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## 43 Abstract :

44 This study aims to profile biomechanical abilities during sprint front-crawl by identifying  
45 technical stroke characteristics, in light of performance level. Ninety-one recreational to world-  
46 class swimmers equipped with a sacrum-worn IMU performed 25m all-out. Intra and inter-  
47 cyclic 3D kinematical variabilities were clustered using a functional double partition model.  
48 Clusters were analyzed according to (1) swimming technique using continuous visualization  
49 and discrete features (standard deviation and jerk cost) and (2) performance regarding speed  
50 and competition caliber using respectively one-way ANOVA and Chi-squared test as well as  
51 Gamma statistics. Swimmers displayed specific technical profiles of intra-cyclic (*smoothy* and  
52 *jerky*) and inter-cyclic stroke regulation (*low*, *moderate* and *high repeatability*) significantly  
53 discriminated by speed ( $p < 0.001$ ,  $\eta^2 = 0.62$ ) and performance caliber ( $p < 0.001$ ,  $V = 0.53$ ). We  
54 showed that combining high levels of both kinds of variability (*jerky + low repeatability*) are  
55 associated with highest speed ( $1.86 \pm 0.12$  m/s) and competition caliber ( $\gamma = 0.75$ ,  $p < 0.001$ ). It  
56 highlights the crucial importance of variabilities combination. Technical skills might be driven  
57 by a specific alignment of stroke pattern and its associated dispersion according to the task  
58 constraints. This data-driven approach can assist eyes-based technical evaluation. Targeting the  
59 development of an explosive swimming style with a high level of body stability should be  
60 considered during training of sprinters.

## 61 Introduction

62 Performance analysis in swimming requires the identification of individual skills and the way  
63 the best swimmers master their movement (Bartlett, 2001). Therefore, monitoring their  
64 biomechanical abilities through technical assessment is at the heart of the understanding of elite  
65 performances. Swimming is a sequence of repeated but not identical body movements targeting  
66 effective motor patterns to achieve optimal performance (Maglischo, 2003). Thus, variability  
67 is inherent to swimming technique and occurs within a stroke cycle or across multiple stroke  
68 cycles, respectively known as intra and inter-cycle variability (Fernandes et al., 2022a). Such  
69 variabilities are of crucial interest as it can affect the swimming speed (Figueiredo et al., 2013)  
70 and reflect underlying regulation of stroke mechanics. Hence, evaluation of both intra and inter-  
71 cyclic kinematical variability, as well as their combination, may provide valuable insights on  
72 the relationship between movement variability and technical skills during swimming.

73 Previous research focused on intra-cycle variability and its relations with performance and  
74 expertise (Fernandes et al., 2022b). Nevertheless, associations between intra-cyclic aspects of  
75 kinematical variability and technical skills remain unclear. Intra-cyclic velocity variations  
76 (IVV) were primarily investigated leading to contradictory findings since opposite correlations  
77 between IVV and performance were observed (Barbosa et al., 2012 ; Barbosa et al., 2005;  
78 Schnitzler et al., 2008). Moreover, divergent outcomes were pointed out regarding the impact  
79 of expertise since better skilled swimmers can show higher, lower or similar IVV (Fernandes  
80 et al., 2023). Despite the identification of IVV as a relevant way to monitor swimming  
81 biomechanical development (Vilas-Boas et al., 2011), inconsistency of literature leads to a  
82 crucial lack of information on regulation of stroke variability. In that respect, considering other  
83 variables than the forward linear velocity to assess intra-cyclic variability may be meaningful.  
84 Indeed, the understanding of the stroke cycle effectiveness refers to the interplay between the  
85 propulsive and drag forces that produce body accelerations (Gonjo et al., 2021). Hence, this  
86 dynamical interaction reflected by kinematics is considered as an efficiency estimator (Barbosa  
87 et al., 2012 ; Figueiredo et al., 2012a). Therefore, analyzing the intra-cyclic acceleration may  
88 be of great interest as it provides relevant diagnostic of front-crawl technical skills (Ichikawa,  
89 1999) and propelling actions (Buchner & Reischle, 2002) by a much direct evaluation of the

90 capacity to propel the body with minimal velocity variations (Gonjo et al., 2021). Acceleration  
91 has been shown as a sensitive measure of swimming performance since correlation between  
92 velocity and root mean square of acceleration was reported (Tella et al., 2008 ; Tella et al.,  
93 2010). Then, it may be considered as a consistent indicator of stroke mechanics performance  
94 and expertise, reflecting a possible advantageous technique (Holmer., 1979) or higher stroke  
95 efficiency (Gil et al., 2012). Moreover, time variation of acceleration (*i.e.* jerk) may also reflect  
96 important technical skills because it quantifies the smoothness that leads to a more efficient  
97 movement (Hreljac, 1993). In that sense, smoothness is a universal feature of skilled movement  
98 which may be used as a window into athletic coordinative proficiency (Kiely et al.,  
99 2019). Thus, the jerk cost has been recently used in swimming to evaluate the technique  
100 (Ganzevles et al., 2019) and stroke regulations (Bouvet et al., 2023). Finally, the acceleration  
101 pattern and its derivative may be valuable for intra-cyclic variability regulation assessment.

102 Swimming stroke analyses generally consider only intra-cyclic aspects of motor pattern in  
103 isolation of adjacent cycles that reduces the understanding of variability. However, considering  
104 also the movement variability between cycles, may provide complementary information about  
105 performance and technical skills characterization (Fernandes et al., 2022b). Given the  
106 traditional approach of movement variability as noise (Preatoni et al., 2013), swimmers with  
107 high inter-cyclic variability may exhibit a greater dispersion in their technique and a lower  
108 repeatability in their kinematics leading to reduced performance. Fernandes et al., (2022a)  
109 suggested that slowest swimmers displayed higher mean velocity oscillations between two  
110 consecutive cycles with higher numbers of cycles presenting extreme variations than the fastest  
111 ones. However, Fernandes et al., (2022b) showed that elite swimmers' velocity in backstroke  
112 were more unstable and complex despite similar intra-cycle variations. Thus, inter-cyclic  
113 variability may contain important information about motor organization and not only refer to  
114 deleterious limitations to performance which should therefore be eliminated.

115 Variability analysis has been achieved using a variety of devices, including video, speedometer,  
116 motion capture and inertial measurement units (IMU) (Fernandes et al., 2023). Among them,  
117 IMU is a relevant embedded tool to assess 3D swimming kinematics in a real environment  
118 (Mooney et al., 2016). Moreover, IMU directly measures the acceleration which is convenient  
119 for movement variability analysis. Indeed, it may avoid errors on acceleration signals that can  
120 arise using numerical derivatives from position and velocities. Therefore, IMU is suitable to  
121 monitor intra-cyclic acceleration pattern allowing to track technical skills and changes in  
122 efficiency (*e.g.* Engel et al., 2022 ; Ganzevles et al., 2019 ; Tella et al., 2008). Furthermore, as  
123 swimming is composed of translational and rotational motions, IMU may enable more insights  
124 on movement variability because it also measures angular velocities. Since IMU data are  
125 multivariate time series, it seems **appropriate** to consider their functional form by continuous  
126 instead of discrete measures of variabilities (Ryan et al., 2006). **To this end, motor control  
127 methodologies present a useful framework for variability analysis based on nonlinear dynamics  
128 in time series (Bravi et al., 2011). Among them, features of complexity, such as the approximate  
129 and the sample entropy, allowed to quantify the temporal structure in the signals through the  
130 unpredictability of its variations. This methodology was applied in swimming kinematics to  
131 provide new insights into variability (Barbosa et al., 2017 ; Fernandes et al., 2022b). However,  
132 even if entropy features proceeds over the entire signal to capture temporal dynamics, and thus  
133 could be considered as an easy-to-use continuous measure, they finally result in a restricted  
134 scalar value (*i.e.*, discretization of the information in a numeric feature), whereas variability  
135 analysis could be improved by considering it as a function of the time. Indeed, function  
136 regression provided more informative and intuitive interpretations of function-valued data, as  
137 time series, than conventional single scalar approaches (Yen et al., 2015). Moreover, entropy  
138 features can't handle the multivariate nature of IMU data, referring to interactions between**

139 dimensions of swimmers' motion variability. As a consequence, this kind of discrete parameters  
140 neglect a part of the temporal and dynamical information in functional data leading to restricted  
141 details on motricity (Richter et al., 2014). Then, numerous studies in swimming were limited to  
142 these non-function-valued methodologies in process-driven approaches, mainly due to the  
143 absence in literature of a suitable statistical model capturing the functional nature of the IMU  
144 swimming data. Thus, it leads to limited data-driven insights regarding kinematical variabilities  
145 profiling and performance explanations. Therefore, taking into account the need to, on the one  
146 hand, consider the entire sequence of data points, and on the other, directly model swimming  
147 variabilities through functional data analysis (FDA) applied to IMU data is crucial.

148 In order to better investigate the kinematical variability recorded by IMU and its relation with  
149 technical skills and performance, FDA depicts a useful way. Actually, FDA can take into  
150 account the shape of kinematical curves, by relying on statistical modeling of data, giving  
151 indications on the motor pattern and helping to classify behavior and relevant characteristics of  
152 performance (Preatoni et al., 2013). Indeed, FDA can outpace traditional approaches relying on  
153 process-driven analysis and computation of discrete features that leads to limited kinematical  
154 information (Mallor et al., 2010). For example, it provides evidence on technical differences  
155 in national and international race-walkers (Donà et al., 2009). Moreover, literature  
156 demonstrated the usefulness of FDA for motion pattern analysis and description of different  
157 performance groups on cyclic biomechanical data such as gait, running and cycling (Andrade  
158 et al., 2014; Forrester & Townend, 2015 ; Helwig et al., 2016). In this way, Barbosa et al., 2021  
159 highlighted differences between international and national-level sprinters using a general FDA  
160 approach, without automatic classification of swimmers. Furthermore, these methods can be  
161 extended, regarding the scope of application and the data specificities, to allow clustering of  
162 functional data (Jacques & Preda, 2014) and then group similar time series of biomechanical or  
163 performance parameters (Leroy et al., 2018). Then, functional data clustering has been  
164 growingly applied in applications of various fields of science and gathering statistical methods  
165 coming from FDA and clustering community (Zhang & Parnell, 2023). Hence, it may provide  
166 identification of trends and features leading to new insights about technique and performance  
167 profiles in sport applications. More generally, cluster analysis is a powerful data-driven tool for  
168 detect performance and technique patterns in various sport applications such as athletes' visual  
169 search strategies (Murray & Hunfalvay, 2017), anthropometric attributes (Zhang et al., 2018)  
170 and coordination pattern in swimming (Seifert et al., 2016 ; Bideault et al., 2013). Then, in its  
171 functional extension, clustering may be a powerful approach to deal with IMU data in order to  
172 profile variabilities in swimming. However, such methodology of functional data clustering  
173 generally required the use of a customized statistical model able to deal with both the specificity  
174 of the input data and the aim of the analysis (Bouveyron et al., 2019). To this end, recent  
175 developments in statistical literature provided an approach explicitly devoted to functional  
176 clustering of swimmers through the modeling of kinematical variabilities recorded by IMU  
177 (Bouvet et al., 2024). It embodies a promising way to perform profiling of biomechanical  
178 abilities during swimming based on both intra and inter-cyclic kinematical variability.

179 The present study aimed at clustering intra and inter-cyclic variability considering the  
180 functional nature of 3D IMU data during sprint front-crawl swimming in order to identify  
181 technical strokes characteristics according to the performance level leading to biomechanical  
182 abilities profiling.

## 183 **Materials and methods:**

### 184 *Participants*

185 91 subjects (31 women, age:  $18.7 \pm 3.20$  y.o.; height:  $170 \pm 6.37$  cm; mass:  $60.1 \pm 6.67$  kg; FINA  
186 points on 50m freestyle short course:  $457 \pm 175$ ) and 60 men, age:  $21.4 \pm 6.65$  y.o.; height:  
187  $183 \pm 8.01$  cm; mass:  $71.8 \pm 12.3$  kg; FINA points on 50m freestyle short course:  $527 \pm 195$ )  
188 participated in this study including recreationally active to world-class swimmers (McKay et  
189 al., 2022). All participants signed an informed consent form in agreement with the French  
190 Ethical Committee (approval obtained under reference 2021-A00250-41).

#### 191 192 *Data collection*

193 Each swimmer performed a 25m wall-start in front-crawl at maximal intensity with the  
194 instruction to not perform underwater kicks and breathing. Participants were instrumented with  
195 one waterproof 3D IMU (Xsens DOT, Movella, Enschede, The Netherlands) sampled at 60 Hz  
196 using a full scale set at 16 g for the accelerometer and 1000 deg/s for the gyroscope. The sensor  
197 was placed on the sacrum, then fixed with double-sided tape and secured with waterproof  
198 medical adhesive (Tegaderm, 3M, Cergy-Pontoise, France). The IMU described a coordinate  
199 system defined with x-axis pointing cranially, y-axis pointing laterally, and z-axis pointing  
200 posteriorly.

#### 201 202 *IMU data preprocessing and functional data clustering model*

203 Raw data were filtered using a second order Butterworth low-pass filter with a 10 Hz cut-off  
204 frequency. The algorithm of Delhaye et al., 2022 was used, on the one hand, to extract only the  
205 front-crawl frames from the signal based on the human activity recognition provided by the  
206 classifier, and to the other hand, to compute average swimming speed as the pool length (i.e.,  
207 25m) divided by the lap time automatically provided by the model.

208 In order to avoid kinematical disturbances in data during the first stroke after swimmer's  
209 breakout and finish, one-second time windows before and after the first and the last front-crawl  
210 frame were removed. In order to prevent temporal drift in swimmer's time series, curve  
211 alignment is performed to enable proper functional modeling. It is achieved by adjusting the  
212 signal starting point at the frame corresponding to a common reference for all swimmers  
213 (Bouvet et al., 2024). To do so, we used a specific and generalizable feature in the IMU signals,  
214 defined as an operational definition of a stroke cycle beginning in swimming literature. The  
215 latter was identified as the first zero-crossing on the medio-lateral acceleration filtered with a  
216 second-order Butterworth band-pass filter between 0.1 and 1 Hz (Ganzevles et al., 2019). For  
217 each cycle, data were time normalized using the previously described zero-crossing detection.  
218 This feature allows, through a highly filtered signal processing approach, to only extract the  
219 waveform characteristics about that IMU axis. Consequently, the repeating elemental pattern  
220 obtained is representative of the body roll during front-crawl (Mooney et al., 2016) and allowed  
221 to both determine the periodicity of the signal as well as extracting the single-cycle data  
222 (Zhuang & Xue, 2019). This method allows to identify the start and end of a stroke cycle while  
223 dealing with high levels of intra and inter-subject kinematical variability as well as noise in  
224 sensor's measurement. Finally, its generalization ability defines consistent time within a stroke  
225 cycle, which is a required step in the functional clustering of kinematics detailed below. Figure  
226 1 shows the preprocessed data for two participants of different levels.

227  
228 [FIGURE 1 NEAR HERE]  
229

230 These data were then clustered using the double partition model of Bouvet et al., (2024). This  
231 FDA framework enables a fully integrated curve clustering based on both kinds of variabilities  
232 and also considers dependency between both partitions. Modeling this dependency during the  
233 clustering process is mandatory since the difficulty of reproducing a swimming pattern (i.e.,  
234 inter-cyclic variability) depends on its shape (i.e., intra-cyclic variability). Then, this approach

235 is able to model and analyze the complex multivariate dynamics of swimming patterns by  
236 aggregating the dependent kinematical variabilities linked to swimming technical skills into  
237 interrelated partitions. As a consequence, this extended FDA approach belongs to the model-  
238 based functional clustering (Jacques & Preda, 2014 ; Bouveyron et al., 2019), and has been  
239 developed for taking into account all of the specificities of the kinematical swimming data  
240 recorded by IMU through a powerful statistical model devoted to technical skills profiling  
241 (Bouvet et al., 2024). Based on a multivariate functional decomposition of IMU signals as well  
242 as squared residuals into Fourier basis, the model considers both the kinematical information  
243 related to stroke pattern as well as the ability to reproduce it. Finally, it led to two partitions  
244 respectively related to intra and inter-cyclic variability clusters. The degrees of each Fourier  
245 basis were selected between four and twenty using a leave-one-out cross-validation. Model  
246 selection was performed using Bayesian Information Criterion considering clusters values  
247 between one and five. Visualization was performed by computing the mean cluster curves (*i.e.*  
248 stroke pattern representing intra-cyclic variability) as well as credibility region (*i.e.* ability to  
249 reproduce the stroke pattern representing inter-cyclic variability).

250

#### 251 *Statistical analysis*

252 Statistical analyses were conducted using RStudio (Version 4.2.2, RStudio, Inc., Boston, MA,  
253 USA). The level of significance was set at  $p < 0.05$ .

254

#### 255 *Technical analysis of clusters*

256 To identify cluster technical profiles, classes were analyzed regarding clustering visualization  
257 and biomechanical parameters computed on each IMU axis. Indeed, considering clusters mean  
258 curves, standard deviation was calculated as a reflection of cycle variation (Dadashi et al., 2016)  
259 and jerk cost (for accelerometric dimension) as a practical evidence of stroke smoothness  
260 (Ganzevles et al., 2019). Regarding cluster credibility region curves, standard deviation was  
261 calculated as the amount of kinematical dispersion.

262

#### 263 *Performance analysis of clusters*

264 To identify cluster performance profiles defining relevant biomechanical abilities, two analyses  
265 were conducted considering different partitions: both single and the cross-partition (*i.e.*  
266 combination of inter and intra-cyclic variability clusters for each subject, reflecting technical  
267 skills profiling). Firstly, a one-way analysis of variance (ANOVA) or t-test was performed to  
268 investigate the link between swimming speed and the partitions. If appropriate, post-hoc tests  
269 were conducted with Tukey test and Bonferroni correction. The magnitude of differences was  
270 interpreted using generalized eta-squared ( $\eta_g^2$ ) for ANOVA or Cohen's d (d) for t-test with  
271 threshold values of respectively 0.01, 0.06, 0.14 and 0.20, 0.50 and 0.80 defining trivial, small,  
272 medium and large effects (Cohen, 1988). Secondly, a Pearson's Chi-squared test was performed  
273 to investigate the dependence between a performance caliber ordinal variable (defined as Tier1,  
274 Tier2-3 and Tier4-5 respectively for recreationally active (tier 1) swimmers,  
275 trained/developmental (tier 2) or highly trained/national level (tier 3) swimmers and  
276 elite/international level (tier 4) or world class (tier 5) swimmers according to McKay et al.,  
277 2022) and the clusters ranked as ordinal variables based on speed. **These modalities of the**  
278 **performance caliber ordinal variables displayed FINA points on 50m freestyle short course of**  
279 **308±128, 455±78 and 742±73 for respectively Tier1, Tier2-3 and Tier4-5.** The magnitude of  
280 differences was interpreted using V Cramer (V) and threshold values of 0.10, 0.20, 0.40, 0.60,  
281 0.80 and 1 defining negligible, weak, moderate, relatively strong, strong and very strong effects  
282 respectively (Cramer, 1946). The strength of the association between performance caliber and  
283 clusters was measured using the Goodman Kruskal's Gamma statistic ( $\gamma$ ) (Goodman & Kruskal,  
284 1954) with 95% confidence intervals and threshold value of 0.01, 0.10, 0.30, 0.60, 0.75 and 1

285 defining no association, negligible, low, moderate, strong, and very strong association  
286 respectively (Rea & Parker, 2014).

287

## 288 **Results**

### 289 *Technical profiles according to cluster*

290 Mean cluster curves and credibility regions for the accelerometric and gyroscopic dimensions  
291 are presented on Figure 2 and Figure 3, respectively. The best model displayed two clusters of  
292 stroke patterns defining intra-cyclic variability and three clusters of ability to reproduce the  
293 stroke pattern defining inter-cyclic variability. Intra-cyclic variability clusters displayed a  
294 specific stroke pattern, especially discriminated by signal amplitude and number of peaks in  
295 longitudinal and anteroposterior acceleration as well as signal amplitude in mediolateral  
296 acceleration. Then, clusters of intra-cyclic variability were named as the *jerky* and the *smoothy*  
297 class. The biomechanical features for the accelerometric and gyroscopic dimensions are  
298 displayed on Table 1 and Table 2, respectively. The *jerky* cluster displayed stroke pattern with  
299 higher variations of 74% and 178% on longitudinal and anteroposterior accelerations and of  
300 181% and 8% on mediolateral and anteroposterior angular velocities, as well as lower variations  
301 of 15% on mediolateral acceleration and 11% on longitudinal angular velocity. The stroke  
302 smoothness of the *jerky* cluster was lower of 830% and 1675% on longitudinal and  
303 anteroposterior accelerations but lower of only 14% on mediolateral acceleration in comparison  
304 with the *smoothy* cluster (see Table 1). Inter-cyclic variability clusters were ordered according  
305 to the magnitude of stroke pattern dispersion. Thus, the resulting three kinds of inter-cyclic  
306 variability were referred as *low (LR)*, *moderate (MR)*, and *high (HR) repeatability* clusters.  
307 Indeed both the credibility region around the mean cluster curve (see Figure 2 and Figure 3)  
308 and the corresponding kinematical variation (see Table 2) were higher as clusters moved closer  
309 to *LR*. For example, the dispersion in longitudinal acceleration was 633% higher in *MR* than  
310 *HR* and 117% in *LR* than *MR* clusters.

311

312 [FIGURE 2 NEAR HERE]

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314 [FIGURE 3 NEAR HERE]

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316 [TABLE 1 NEAR HERE]

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318 [TABLE 2 NEAR HERE]

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### 320 *Performance profiles according to cluster*

321 Swimming speeds according to the different classes coming from the intra and inter-cyclic  
322 variability clustering are presented on Figure 4, as well as the classes coming from the cross-  
323 partition on Figure 5. Regarding clustering of mean stroke pattern (*i.e.* intra-cyclic variability),  
324 the *jerky* class showed a significantly higher swimming speed of 29.6% compared to the  
325 *smoothy* class with a large effect size (1.84 [1.79 ; 1.89]  $\pm$ 0.12 vs. 1.42 [1.38 ; 1.47] $\pm$ 0.18,  
326  $t(68.0)=12.8$ ,  $p<0.001$ ,  $d=2.72$ ). Regarding clustering the ability to reproduce the stroke pattern  
327 (*i.e.* inter-cyclic variability), there was a large significant swimming speed difference between  
328 the three clusters ( $F(2.88)=21.7$ ,  $p<0.01$ ,  $\eta^2=0.33$ ). Regarding the cross-partition, there was a  
329 large significant swimming speed difference between the five clusters ( $F(4.86)=34.6$ ,  $p<0.01$ ,  
330  $\eta^2=0.62$ ). Table 3 presented the significant pairwise comparisons for both the inter-cyclic  
331 variability partition and the crossing partition, with all  $p<0.01$ .

332 [TABLE 3 NEAR HERE]

333

334



335 [FIGURE 4 NEAR HERE]

336 [FIGURE 5 NEAR HERE]

337  
338  
339 Performance caliber distribution according to the different classes coming from the intra and  
340 inter-cyclic variability clustering are presented on Figure 6, as well as the classes coming from  
341 the cross-partition on Figure 7. Clusters of mean stroke pattern are strongly dependent on  
342 performance caliber ( $\chi^2(2)=49.9$ ,  $p<0.001$ ,  $V=0.74$ ) with a very strong significant association  
343 between the more the stroke pattern is *jerky*, the higher is the performance caliber ( $\gamma=0.97$  [0.93  
344 ; 1.00],  $p<0.001$ ). Clusters of ability to reproduce the stroke pattern are moderately dependent  
345 of performance caliber ( $\chi^2(4)=28.0$ ,  $p<0.001$ ,  $V=0.39$ ) with a strong significant association  
346 between the more there is *low repeatability* stroke pattern, the higher is the performance caliber  
347 ( $\gamma=0.63$  [0.42 ; 0.84],  $p<0.001$ ). Clusters of the cross-partition are relatively strongly dependent  
348 of performance caliber ( $\chi^2(10)=51.5$ ,  $p<0.001$ ,  $V=0.53$ ) with a very strong significant  
349 association between the more the stroke pattern is *jerky+low repeatability* the higher is the  
350 performance caliber ( $\gamma=0.75$  [0.60 ; 0.89],  $p<0.001$ ).

351 [FIGURE 6 NEAR HERE]

352 [FIGURE 7 NEAR HERE]

## 353 Discussion and Implication

354  
355  
356 This study aimed at clustering intra and inter-cyclic 3D kinematics during sprint front-crawl to  
357 identify technical strokes characteristic according to performance level based on an embedded  
358 IMU on the sacrum. To this end, a data-driven process based on a large database and including  
359 an heterogeneous level, ranging from recreationally active to world-class swimmers, was  
360 applied for multivariate functional clustering considering the specificities of IMU swimming  
361 data. Specific profiles of technique variability were identified. Indeed, two clusters of intra-  
362 cyclic stroke regulation (*smoothy* and *jerky*) and three clusters of inter-cyclic stroke regulation  
363 (*LR*, *MR*, and *HR*) were identified. All of them were analyzed according to swimming speed  
364 and performance caliber supporting the identification of relevant biomechanical abilities for  
365 front-crawl sprint.

366  
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368 Regarding the intra-cyclic clusters defining magnitude of variability, the *smoothy* class presents  
369 a more fluent acceleration pattern than the *jerky* one with continuity of propulsive actions. It is  
370 characterized by a lower acceleration variation along the longitudinal and anteroposterior axes  
371 and a higher variation of longitudinal angular velocity in addition to mediolateral acceleration.  
372 The *jerky* class includes a more explosive and rough stroke pattern leading to a higher jerk cost  
373 along longitudinal and anteroposterior reflecting degradation of stroke smoothness. Indeed,  
374 smooth swimming movements referring to a low jerk cost, are those without abrupt, intermittent  
375 and discontinuous changes in accelerations, whereas non-smooth stroke patterns reflect  
376 abruptness and erratic discordance (Kiely et al., 2019). A higher jerk cost might lead to a faster  
377 swimming (Ganzevles et al., 2019) as it implies greater intra-cycle acceleration and deceleration  
378 that can be converted into higher speed with appropriate technical skills. Indeed, our results are  
379 in line with such behavior because the *jerky* participants swim significantly faster than the  
380 swimmers of the *smoothy* cluster while being the ones demonstrating the higher performance  
381 caliber. Thus, the *jerky* cluster gathers almost all of the elite and world-class swimmers, whereas  
382 the *smoothy* cluster includes all the recreationally active swimmers and the majority of the  
383 trained and highly trained swimmers. It may be explained by a larger speed curve amplitude in  
384 faster sprinters (Barbosa et al., 2021) as well as higher peaks in speed with similar minimal

385 speeds (Leblanc et al., 2007). However, the lower stroke smoothness induced by higher intra-  
386 cyclic variability in the *jerky* stroke pattern may also be associated with higher energy  
387 expenditure leading to a lower stroke efficiency (Fernandes et al., 2023). Nevertheless, the *jerky*  
388 cluster displays reduced variations in both mediolateral acceleration and longitudinal angular  
389 velocity than the smoothy one, reflecting more core stability and a better overall alignment of  
390 the body by possibly a decrease of body roll. However, body roll is not directly assessed in this  
391 work. To the author's knowledge, only the biomechanical model of Bächlin & Tröster (2012)  
392 tracked body roll angle from IMU data under strong mechanical assumptions. Indeed, body  
393 angles assessment from IMU data requires a sensor-to-segment calibration, combined with a  
394 reliable computing of the sensor orientation, which involves very complex processings in the  
395 water environment (Mangia et al., 2017). Hence, in this work, we consider the association  
396 between medio-lateral acceleration recorded from a sacrum IMU during front-crawl and body  
397 roll previously used in literature (Mooney et al., 2016 ; Callaway, 2015). Since the medio-lateral  
398 acceleration with respect to the swimmer mainly reflects the roll movements during front-crawl  
399 (Ganzevles et al., 2019), we use this indirect relationship as a proxy for interpretation of our  
400 functional clustering. Then, the higher stability that could be induced by this reduced body roll  
401 seems to especially occur during the critical propelling phases of the cycle (i.e., extrema of  
402 longitudinal acceleration). This finding is in line with previous literature pointing out a  
403 reduction of whole-body roll, shoulder roll and hip roll amplitude in front crawl as pace  
404 increases (Gonjo et al., 2021). It allows to improve stroke rate by reducing the stroke cycle  
405 duration (Psycharakis & Sanders, 2008) while avoiding disturbance of propulsion caused by a  
406 large amount of torque around longitudinal axis (Yanai, 2003). Then, the *jerky* stroke pattern  
407 matches the requirements of the maximal exercise performed since reducing amplitude of body  
408 roll is expected from sprinters as they use higher stroke frequency and a possible more  
409 continuous inter-limb coordination (Seifert et al., 2010).

410 In summary, faster front-crawl sprinters display specific regulations of stroke pattern  
411 variability, reflected as *jerky*, targeting two goals. Firstly, producing high intra-cyclic  
412 acceleration fluctuations along both forward and upward axes leading to a degradation in  
413 overall stroke smoothness and an increase in energy expenditure. Secondly, presenting a higher  
414 body stability during the critical instants of forward propulsion, that is the stroke cycle timings  
415 with the higher forward speed variations (i.e., peaks and valleys on longitudinal acceleration),  
416 might lead to faster swimming. More precisely, it may be enabled by reducing body roll in order  
417 to increase the stroke rate.

418  
419 Regarding the inter-cyclic clusters defining the structure of variability, three profiles arise from  
420 two characteristics. On the one hand, the non-constant credibility regions (as depicted on Figure  
421 2 and Figure 3) refer to unequal variance in inter-cyclic kinematics. It indicates various stroke  
422 pattern dispersions and uneven variability according to the instant within the stroke cycle. More  
423 precisely, the highest dispersion occurs during the peaks on accelerations that lead to swimming  
424 velocity generation. Thus, such findings are in line with previous outcomes showing that the  
425 higher velocity oscillations in extreme cycles occurred mainly during propulsive phases of the  
426 cycle (Fernandes et al., 2022a). On the other hand, faster swimmers display significantly lower  
427 repeatability of stroke pattern indicating that higher kinematical inter-cyclic variation is  
428 associated with better sprint performance. Indeed, 62% of the *LR* cluster is composed of elite  
429 to world class swimmers. Fernandes et al., (2022b) showed that elite swimmer's kinematics  
430 (i.e. velocity variability) in sprint backstroke were more unstable than non-elite's ones which  
431 is in line with our result as the *LR* cluster is the fastest. However, these authors assess the inter-  
432 cyclic variability in a process-driven approach, using features of nonlinear dynamics (i.e.,  
433 sample entropy and Largest Lyapunov Exponent) that captures the notion of stability and  
434 complexity in the raw kinematical signal. Nevertheless, in the present approach, relying on

435 multivariate functional clustering, inter-cyclic variability is assessed through a modeling of the  
436 ability to reproduce the swimming pattern. This methodology presents relevant advantages in  
437 comparison to discrete features of nonlinear dynamics (Bouvet et al., 2024). Indeed it allows,  
438 on the one hand, to deal with multivariate time series in order to consider at the same time all  
439 the IMU dimensions as well as their interactions, and on the other hand, to quantify both the  
440 magnitude of inter-cyclic variability as well as the the timings in stroke cycle at which it occurs.  
441 It opens the door to data-driven approach by applying curve clustering in sport settings (Chu et  
442 al., 2020 ; Leroy et al., 2018). By gathering of FDA tools and clustering tools, respectively  
443 towards suitable functional basis decomposition of the swimming IMU signals and double  
444 partition of multivariate data allowing for dependency, the methodology used in this work  
445 enable the identification of heterogeneous morphological patterns in swimming kinematics  
446 (Zhang & Parnell, 2023). Despite the inherent methodological differences with features of  
447 nonlinear dynamics, that could lead to further works comparing or combining them with  
448 specific FDA approach to help in the understanding of the inter-cyclic variability (Barbosa et  
449 al., 2017), congruent results are highlighted regarding the association between inter-cyclic  
450 variability of kinematics and sprint swimming performance. Nonetheless, it seems  
451 counterintuitive as traditional approaches of literature generally perceive movement variability  
452 as noise indicating poor technique or inefficiencies in movement patterns detrimental to  
453 performance (Abernethy et al., 2008). This apparent paradoxical effect of inter-cyclic  
454 variability on performance could be explained by the specificity of our population and sprint  
455 task. Indeed, we consider a large database with multiple skill levels. Actually, the impact of  
456 expertise on kinematical variability management remains unclear and would imply an  
457 adaptation to the task constraints rather than reproducing a predetermined motor pattern  
458 (Fernandes et al., 2022a). Thus, the inverse relationship between movement variability and  
459 expertise, skills or performance is not fully acknowledged in the literature, leading to a  
460 contentious role in sport technique (Preatoni et al., 2013 ; Glazier & Davids, 2009). Indeed,  
461 recent studies about swimming provided evidence that highly skilled athletes display larger  
462 levels of movement variability to maximize their swimming speed during 50m freestyle  
463 (Ganzevles et al., 2019 ; Morais et al., 2023). Moreover, Fernandes et al., 2022a demonstrated  
464 that variability characterizes the sprint swimming. In that respect, sprint performance would be  
465 associated with kinematical variability since elite swimmers adopted strategies to manage it,  
466 referring the movement variability as an emergent behavior under highly constrained aquatic  
467 environment and sprint task (Fernandes et al., 2022b). Then, movement variability is not always  
468 detrimental to performance (Seifert et al., 2013). It can be adaptive as world class swimmers  
469 must explore the environment to provide functional regulations of motor patterns leading to  
470 effective outcomes (Seifert et al., 2016 ; Seifert et al., 2011). As a consequence, movement  
471 variability is a way to distinguish elite athletes as previously shown in race walking (Preatoni  
472 et al, 2010), and may also contribute to human movement optimization to ensure success in  
473 technique as highlighted in gymnastics (Hiley & Yeadon, 2013). Furthermore, swimming at  
474 high intensity in front-crawl implies biomechanical constraints leading to technical adaptations  
475 of movement variability and coordination pattern (Seifert et al., 2016). The latter may be related  
476 both to swimmer's speciality (*i.e.* sprint or distance swimming) and swimmer's characteristics  
477 (*i.e.* expertise level or gender) (Figueiredo et al., 2012b ; Bideault et al., 2013). However,  
478 variability may also reflect fatigue which can negatively affect the performance.  
479 Finally, it is crucial to monitor kinematical variability in a data-driven framework to identify  
480 when it reflects functional adaptations supporting performance versus when it indicates a need  
481 for technical corrections. In that respect, the **curve clustering framework** used in the present  
482 study can help on-field end-users for this purpose of technical profiling **by using a functional**  
483 **statistical model suited with the specificities of swimming kinematical data.**  
484

485 Regarding the cross-partition clusters defining technical skills profiling, both the *jerky+LR* and  
486 the *jerky+MR* are the fastest clusters. Indeed, they are both composed of more than 70% by  
487 elite to world-class swimmers with no one recreationally active. Such finding is consistent with  
488 aforementioned results highlighting distinct association of intra and inter-cyclic variability  
489 clusters with performance. More precisely, specific congruence of variabilities by the  
490 combination of both high levels of intra and inter-cyclic variability turns out to be a highly  
491 discriminative aspect in the context of a sprint task. The present analysis did not reveal any  
492 swimmers belonging to the *jerky+HR* cluster that represents a non-congruence of the two kinds  
493 of variability (*i.e.* high level of intra but low level of inter-cyclic variability). Actually, a *jerky*  
494 but repeatable swimming may refer to a lack of technical skills to convert kinematical variations  
495 to effective propulsion, while a *jerky* and unsteady swimming could refer to proficient  
496 functional adaptation to sustain the highest possible speed during sprint swimming. By this  
497 way, it can be hypothesized that the biomechanical ability of swimmers to establish congruence  
498 between two kinds of stroke variabilities (*i.e.* mean stroke pattern and associated dispersion)  
499 according to the constraints of the task (*i.e.* sprint swimming vs. long distance swimming)  
500 define technical skills and swimming expertise. Indeed, the opposite cluster of congruent  
501 variability (*i.e. smoothy+HR*) displays low performance level with only 2% of elite to world-  
502 class swimmers. Such results could be explained by the specificity of the sprint exercise  
503 involving large constraints on swimmer's motricity through the requirement of maximal  
504 propulsive forces by large kinematical variations at the expense of the swimming economy.  
505 Indeed, swimmers are not concerned about saving energy during maximal trials and adopt a  
506 strategy based on generating greater propulsive forces and less efficient technique (Lopes et al.,  
507 2023). Nevertheless, we may expect the *smoothy+HR* cluster to be a relevant technique for  
508 other tasks including longer duration and lower intensity. Indeed, the technical requirements  
509 are likely to be different between long, middle and short-distance events as resistive and  
510 propulsive forces differ between low and high speed in front-crawl (Takagi et al., 2021). For  
511 example, longer distance swimming as open water races requires conservative strategy in order  
512 to improve stroke efficiency by lowering energy cost from a given pace (Bouvet et al., 2023)  
513 whereas overcoming a large drag by maximizing thrust force through mechanical power output  
514 is essential in sprint swimming technique to achieve high velocities (Gatta et al., 2018). These  
515 specific task constraints can then widely affect the kinematics of swimmers by modifying the  
516 management of movement variabilities. By the way, swimmers adapt their technique in order  
517 to maximize performance.

518 In summary, it seems that the intra-cyclic variability is the most impacting kind of variability  
519 on performance for sprint swimming. Indeed, the present results do not highlight any significant  
520 differences in terms of speed for the different inter-cyclic pattern given the intra-cyclic pattern,  
521 albeit all of the three *smoothy* clusters are significantly different from the two *jerky* clusters.  
522 Therefore, it results in distinctive profiles combining intra and inter-cyclic variability and  
523 defining relevant biomechanical abilities.

524  
525 Further assessment of variabilities regarding tasks constraints is necessary to fully understand  
526 stroke regulations leading to swimming performance. Extending the current approach to longer  
527 swimming duration can be a powerful way to interpret variabilities profiles according to race  
528 distance and define effective swimming technical skills. A limitation of this study is the lack of  
529 anthropometric and gender data that may impact the preferential kinematics. Moreover,  
530 combining present **functional** clusters of **variabilities** with conventional stroke parameters as  
531 stroke length, stroke rate and stroke index would contribute to the improvement of the  
532 identification of relations between technical regulations and their spatio-temporal outcomes..  
533

534 In conclusion, the present study provided the first data-driven approach to profile technical  
535 stroke profiles during sprint front-crawl based on kinematical **curve profiling of both** intra and  
536 inter-cyclic variability. In this way, it provides a novel method, **based on an adapted functional**  
537 **clustering model**, for variabilities determination in swimming using embedded sensors, as it is  
538 a hot topic in literature (Fernandes et al., 2023). This study demonstrates the importance of  
539 variabilities combination through their congruence to adapt the swimming technique. Indeed,  
540 technical skills might be driven by a specific management of both variabilities, in order to align  
541 stroke pattern and its associated dispersion, according to the performance features required by  
542 the task constraints. Therefore, sprint swimming requires both a high level of intra and inter-  
543 cyclic variability through a jerky and unsteady stroke pattern. In contrast, polarization of  
544 variabilities seems dysfunctional. The contributions of this study can assist eyes-based technical  
545 evaluation using an automatic and non-invasive continuous method, **explicitly devoted to**  
546 **swimming kinematical clustering**, to provide objective data on variabilities regulations.  
547 Consequently, it allows coaches to profile technical skills while providing benchmarks to target  
548 the development of an explosive swimming style with a high level of body **stability** for their  
549 sprinters.

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## 557 **Declaration of interest statement**

558 The authors have no conflict of interests.

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**Table 1.** Biomechanical features computed by IMU axis from the mean curves of the intra-cyclic variability cluster. LON: longitudinal. MED: mediolateral. ANT: anteroposterior

Cluster	Acceleration standard deviation (x10.g)			Angular velocity standard deviation (deg/s)			Jerk cost (x10.g <sup>2</sup> /s <sup>2</sup> )		
	LON	MED	ANT	LON	MED	ANT	LON	MED	ANT
<i>Jerky</i>	15.4	47.7	9.12	101	11.9	18.1	17.3	22.8	7.10
<i>Smoothy</i>	8.84	56.3	3.28	113	4.23	16.7	1.86	20.0	0.40

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925 **Table 2.** Biomechanical features computed by IMU axis from the credibility regions of the  
926 inter-cyclic variability cluster. LON: longitudinal. MED: mediolateral. ANT: anteroposterior.  
927 *LR: low repeatability. MR: moderate repeatability. HR: high repeatability*

	Cluster	Acceleration ( $\times 10^2$ g)			Angular velocity (deg/s)		
		LON	MED	ANT	LON	MED	ANT
Standard deviation	<i>LR</i>	2.39	1.32	0.39	426	334	87.0
	<i>MR</i>	1.10	1.14	0.36	284	96.8	81.0
	<i>HR</i>	0.15	0.38	0.07	117	21.3	28.1

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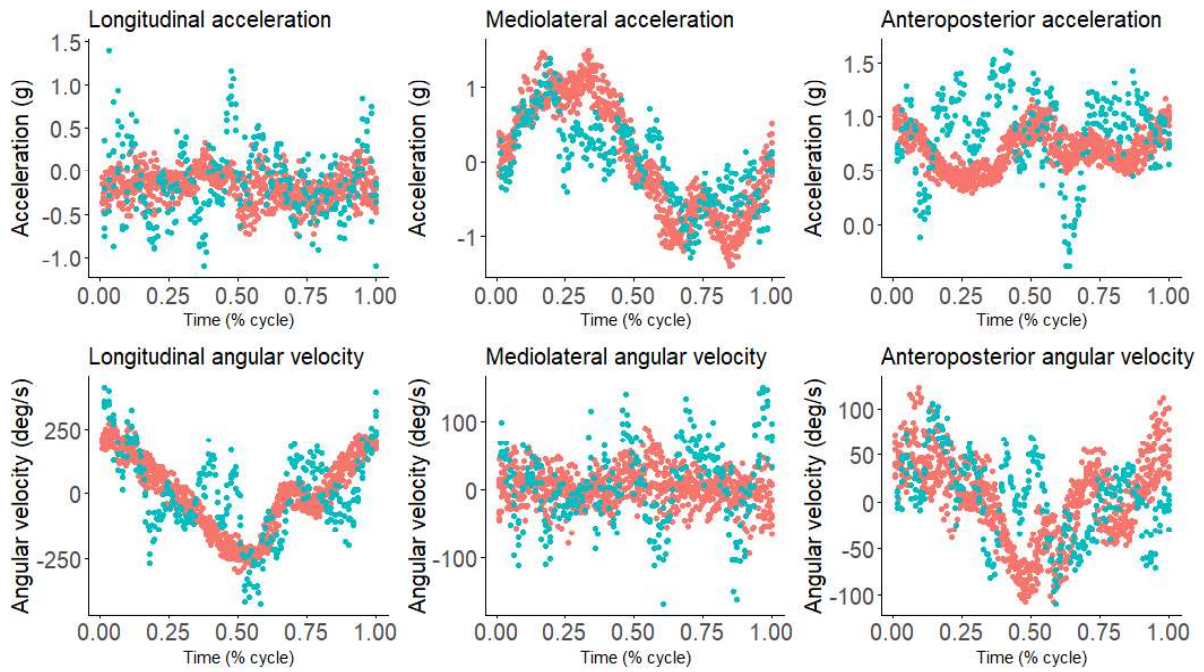
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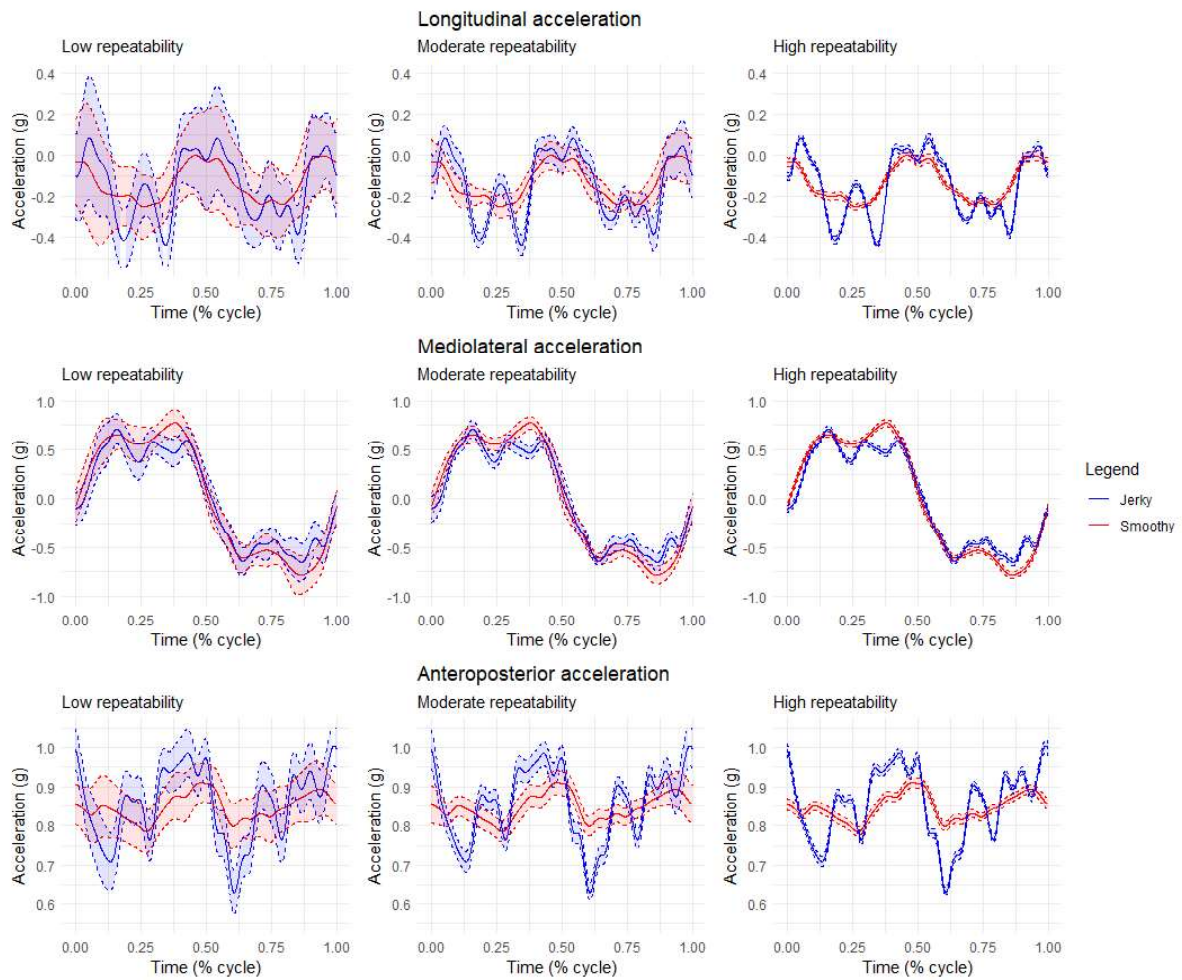
**Table 3.** Significant pairwise comparisons of clusters for both the inter-cyclic variability partition and the crossing partition. LR: low repeatability. MR: moderate repeatability. HR: high repeatability

Partition	Cluster pairwise comparisons	Mean±SD and 95% confidence intervals of swimming speed (m/s)	Difference (%)	Effect size (Cohen's d)
Inter-cyclic variability	LR vs. HR	1.75 [1.63;1.87]±0.27 vs. 1.40 [1.35;1.46]±0.17	+25.0	1.67
	MR vs. HR	1.62 [1.53;1.70]±0.21 vs. 1.40 [1.35;1.46]±0.17	+15.7	1.15
Crossing intra-cyclic and inter-cyclic variability	<i>Jerky</i> +LR vs. <i>Smoothy</i> +HR	1.86 [1.80;1.92]±0.12 vs. 1.40 [1.35;1.46]±0.17	+32.9	2.86
	<i>Jerky</i> +LR vs. <i>Smoothy</i> +LR	1.86 [1.80;1.92]±0.12 vs. 1.30 [0.88;1.71]±0.26	+43.1	3.68
	<i>Jerky</i> +LR vs. <i>Smoothy</i> +MR	1.86 [1.80;1.92]±0.12 vs. 1.50 [1.42;1.58]±0.15	+24.0	2.60
	<i>Jerky</i> +MR vs. <i>Smoothy</i> +HR	1.81 [1.72;1.90]±0.13 vs. 1.40 [1.35;1.46]±0.17	+29.3	2.49
	<i>Jerky</i> +MR vs. <i>Smoothy</i> +LR	1.81 [1.72;1.90]±0.13 vs. 1.30 [0.88;1.71]±0.26	+39.2	2.97
	<i>Jerky</i> +MR vs. <i>Smoothy</i> +MR	1.81 [1.72;1.90]±0.13 vs. 1.50 [1.42;1.58]±0.15	+20.7	2.15

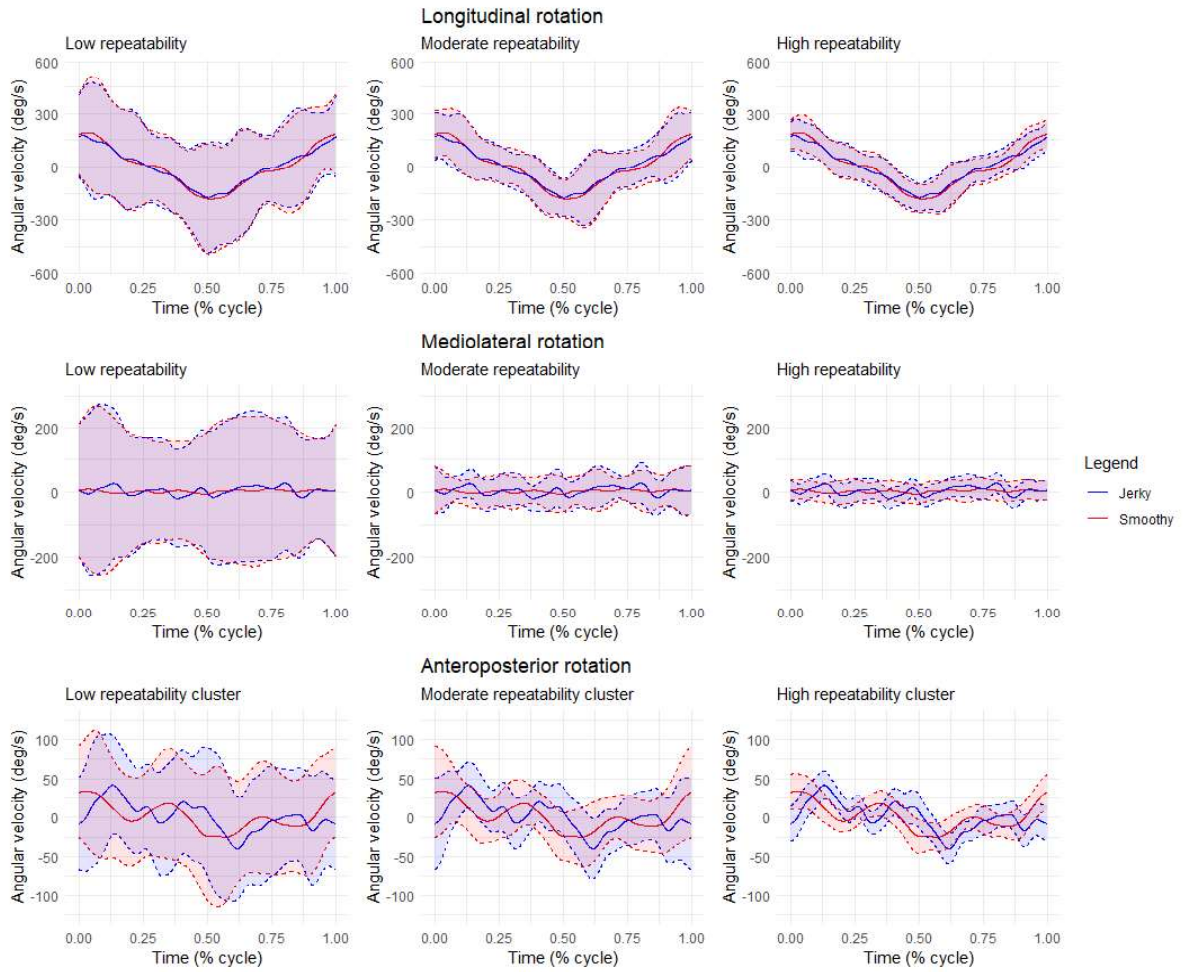
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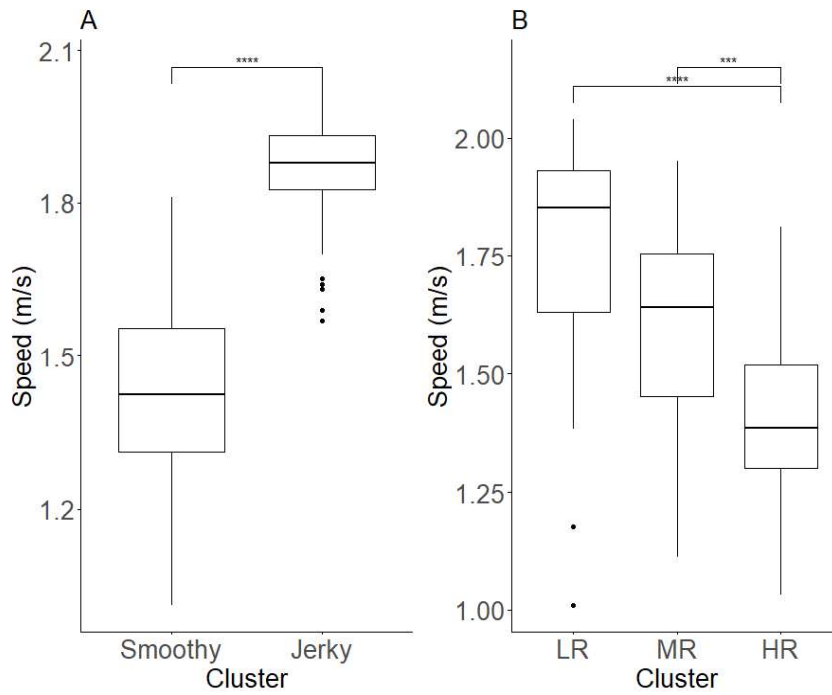
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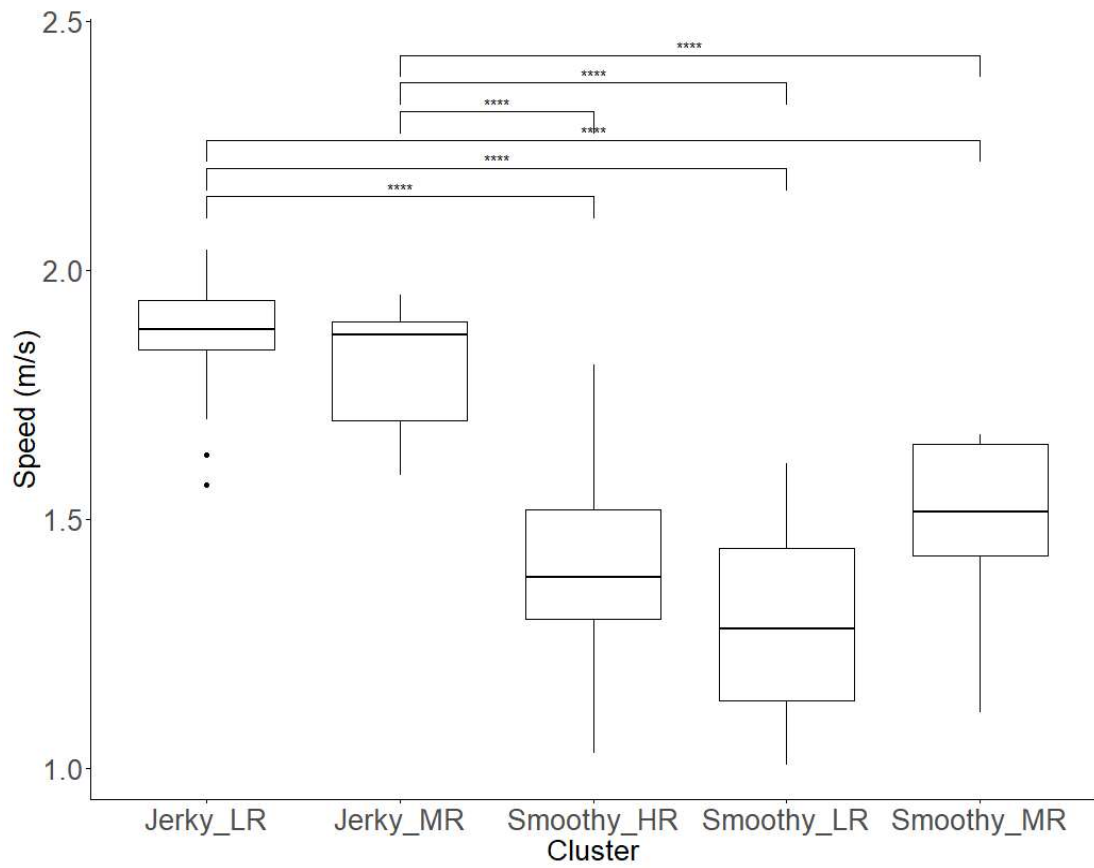


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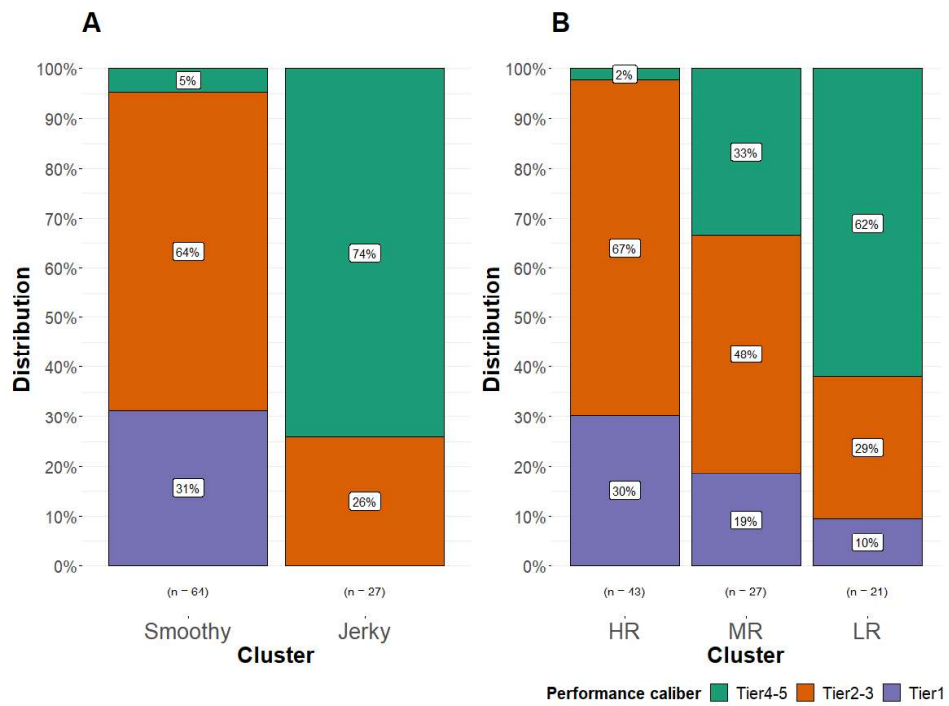


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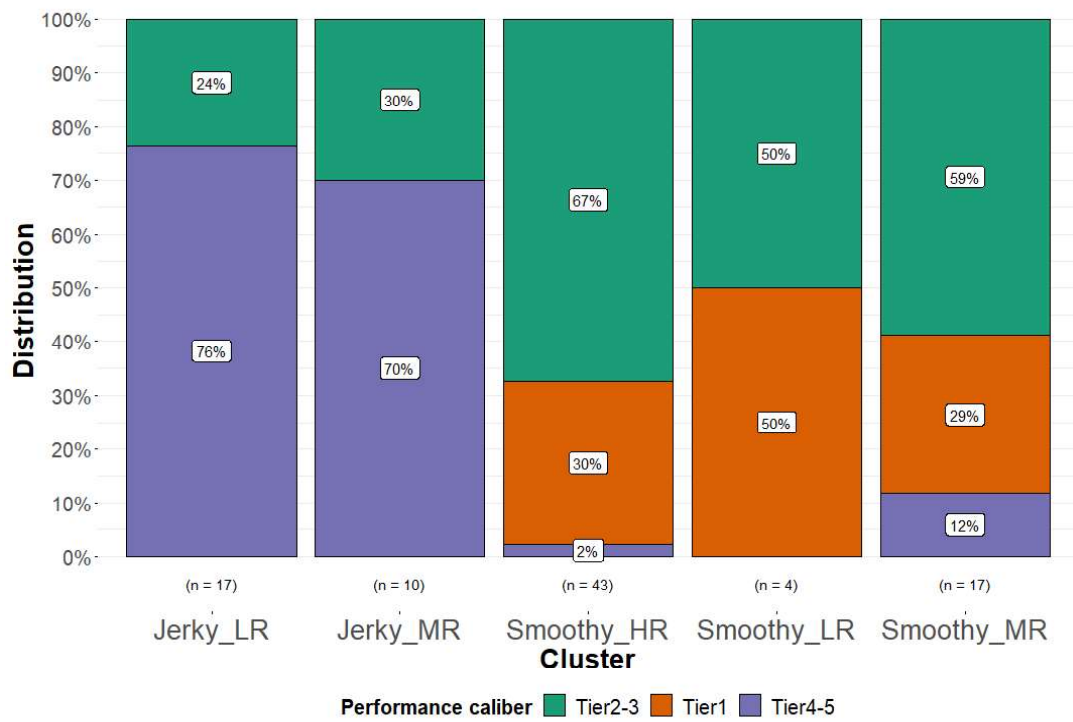




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1000 **Figure 1.** Preprocessed data of two participants with different levels (blue: world-class  
1001 swimmer (tier 5), red: recreationally active swimmer (tier 2)). Performance caliber defined  
1002 according to the classification of McKay et al., 2022

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1004 **Figure 2.** Intra-cyclic clustering (*jerky* and *smoothy* stroke patterns) and inter-cyclic  
1005 clustering (*low*, *moderate* and *high repeatability* credibility regions) of 3D accelerations

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1007 **Figure 3.** Intra-cyclic clustering (*jerky* and *smoothy* stroke patterns) and inter-cyclic  
1008 clustering (*low*, *moderate* and *high repeatability* credibility regions) of 3D angular velocities

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1010 **Figure 4.** Swimming speed according to the classes coming from the partitions of (A) intra-  
1011 cyclic variability clustering, (B) inter-cyclic variability clustering

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1013 **Figure 5.** Swimming speed according to the classes coming from the cross-partition

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1015 **Figure 6.** Performance caliber distribution according to the classes coming from the partitions  
1016 of (A) intra-cyclic variability clustering, (B) inter-cyclic variability clustering

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1018 **Figure 7.** Performance caliber distribution according to the classes coming from the cross-  
1019 partition

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