rate and a U-shaped curve for jerk cost whereas G2 swimmers displayed
 259 J-shaped without end-spurt curve for stroke rate and a reverse J-shaped curve for jerk cost. G3
 260 swimmers displayed a reverse L-shaped (negative) curve in both stroke rate and jerk cost. In
 261 particular, best performers are able to firstly reduce both kinematical parameters after the
 262 beginning of the race until 30% of the race for stroke rate and 38% for jerk cost. During this
 263 period, stroke rate decreased from 1.025 to 0.953 times the mean value whereas jerk cost
 264 decreased from 1.284 to 0.814 times the mean value. After this first tipping-point, swimmers
 265 from G1 progressively increased their stroke rate from 0.953 to 1.072 times the mean value
 266 until the end of the race while jerk cost raised from 0.814 to 1.321 times the mean value.
 267 Swimmers from G2 depicted a relatively close profile to G1 until 75% of the race. Differences
 268 occurred around this second tipping-point, when swimmers from G2 were not able to increase
 269 the stroke rate as shown by the plateau on the curve at 1.040 times the mean value. Similar
 270 behaviors were observed regarding the jerk cost with a first decrease after race start followed
 271 by a progressive increase after 34% of the race. However, the jerk cost of G2 dropped from
 272 1.110 times the mean value at about 76-85% of the race to 1.064 times the mean value at the
 273 end. Stroke rate and jerk cost of G3 remained close to their average values from 0% to 75-80%
 274 of the race and then increased to respectively 1.036 and 1.172 times the mean value until finish.



275

276 **Figure 3.** Kinematical profiles normalized by the average over the race: stroke rate (A) and
 277 jerk cost (B) time histories during race for the three performance groups including 95%
 278 confidence intervals in dashed areas.

279 Discussion

280 This study aimed at analyzing the stroke rate and jerk cost regulation profiles during
 281 international open water races according to the final performance based on embedded IMU.
 282 Specific regulation profiles were identified according to the performance level and two tipping-
 283 points in stroke regulation timing were highlighted during the race progression supporting the
 284 understanding of pacing strategies.

285 Average values of stroke rate and speed over the race were not significantly different between
 286 best and intermediate performers. Such results are consistent with previous findings showing
 287 that the performance level did not affect the overall stroke rate values during open water races
 288 (Rodríguez et al., 2021). These authors hypothesized that swimmers of a greater expertise
 289 could achieve the same velocity with a lower stroke rate than swimmers with lesser technical
 290 ability and employed a lower energy cost to modify their stroke rate (Wakayoshi et al., 1995).
 291 Indeed, we found a significantly lower overall jerk cost value for better performers suggesting
 292 their higher efficiency as well as lower impact of stroke rate increase during race on stroke
 293 smoothness degradation. This higher smoothness could be the reflection of a more proficient
 294 movement as illustrated in other cyclic sports such as running (Kiely et al., 2019). However,
 295 this lower jerk cost may also reflect various combinations of stroke length and stroke rate at a
 296 given speed due to individual differences in anthropometrics, muscle flexibility or motor
 297 coordination (Psycharakis et al., 2008).

298 Unlike absolute overall kinematics, our results suggest the crucial role of regulation timings of
 299 kinematical parameters during the race. Each performance group demonstrated specific
 300 evolving stroke abilities during the race as shown by respective stroke rate and jerk cost
 301 evolution ranging from conservative strategy, as J-shape with end-spurt and U-shape for the
 302 best performers as well as J-shape without end-spurt and reverse J-shape for intermediate
 303 performers, to negative strategy with reverse L-shape in both stroke rate and jerk cost for lower
 304 level performers. Indeed, we identified two tipping-points that structure stroke regulations of
 305 best performers. The first one occurred around 30% of the race with a continuous and
 306 progressive decrease of both kinematical parameters from the start. It represents the end of a

307 stroke economy period toward progressive increase in mechanical parameters until the finish.
308 Such an economy at the initial stage is required to save energy and regulate pace to profit from
309 drafting effect within the pack (Veiga et al., 2019) that may allow to save up to 20% energy
310 cost (Chatard & Wilson, 2003). Indeed, decrease in jerk cost indicates higher stroke smoothness
311 suggesting the ability of best performers to use less mechanical energy to achieve the same
312 speed in the peloton. This reduction in stroke kinematics is in line with the strategy of
313 conservative pacing profile in open water described in literature during Olympic Games, World
314 championships and European championships. Thus, it enables to prepare for a fast end-spurt
315 during the last quarter of the race which is commonly described as a discriminant feature for
316 open water performance in international championships (Rodríguez & Veiga, 2018 ; Veiga et
317 al., 2019). The second one initiated around 75% of the race marked another tipping-point
318 associated with a higher increase in both stroke rate and jerk cost. We confirmed the ability to
319 significantly modify stroke rate throughout the race as a discriminant characteristic regarding
320 final performance (Rodríguez et al., 2021) while pointing out the fundamental role of increasing
321 it in the last quarter of the race. This successful end-spurt has been previously identified in
322 marathon runners (Renfree & Gibson, 2013; Hanley, 2016) and in track running (Thiel et al.,
323 2012). Similarly, in pool swimming, a pronounced end-spurt is associated with a higher
324 performance level and longer race distance in long-distance freestyle (Neuloh et al., 2021;
325 Neuloh et al., 2022). Then, the aforementioned tipping-points in stroke regulation might be the
326 biomechanical expression of the great anaerobic reserve required to accelerate at the end of the
327 races in endurance events (Renfree & Gibson, 2013; Baldassarre et al., 2019b). In summary,
328 successful open water swimmers demonstrate kinematical abilities to save energy during the
329 first third of the race to enable subsequent fast end-spurt during the final part.

330 Smaller energy expenditure could be achieved by swimming with lower jerk cost for the same
331 speed (Ganzevles et al., 2019), which may enhance efficiency in order to spare energy
332 substrates and delay fatigue (Zamparo et al., 2005). Whereas all participants swam at the same
333 speed until the first tipping-point, we showed a reduction in jerk cost for successful performers.
334 Thus, an increase in stroke smoothness during this period might be energetically advantageous
335 and discriminant for open-water performance that reflects technical abilities supporting
336 previously described conservative pacing strategy for 10km races (Rodríguez & Veiga, 2018;
337 Saavedra et al., 2018; Baldassarre et al., 2019a; Veiga et al., 2019). This strategy might be
338 useful in order to save glycogen reserves (Padilla et al., 2000) and to be able to subsequently
339 trigger an end-spurt of greater magnitude (De Koning et al., 2016) at the second race tipping-
340 point. The higher jerk cost after the first tipping-point might lead to faster swimming
341 (Ganzevles et al., 2019) since it is associated with greater intra-cycle accelerations and
342 decelerations (Leblanc et al., 2007). However, only best performers were able to significantly
343 increase jerk cost after the second tipping-points supporting more pronounced end-spurt
344 launching. It might illustrate the critical importance of a greater anaerobic reserve (Baldassarre
345 et al., 2019b) to produce these acceleration fluctuations after prolonged effort. Nevertheless,
346 technical skills are necessary to convert stroke smoothness degradation into higher speed.
347 Indeed, jerk cost is differently related to final ranking with a significant negative correlation
348 only for best performers highlighting discriminating ability to “feel the water” (Leblanc et al.,
349 2007, p. 146). Conversely, significant positive correlation between stroke rate and final ranking
350 for lower level performers indicates their biomechanical limitations to turn stroke mechanical
351 parameters into speed as previously described (Rodríguez et al., 2021). This illustrates that an
352 increase in stroke rate is not always associated with a greater propelling efficiency (Barbosa et
353 al., 2015) for low levels of expertise.

354 The previously described stroke profiles highlights distinct biomechanical regulations of lower
355 level performers which may explain the different pacing of less successful swimmers as

356 previously shown (Rodríguez & Veiga, 2018). Their reverse L-shape pattern may indicate that
357 they are not able to meet the requirement of success during open water races, especially until
358 the first tipping-point targeting stroke economy. Then, the swimming pace driven by the leaders
359 probably outperformed their capacity (Renfree et al., 2015) and led them falling behind
360 (Rodríguez & Veiga, 2018) that may lead to their drop from the head pack after the first tipping-
361 point when the pace increases.

362 Differences between best and intermediate performers (non-top 7 swimmers) occur at the
363 second tipping-point at which the latter display an inability to maintain both stroke rate and jerk
364 cost increase. In this way, the notion of “stroke rate reserve” is likely a technical skill supporting
365 successful pacing. Finally, we highlighted two discriminant features for open water
366 performance referring to two race tipping-points. Such points lead to typical parabolic-shaped
367 profiles (Abbis & Laursen, 2008) of best performers, respectively J-shaped and U-shaped for
368 stroke rate and jerk cost, driven by kinematical regulations of stroke according to the following
369 tipping-points: (1) reducing jerk cost for the same speed (i.e. saving energy) during the first
370 third of the race by taking advantage of drafting effect in packs to anticipate for the pacing
371 increase and, (2) exploit anaerobic reserve to enhance stroke rate and jerk cost during the last
372 quarter of the race to support a decisive end spurt. Then, open water races follow a high-grading
373 dynamics involving specific physical preparation of swimmers as well as stroke regulations to
374 meet these both tipping-points.

375 A limitation of the study regarding the interpretation of change in biomechanical parameters
376 lies in the lack of measurement of the instantaneous speed during the race. Further continuous
377 monitoring of stroke parameters during competition regarding instantaneous pacing is
378 necessary to fully understand regulations leading to open-water performance. More precisely,
379 future research combining IMU and GPS data could be a powerful way to interpret stroke
380 profiles in relation to speed using a cycle-to-cycle approach. It may also provide useful data to
381 compute other discriminant kinematical parameters such as stroke length and stroke index
382 which are related to efficiency (Costill et al., 1985). Moreover, the present study suffers from a
383 lack of anthropometric characteristics of swimmers that could affect stroking rate data
384 (Rodríguez et al., 2021). Another limitation is the impossibility to estimate the impact of
385 external and specific conditions on each race outcome such as wind, currents (Saavedra et al.,
386 2018), structure of the course, temperature (Abbis & Laursen, 2008) and subsequent use of
387 neoprene suits increasing propelling proficiency (Quagliarotti et al., 2023). These
388 environmental constraints combined with inherent factors to each swimmer like motivation, sex
389 and refueling strategies can certainly affect pacing, tactical positioning (Veiga et al., 2019) and
390 therefore the stroke parameters assessed in this study. Another potential limitation lies in the
391 merging of different race distances as well as male and female swimming in the analysis.
392 However, contradictory findings have been previously pointed out. While previous studies
393 showed that dynamic of pacing profiles as well as the tactical positioning of the competitors
394 depended on the race distance and on gender (Veiga et al., 2019), common stroke rate
395 regulations, trivial average stroke rate differences on 10km (Rodríguez et al., 2021) and
396 identical conservative strategy was employed between sex (Saavedra et al., 2018), as well as
397 similar pacing strategies between 5 and 10km (Baldassarre et al., 2018) have been reported.
398 Consequently, investigating specific differences of stroke regulations timing between sex and
399 race distance may be an interesting perspective.

400 In conclusion, the present study provided the first cycle-to-cycle monitoring of stroke
401 parameters coming from in-situ data collection during full international open water events. This
402 work showed the importance of kinematical regulation to support effective pacing leading to
403 open water performance conducting to specific patterns of stroke rate and jerk cost,

404 correspondingly as J-shape with end spurt and U-shape, J-shape without end-spurt and reverse
405 J-shape, as well as both reverse L-shape, for respectively best, intermediate and lower level
406 performers. Indeed, it showed that open water races follow high-grading dynamics requiring
407 specific timing of biomechanical regulations through two tipping-points. Best swimmers
408 displayed a stroke rate reserve and a specific management of stroke smoothness to follow these
409 milestones in stroke regulation. They respectively reflected the end of a stroke economy period
410 at the beginning of the race including enhancing of stroke smoothness and reduction of stroke
411 rate to preserve energy (0-30%) as well as the end of a continuous increase in stroke parameters
412 (30-75%) towards launching a decisive end-spurt (75-100%). The findings of this study can
413 assist coaches and athletes when designing training sessions to target development of these
414 skills including anaerobic reserve and ability to widely manage stroke smoothness over the race
415 to develop qualities meeting the requirements of international open-water races.

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423 **Disclosure of conflicts of interest**

424 The authors have no conflict of interests.

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