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Predicting eggbeater kick performances from hip joint function testing in artistic swimming

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ABSTRACT

The eggbeater kick is an important skill in artistic swimming necessary to lift the body above water level. Previous attempts to model its performance included complex biomechanical parameters that cannot be easily used to guide strength and conditioning training. The objective of this study was to model the relationship between hip strength and eggbeater performance through a machine learning algorithm. We assessed hip function of 92 elite artistic swimmers with six easily performed isometric tests. These data were fed to a gradient boosting model to predict three technical variables: body boost height [BB-H], eggbeater height [EB-H] and eggbeater force [EB-F]. Group mean differences ($\Delta\mu$) between predicted and measured variables were reported. Then, the model was used to propose training tips for two hypothetical case studies. Our model predicted performances with errors within the resolution of the scale used during competitions: absolute error of 0.32 ± 0.21 and 0.49 ± 0.39 in EB-H and BB-H, respectively. The predicted performance was similar to the measured one for all technical tests (EB-F: $\Delta\mu = 0.29$; EB-H: $\Delta\mu = 0.13$; BB-H: $\Delta\mu = 0.23$). We illustrated some of the important predictors (hip internal rotation, abduction, and left-right imbalances) of the eggbeater kick performance and highlighted personalized strategies to improve performance

INTRODUCTION

Artistic swimmers keep their heads out of the water for about 40% of their routine duration.[1] Most of that time is associated with the use of eggbeater kicks. The eggbeater kick is a complex movement,[2,3] but an efficient technique to keep the body above the water surface allowing the swimmer to perform artistic arm movements.[4] It can be used to maintain the body in an elevated pose (termed as sustained) or can be modified to drive the body explosively out of water (termed as body boost). The quality of the eggbeater is evaluated based on the FINA guiding scale for height from 3.5 to 9.5 points.[5] This guide attaches a score to the stable or dynamic height reached, based on the water level of body parts.

While the eggbeater is a fundamental skill in artistic swimming, its complexity makes it difficult to train. Various studies tried to investigate the eggbeater kick to improve teaching, and ultimately performance. Highly eggbeater-skilled swimmers seemed to favor a “horizontal kick type” rather than a vertical one.[3] They achieved it through widening their knees, and holding their heels near the water surface with a strong internal rotation of the thighs.[3] Indeed, Sanders[2] concluded that an effective sustained eggbeater technique is one that utilizes lift forces more than drag forces through sculling the feet with large horizontal components. Similar conclusions were reached to achieve a higher body boost.[6] To achieve this sculling motion, Sanders[7] recommended training all hip muscle groups for strength, power and flexibility. Particularly, as the feet need to move quickly throughout the kick, it becomes important to train lower limb joints for strength to ensure speed despite the unnatural position at the time of maximal hip abduction.[2] Zinner et al.[8] showed that water-polo players with higher isometric hip abductor muscle strength performed better in eggbeater kick, consolidating the link between hip strength and eggbeater performance. Finally, the importance of both lower limbs in the eggbeater was underlined, since downward forces produced by the non-dominant limb led to a decreased propulsive force.[9] While this study concluded that differences during the cycle are not related to bilateral differences in strength, the authors only examined knee and ankle strengths. However, they observed significant differences in hip joint kinematics between both limbs. This could point out to the importance of the hip joint strength balance between the left and right side.

Despite the apparent link between hip joint and eggbeater kick proficiency,[10] it remains difficult to establish training programs for a given swimmer. Thus, models that link each of the hip joint parameter to the eggbeater performance are needed to improve this skill’s training. Sanders[2,6] performed multiple linear regressions to predict height based on foot speed, range of knee extension and initial angle of the upper body. Their predictive models of sustained and dynamic height explain 90% and 79% of the variance. Similarly, Oliveira et Sanders[9] and Homma et Homma[3] reported modest to strong correlations between height and kinematics variables such as orientation and speed of the limbs. Unfortunately, these predictive models are based on small samples size ($4 < n < 16$) and were not cross-validated. Furthermore, they cannot easily be implemented in a training environment as they rely on biomechanical parameters that require 3D kinematic analyses.

Machine learning algorithms have been gaining popularity as a tool for performance prediction.[11–13] They seem to be able to outperform more classical regression approaches.[11,12,14] Particularly, gradient boosting algorithms are a tree-based approach that uses sequential learning to improve weak learners. They are highly customizable and powerful tools for learning and analyzing problems with heterogeneous parameters and noisy data with complex interactions.[15] However, their increased accuracy sacrifices their interpretability. A recent unified framework for interpreting machine learning predictions[16] might offer a tool to harness gradient boosting models to develop personalized training plans for athletes.

The current study aims to investigate the relationship between hip muscle strength in elite artistic swimmers and performance in eggbeater kicks using a gradient boosting algorithm. The predictive model accuracy should be inferior to the FINA guiding scale for height resolution (0.5 points), and its input data should be easily accessible in a training environment. A supplementary objective is to illustrate how the model can be used to develop a data-driven conditioning support system.

METHOD

Participants

Artistic swimmers with provincial, national and international levels participated in the study (n=92; age: 12-25 years old; height: 164.6±7.0 cm, weight: 55.4±7.7 kg; training load: "≥ 4" days/week). They were free from hip pain or injury at the time of testing and had no history of hip surgery. Prior to the experimental procedure, the participants—and their guardians for swimmers under 17 years old—signed an informed consent form approved by the ethics committee (17-163-CERES-D).

Experimental procedures

First, swimmers hip function was assessed using three maximal voluntary isometric contractions (MVIC) lasting three seconds each in six positions (Figure 1, with details in appendix 1). MVIC were recorded after a standard dry-land warm up using the Groin Bar (Vald Performance, Queensland, Australia; 0.5 N resolution) at 50 Hz. Participants were strongly encouraged and were given at least 5-s rest between contractions.[17] Swimmers then performed three technical tests to assess the quality of the eggbeater kick (Figure 2, with details in appendix

2). First, the maximal height attained after a body boost (BB-H) and the mean sustained height during a 15-seconds double arm eggbeater (EB-H) were evaluated using the FINA guiding scale for height.[5] Heights were estimated from 120 frames-per-second videos. The maximal upward force during a 5-s sustained eggbeater (EB-F) was measured using a hand-held dynamometer at 40 Hz (Lafayette Model 01165, Indiana, USA). The evaluator positioned the dynamometer on the athletes' heads. They were instructed to push vertically with their head using solely their eggbeater kick for 5 s. Each test was repeated twice.

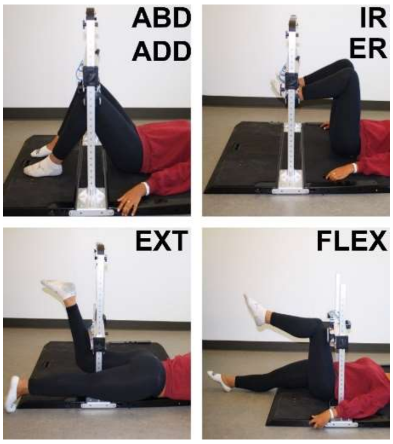

Figure 1. Isometric hip strength positions using the GroinBar. Positions included abduction and adduction (ABD – ADD), internal and external rotations (IR – ER), extension (EXT) and flexion (FLEX). More detailed descriptions are included in appendix 1.

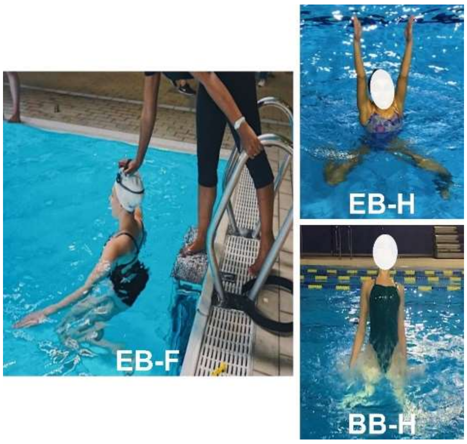

Figure 2. Description of the technical tests: The evaluator positioned the hand-held dynamometer on the swimmer's head. Using solely their eggbeater kick, the swimmer pushed vertically with their head against the dynamometer (EB-F); The swimmer sustained an eggbeater kick for 15 seconds (EB-H). According to the FINA scale, the body part at water surface level defined the EB-H score; The swimmer propelled out of the water using a body-boost kick (BB-H). Similar to EB-H, the body part at water surface level defined the BB-H score. More detailed descriptions are included in appendix 2.

Modeling

From the tests previously described, MVIC force signals were low-pass filtered using a zero-lag fourth-order 10 Hz Butterworth filter MVIC envelopes were extracted using a moving root-mean-squared average on a 200-ms window. These timeframe envelopes were then reduced by taking the mean of the highest consecutive values during 0.2 second. From these values, a force score was calculated using forces from left and right legs such as $F = 2 \times \frac{left \times right}{left + right}$. Left-right imbalance was also computed using the relative difference.

The predictive model had 14 input variables: force scores and imbalances for the 6 hip tests as well as anthropometric measurements (height and mass, described in appendix 3). We used the three technical tests (maximum BB-H, mean EB-H and mean EB-F) as output variables. This dataset, composed of the input and output variables mentioned above, was randomly split into training (80%, $n = 73$) and test (20%, $n = 19$) sets.

A gradient-boosting algorithm was fitted for each output variable (BB-H, EB-H and EB-F) with the training set using the Python Catboost library.[18] This particular algorithm was chosen as it provided the best cross-validation error on our dataset. Once trained, we evaluated the generalization error on the test set and reported the difference in mean absolute error (MAE) and mean absolute percentage error (MAPE). MAPE differences between real and predicted performance were investigated using Bayesian estimation described in Kruschke,[19] which provides distributions of credible values for the effect size (d) and the group means differences ($\Delta\mu$). We reported the mean of the posterior distribution and the 95% highest posterior density (HPD) interval, which contains 95% of the posterior distribution. We define a statistically significant difference when the HPD of the difference between predicted and real values does not contain zero. The percentile of the HPD within which a zero mean difference can be found are also reported ($p_{min} < 0 < p_{max}$). The most important variables and their impact on the technical tests are evaluated using the Shap Python library.[16]

To showcase how the model can help define conditioning goals to improve the eggbeater performance, two random participants (swimmers A and B) were selected as the subjects of two case studies. In the first, we evaluated the projected performance in BB-H with an independent increase (10%) of each force score or decrease in imbalance. In the second, we predicted the minimum change required to achieve a 0.5-points improvement (F_{obj}) in BB-H. We solved an unconstrained multi-objective (F_{obj}, minimize change in forces and imbalances) optimization problem with a particle swarm optimization algorithm.[20] The variables were weighted by the normalized impact factors estimated by the Shap library to ensure a fast convergence of the evolutionary algorithm toward a global optimal solution.

Results

Variables distribution

Hip adduction-abduction generated the highest forces among the MVIC (ADD: 26.1 ± 4.8 kg, ABD: 23.1 ± 4.5 kg), followed by hip flexion-extension (FLEX: 17.1 ± 3.5 kg, EXT: 16.7 ± 6.1 kg) and hip internal-external rotations (IR: 9.8 ± 2.5 kg, ER: 8.2 ± 1.6 kg) (Figure 3, left panel). With $22.3 \pm 18.4\%$, EXT reached the highest left-right imbalance (Figure 3, right panel) while all other tests did not exceed 10% (FLEX: $9.5 \pm 7.6\%$, IR: $9.5 \pm 7.2\%$, ER: $8.1 \pm 6.6\%$, ABD: $5.7 \pm 4.5\%$ and ADD: $4.9 \pm 3.7\%$).

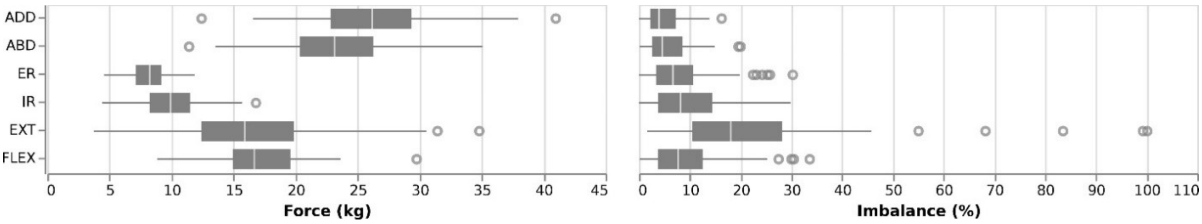

Figure 3. Tukey box plot showing force (left panel) and imbalance (right panel) evaluated on the MVIC with median (vertical lines), first-third interquartile range (bars, $IQR = [Q1, Q3]$), whiskers range (horizontal lines, $[Q1 - 1.5 * IQR, Q3 + 1.5 * IQR]$). Data beyond the whiskers are considered outliers (circles).

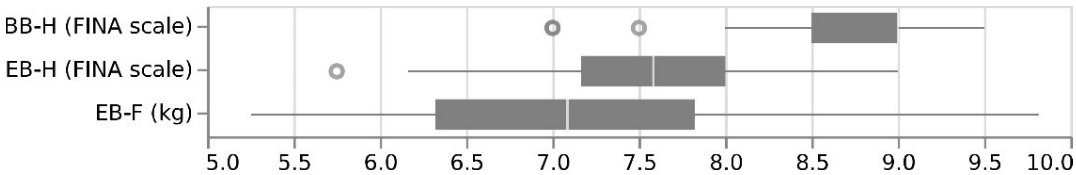

Figure 4. Tukey box plot showing the three sport-specific tests performances with median (vertical lines), first-third interquartile range (bars, $IQR = [Q1, Q3]$), whiskers range (horizontal lines, $[Q1 - 1.5 * IQR, Q3 + 1.5 * IQR]$). Data beyond the whiskers are considered outliers (circles).

Model evaluation

Our predictive model averaged a MAPE of $6.10 \pm 5.86\%$ on the test set. The largest errors (Figure 5) were found in EB-F (MAE: 0.66 ± 0.71 kg, MAPE: $8.71 \pm 8.42\%$) although the predictions remained similar to the measured performances ($\Delta\mu = 0.29$ kg, $17.0\% < 0 < 83.0\%$, $d = 0.32$, posterior distribution in appendix 4). The MAE error in BB-H (MAE: 0.49 ± 0.39, MAPE: $5.38 \pm 4.18\%$) and EB-H (MAE: 0.32 ± 0.21, MAPE: $4.21 \pm 2.62\%$) predictions were smaller than the resolution of the FINA guiding scale for height (0.5 points). The predicted performance was similar to the measured performance for both BB-H ($\Delta\mu = 0.23$, $10.8\% < 0 < 89.2\%$, $d = 0.40$) and EB-H ($\Delta\mu = 0.13$, $24.7\% < 0 < 75.3\%$, $d = 0.22$).

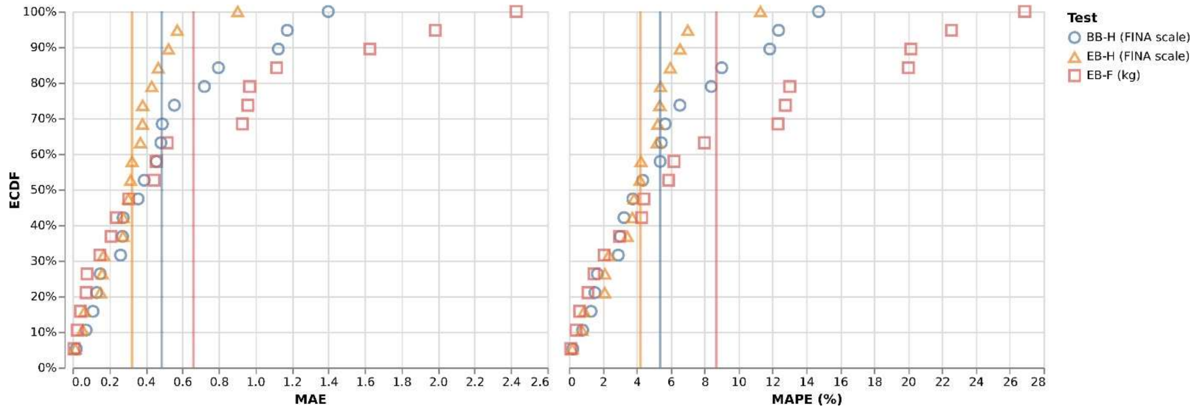

Figure 5. Empirical cumulative distribution function (ECDF) of the MAE (left panel) and MAPE (right panel) measured on the test set (n=19) for BB-H (blue), EB-H (orange) and EB-F (red). The ECDF evaluated at *x* is defined as the fraction of data points that are ≤ *x*. Mean value are also displayed (vertical lines).

A different set of feature importance was reported for each technical test (Figure 6). The three technical tests had a weak relationship as their correlation coefficients ranged from 0.01 (EB-H and EB-F), to 0.16 (BB-H and EB-F) and 0.30 (BB-H and EB-F). While BB-H requires to be tall and have strong internal rotation according to the model (Figure 6, left panel), EB-H is likely to increase with strong external and internal rotations and a low internal rotation imbalance. (Figure 6, middle panel). Heavier athletes with a moderately strong external rotation and extension, and a strong abduction seem to perform better in EB-F (Figure 6, right panel).

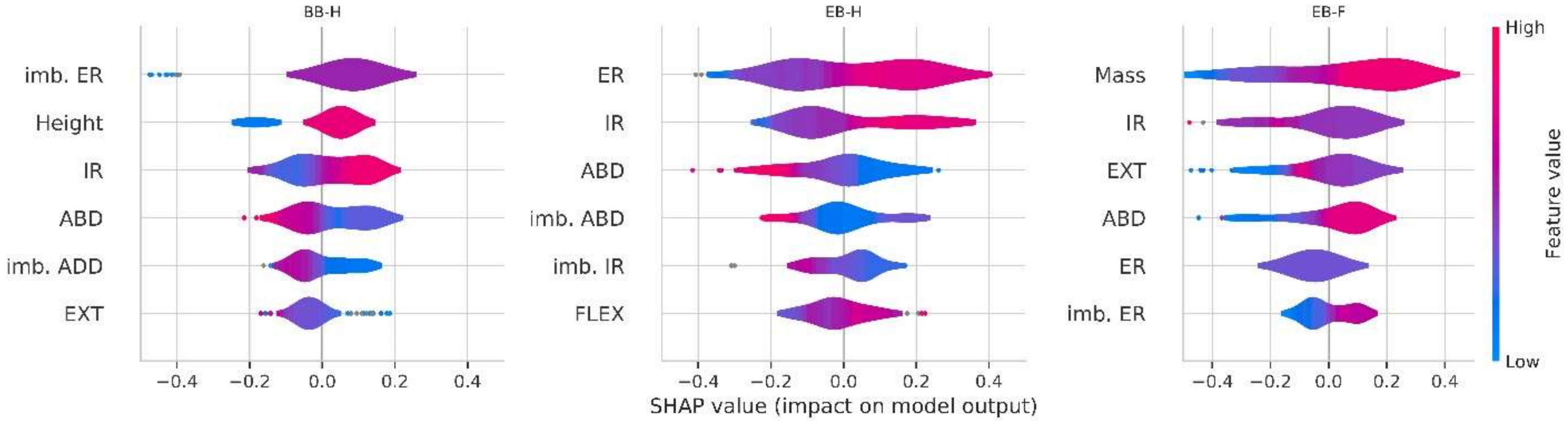

Figure 6. SHAP summary plot of the three gradient boosting models (left: BB-H, middle: EB-H, right: EB-F). The higher the SHAP value (x-axis) of a feature (y-axis), the higher the log of the target output. Only the six most important variables are displayed and ranked from most important (top) to least (bottom). Every participant is run through each model and a dot is created for each feature attribution value. Dots are colored by the feature value (red when the variable is high, blue when it is low) and pile up vertically to show density. For example, BB-H predicted performance increases if IR increases.

Model interpretation and conditioning goals

The BB-H performance projection after the strength increase or the imbalance decrease differed between the two athletes. A 10% strength increase in flexion was slightly beneficial for the swimmer A (Figure 7, top-left panel), while a 10% decrease in imbalance seemed to be most beneficial in abduction (+0.23) and internal rotation (+0.13). On the other hand, the performance of swimmer B was not likely to improve with a 10% imbalance decrease (Figure 7, bottom-right panel). Additionally, while a 10% stronger external rotation was likely beneficial (+0.10), a stronger abduction would slightly decrease the BB-H performance.

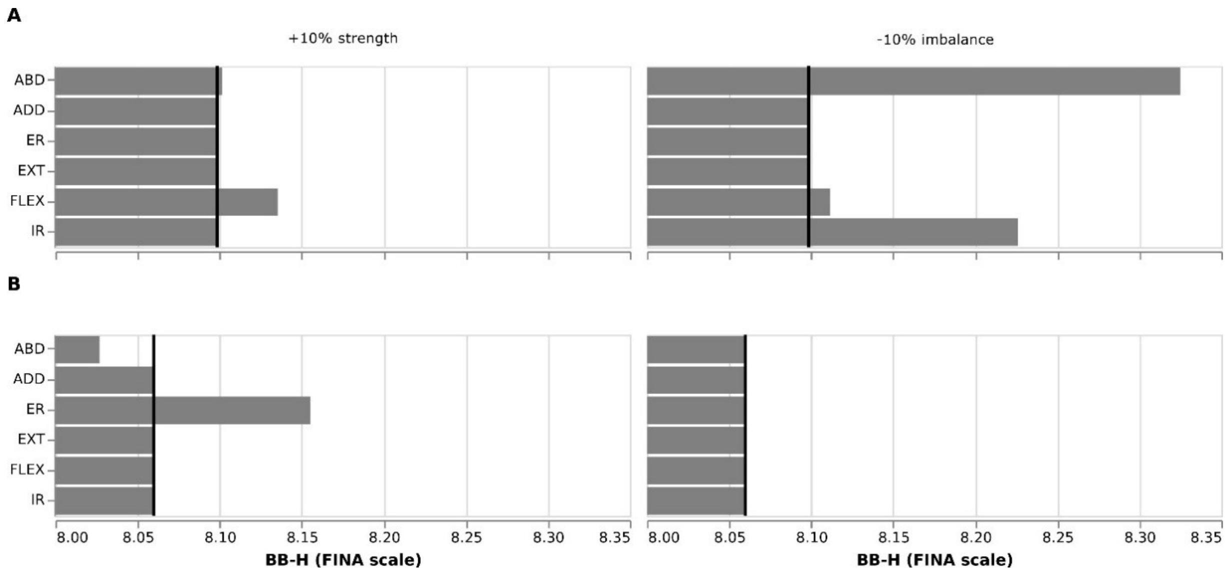

Figure 7. First simulation with a 10% increase in strength (left panel) and a 10% decrease in imbalance (right panel) in each individual hip strength test (y-axis) and its impact on the BB-H performance prediction (x-axis) for two random swimmers (A and B). The baseline prediction is also displayed (vertical lines).

The second simulation, while sharing similarities with the first one, predicted different strategies to achieve a 0.5-point improvement (Figure 8). First, and similarly to the first simulation, the optimization tried to reduce the left-right imbalance in swimmer A in ABD (-4.62%), FLEX (-2.97%) and IR (-1.24%) but also in ER (-2.40%), ADD (-1.22%) and EXT (-1.02%), while imbalance remained the same for swimmer B. Second, and in contrast with the first simulation, the optimization increased strength in ABD (+5.36 kg), ADD (+4.36 kg), ER (+0.35 kg) and EXT but also in FLEX (+2.41 kg) in swimmer A and in ADD (+5.56 kg) and FLEX (+2.94 kg) in swimmer B. Some large decrease in strength occurred in EXT (-7.51 kg) and IR (-3.05 kg) in swimmer B.

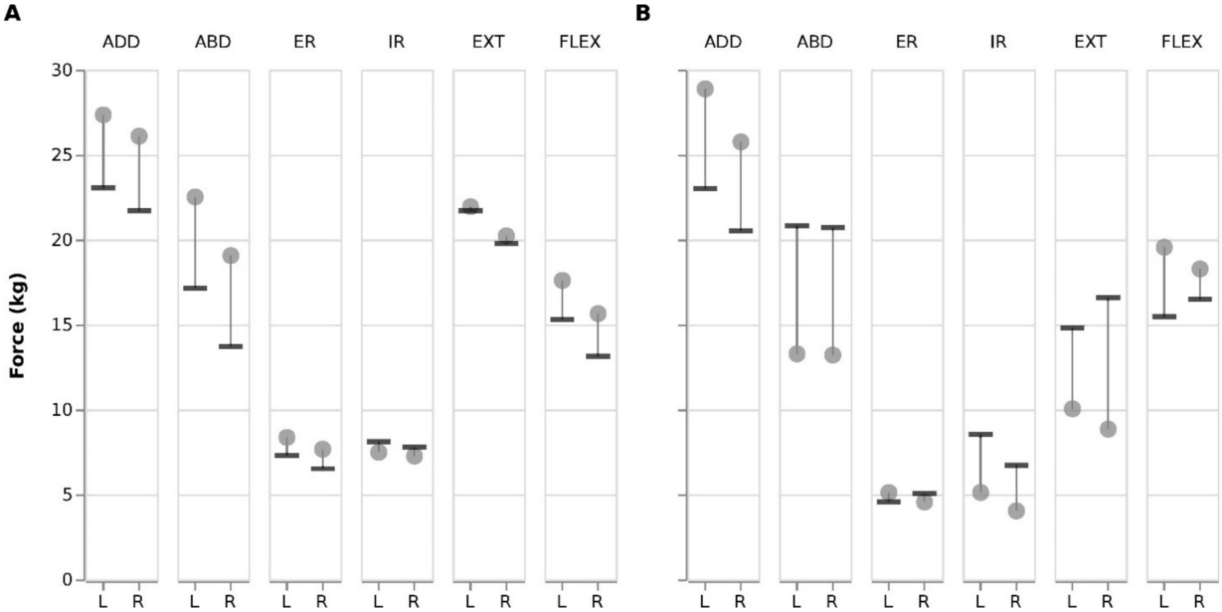

Figure 8. Second simulation with the optimal set of hip strength of both left (L) and right (R) legs (points) to achieve an improvement of 0.5 points in BB-H for two random swimmers (left panel: A, right panel: B). The baseline values are also displayed (horizontal lines).

Discussion

Research at the intersection of sports sciences and machine learning offers great promise to advance training decision-making and human movement research. In this study, we used a machine learning algorithm to model the relationship between a series of six hip MVIC and the performance of key skills in artistic swimming. In accordance with our hypothesis, our results showed that hip muscle strength can be used to predict eggbeater kick performance in elite artistic swimmers. The model predictions could help in building personalized and potentially efficient conditioning programs, as well as guide decisions in a selection setting.

Variables distribution

The model was fed with body mass, height and six hip MVIC recorded with a GroinBar, an easy-to-use and reliable hip strength assessment system.[17] Swimmers generated the highest forces during hip adduction-abduction, followed by hip flexion-extension and hip internal-external rotations. These forces levels are consistent with those reported by Cichanowski et al.[21] in female collegiate athletes (once normalized by body mass, see appendix 5). The increased inter-participant and inter-leg variability observed for the extension test suggests that hip extension is a difficult test to perform and replicate, as reported in Scott et al.[22] As the maximum height was calculated from the head in Sanders,[2] from the hand in Stirn et al.[23] and using the FINA guiding scale for height[5] in the present study, it is difficult to compare performance with previous studies. The upward force magnitude was comparable to the force reported for female water-polo athletes (60-120 N).[24]

Model evaluation

A common study design in machine learning is to split the sample into a training set to train the model and an independent test set to evaluate its performance on unseen data. This design remains unusual is sports sciences due to small sample sizes.[25] Unlike previous models of sustained and dynamic eggbeater height,[2,3,9] we used a train-test split to make sure that our evaluation is representative of the generalization error of the model. The predictions were comparable to the real performances in all three tests, with an average relative error of 4%, 5% and 9% in the predicted BB-H, EB-H and EB-F, respectively. Measured EB-F large variability could explain its higher prediction error. Since the gradient booster algorithm performs well on medium to larger datasets, we expect our current result to improve if we increase the number of athletes. Nevertheless, as we used a Bayesian approach to evaluate the difference between the model's prediction and the test set, we can draw better conclusions about the credibility of the model. The current posterior distribution mean difference mean value for BB-H ($\Delta\mu = 0.23$) and EB-H ($\Delta\mu = 0.13$) is smaller than half the FINA resolution. Thus, the prediction error is within the measurement error of the training set. As, for EB-F ($\Delta\mu = 0.29$ kg), the use of a handheld-dynamometer might have not offered a great accuracy, as the measured force might have not always been aligned with the exact vertical axis. Accordingly, an improved eggbeater force measuring technique might decrease the prediction error.

Model interpretation and conditioning goals

Different sets of feature importance were reported for each of the three technical tests, which suggest that these tests would require different physical capacities. Anthropometry could improve only BB-H (taller athletes) and EB-F (heavier athletes). Being taller can be beneficial for a body booster as longer limbs increase the contact surface.[26,27] On the other hand, as the EB-F counteracts in part the body weight, a heavier athlete will require a higher force to achieve a similar EB-H. Despite these differences, some criteria seem to be important for all technical tests. First, having a high internal rotation strength is beneficial for an improved height score, which is coherent with coaching tips.[3] On the other hand, a high internal rotation could lead to a decreased EB-F. Indeed, it has been observed that with fatigue, swimmers vertical force decreased while their internal rotation increased.[10] Oliveira et al.[10] suggested that this increase might be an adaptation to counter the fatigue-induced weakness of the hip abductors and flexors, as internal rotation migh be less demanding. Thus, the athletes with stronger internal rotation might have developed overtime this strength to counter their abduction weakness. This adaptation might not be the best scheme, as it would put the athlete at a greater risk of patella misalignment and injury.[10] Second, an increase in abduction hip strength was not necessarily linked to a higher eggbeater, yet seemed to increase the eggbeater force. Hip abduction is used during the recovery phase of the kick. Due to the drag force, a stronger abduction at this phase might sink the hip deeper. From a deeper starting position, the athlete would require a higher EB-F to move a larger portion of the body out of the water, without necessarily achieving a higher kick. Thus, the flexibility of the hip joint in abduction might be a better indicator of performance.[3] Endurance in abduction could also be a required quality to sustain high eggbeater kick performance and we could therefore include such tests in the hip function assessment.[10] Finally, an increase in left-right imbalance-based variables was not always associated with decreased performance. As asymmetries observed in the kinematics were attributed to neurological differences,[9] the link between strength asymmetry and performance might not be straightforward. This highlights the necessity for models that can account for various input parameters and their interactions. Note that these interpretations just explain how the model works. Since the model is trained from observational data, it is not necessarily a causal model, and just because changing a factor increased the model's prediction of performance, it does not necessarily mean it would raise the actual performances—despite the acceptable generalization error.

A secondary objective of this study was to illustrate how the model can be used to build personalized and potentially efficient conditioning programs. First, we evaluated how a 10% increase in force score or a 10% decrease in imbalance could modify BB-H score. Interestingly, despite having a similar BB-H, swimmers A and B had different BB-H projections following strength and balance modifications. This highlights that different techniques could be used to achieve a similar score. Thus, an optimal training plan is one that accounts for the hip strength at that time. Nevertheless, it would practically be difficult to modify solely one of the inputs of the BB-H model. Thus, the second simulation might offer more flexibility to coaches. Swimmer A conditioning plan seems easier to implement, as she would need to overall improve her muscle strength and left-right balance. Swimmer B plan might be more problematic particularly as reducing abduction and extension while increasing adduction and flexion might lead to hip dysfunction. Swimmer B might benefit from flexibility or endurance training. Thus, including such variables will most probably improve our models.

Methodological considerations

Our study had some limitations. First, we only included high-level artistic swimmers, which led to a small variability of both sustained and dynamic eggbeater heights (SD of 0.6 points). Since the FINA guiding scale for height resolution is 0.5 points, the low variability of these target variables may lead to a model with poor predictive capability for sports applications. Including low-level swimmers may reduce the predictive accuracy since this population is more heterogeneous in terms of technique and flexibility, which are essential for the eggbeater skill.[2,3] Including data from water polo players could also extend the reach of the model by increasing the variability in both predictor and target variables. Additional tests on complementary skills—such as technique and flexibility—could help to include swimmers with various levels and coming from various sports. Second, despite the eggbeater being a dynamic skill, we used isometric predictors. While isokinetic force assessment, as in Yamamura et al.,[28] would provide a more accurate prediction, isometric tests are more suited for training settings as they can be easily implemented. Third, the performance in sustained eggbeater kick was defined as an average value. The standard deviation in force and height might also be a key performance indicator associated with hip function. Oliveira et al.[29] showed force variation of about 40% throughout the eggbeater cycle. This variation may be related to bilateral asymmetries[9] as well as a variable feet speed throughout the cycle.

Practical applications

Our results showed that hip joint isometric strength could be used to predict eggbeater kick performance in elite artistic swimmers within the resolution of the sport's notation scale. We also highlighted some of the important predictors of key technical skills in artistic swimming. Those new findings support the use of predictive modelling to select athletes and to design personalized conditioning goals. It also provides coaches, athletes and other researchers in sports physiology and sports performance with hip strength normative data in elite artistic swimmers.

Our model may accurately predict future performances as the generalization error was comparable to the resolution of the FINA guiding scale for height. In addition, we used a set of interpretation and simulation methods to show that our model could provide practical guidelines to build effective and personalized conditioning programs. The model can be easily implemented in elite training structures as the required tests can easily be performed on a weekly basis, without the need for a physiotherapist or a scientist. We hope that our results would provide sports scientists and coaches with new opportunities upon which to build modern training programs that enhance the athlete's performance.

Acknowledgements

This study was funded by Institut National du Sport du Québec. We wish to thank Artistic Swimming Canada for the data collection during their training camp, and the coaches of the clubs of Dollard Synchro, Montréal Synchro and Gatineau Synchro for providing us access to the athletes. We also thank Patrick Marion and Nicolas Bourret who helped with the data collection.

Appendices

Appendix 1

Table 1. Description of the isometric hip strength tests

Test		Body position	Hip flexion	Knee flexion	Sensor position
Hip bilateral	Abduction (ABD)	Supine	60°	60°	Lateral femoral condyles
	Adduction (ADD)	Supine	60°	60°	Medial femoral condyles
	Internal rotation (IR)	Supine	90°	90°	Lateral malleoli
	External rotation (ER)	Supine	90°	90°	Medial malleoli
Hip unilateral	Flexion (FLEX)	Supine	90°	90°	Distal part of the quadriceps
	Extension (EXT)	Prone	Neutral	90°	Distal part of the hamstring

Appendix 2

Table 2. Description of the technical tests

Test	Duration	Body position	Metric	Indicator
Body boost height (BB-H)	N/A	Arms along the body	FINA guiding scale for height	Max
Eggbeater height (EB-H)	15 s	Arms extended vertically above the head	FINA guiding scale for height	Mean
Eggbeater force (EB-F)	5 s	Arms parallel to and above the water	kg	Max

Appendix 3

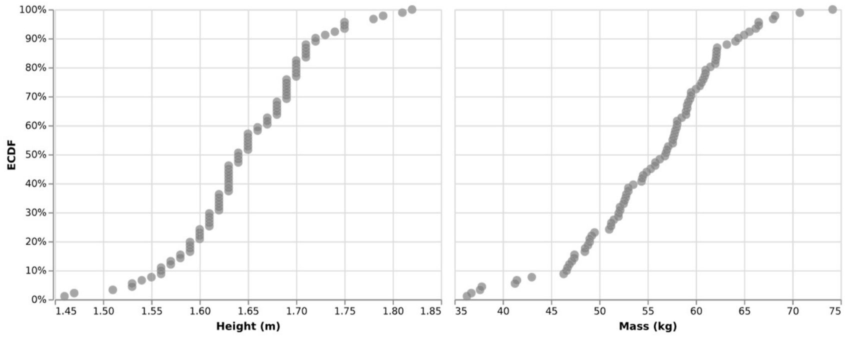

Figure S1. Empirical cumulative distribution function (ECDF) of the participant's height (left panel) and mass (right panel). The ECDF evaluated at x is defined as the fraction of the data points that are $\leq x$.

Appendix 4

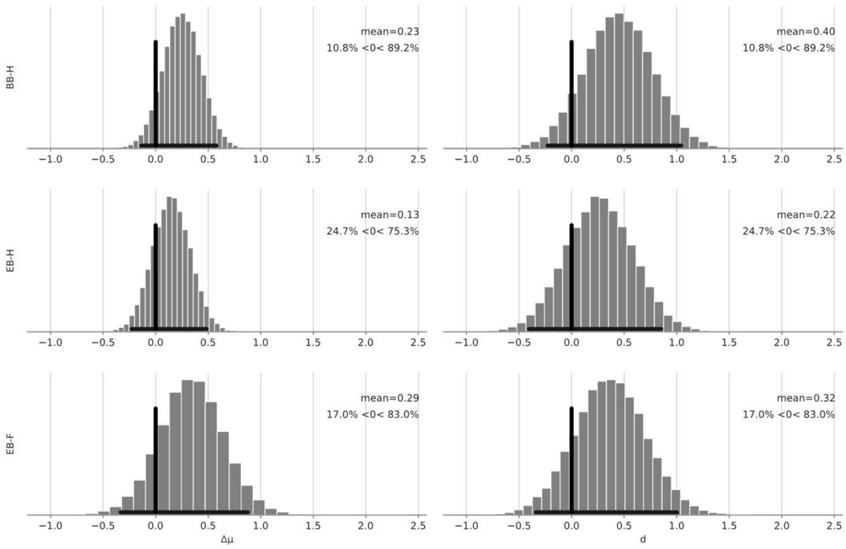

Figure S2. Posterior distributions (bars) of the mean difference (left panel) and effect size (right panel) estimated with the Bayesian model described in Kruschke[19] with 95% HPD (horizontal lines) for every sport-specific test. Mean and proportions relative to zero (vertical lines) are displayed in the top right of each plot.

Appendix 5

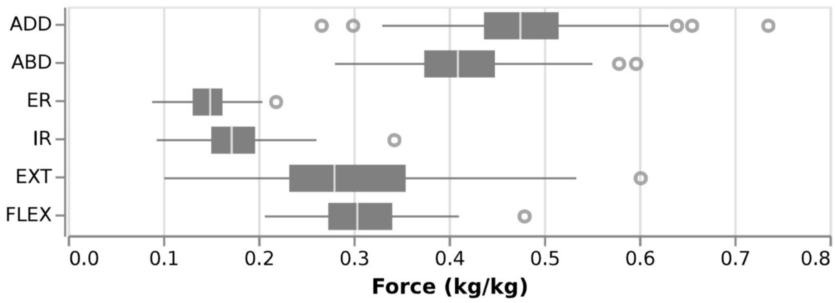

Figure S3. Tukey box plot showing the normalized force evaluated on the MVIC with median (vertical lines), first-third interquartile range (bars, $IQR = [Q1, Q3]$), whiskers range (horizontal lines, $[Q1 - 1.5 * IQR, Q3 + 1.5 * IQR]$). Data beyond the whiskers are considered outliers (circles).

REFERENCES

1. Alentejano T, Marshall D, Bell G. A Time–Motion Analysis of Elite Solo Synchronized Swimming. *International Journal of Sports Physiology and Performance*. 2008;3(1):31-40. doi:10.1123/ijspp.3.1.31

2. Sanders RH. Analysis of the Eggbeater Kick Used to Maintain Height in Water Polo. *Journal of Applied Biomechanics*. 1999;15(3):284-291. doi:10.1123/jab.15.3.284

3. Homma M, Homma M. Coaching Points for the Technique of the Eggbeater Kick in Synchronized Swimming Based on Three-Dimensional Motion Analysis. *Sports Biomechanics*. 2005;4(1):73-87. doi:10.1080/14763140508522853

4. van Duijn T, Button C, Masters RSW. A Multidisciplinary Comparison of Different Techniques Among Skilled Water Treaders. *Frontiers in Physiology*. 2021;12. Accessed May 3, 2022. https://www.frontiersin.org/article/10.3389/fphys.2021.719788

5. FINA. *FINA Artistic Swimming Manual for Judges, Coaches and Referees.* Fédération Internationale de Natation; 2018.

6. Sanders RH. A Model of Kinematic Variables Determining Height Achieved in Water Polo Boosts. *Journal of Applied Biomechanics*. 1999;15(3):270-283. doi:10.1123/jab.15.3.270

7. Sanders R. Strength, flexibility and timing in the eggbeater kick. In: ; 2002.

8. Zinner C, Sperlich B, Krueger M, Focke T, Reed J, Mester J. Strength, Endurance, Throwing Velocity and in-Water Jump Performance of Elite German Water Polo Players. *Journal of Human Kinetics*. 2015;45(1):149-156. doi:10.1515/hukin-2015-0015

9. Oliveira N, Sanders RH. Kinematic and kinetic evidence for functional lateralization in a symmetrical motor task: the water polo eggbeater kick. *Exp Brain Res*. 2015;233(3):947-957. doi:10.1007/s00221-014-4166-8

10. Oliveira N, Saunders DH, Sanders RH. The Effect of Fatigue-Induced Changes in Eggbeater-Kick Kinematics on Performance and Risk of Injury. *International Journal of Sports Physiology and Performance*. 2016;11(1):141-145. doi:10.1123/ijspp.2015-0057

11. Maier T, Meister D, Trösch S, Wehrlin JP. Predicting biathlon shooting performance using machine learning. *Journal of Sports Sciences*. 2018;36(20):2333-2339. doi:10.1080/02640414.2018.1455261

12. Pantazopoulos A, Maragoudakis M. Sports & Nutrition Data Science using Gradient Boosting Machines. In: *Proceedings of the 10th Hellenic Conference on Artificial Intelligence.* SETN ’18. Association for Computing Machinery; 2018:1-7. doi:10.1145/3200947.3201060

13. Ofoghi B, Zeleznikow J, Dwyer D, Macmahon C. Modelling and analysing track cycling Omnium performances using statistical and machine learning techniques. *Journal of Sports Sciences*. 2013;31(9):954-962. doi:10.1080/02640414.2012.757344

14. Abut F, Akay MF. Machine learning and statistical methods for the prediction of maximal oxygen uptake: recent advances. *MDER*. 2015;8:369-379. doi:10.2147/MDER.S57281

15. Natekin A, Knoll A. Gradient boosting machines, a tutorial. *Frontiers in Neurorobotics*. 2013;7. Accessed May 5, 2022. https://www.frontiersin.org/article/10.3389/fnbot.2013.00021

16. Lundberg SM, Lee SI. A Unified Approach to Interpreting Model Predictions. In: Guyon I, Luxburg UV, Bengio S, et al., eds. *Advances in Neural Information Processing Systems*. Vol 30. Curran Associates, Inc.; 2017:4765-4774. https://proceedings.neurips.cc/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf

17. Desmyttere G, Gaudet S, Begon M. Test-retest reliability of a hip strength assessment system in varsity soccer players. *Physical Therapy in Sport*. 2019;37:138-143. doi:10.1016/j.ptsp.2019.03.013

18. Dorogush AV, Ershov V, Gulin A. CatBoost: gradient boosting with categorical features support. *arXiv:181011363 [csLG]*. Published online October 24, 2018. Accessed May 3, 2022. http://arxiv.org/abs/1810.11363

19. Kruschke JK. Bayesian estimation supersedes the t test. *J Exp Psychol Gen*. 2013;142(2):573-603. doi:10.1037/a0029146

20. Nebro AJ, Durillo JJ, Garcia-Nieto J, Coello Coello CA, Luna F, Alba E. SMPSO: A new PSO-based metaheuristic for multi-objective optimization. In: *2009 IEEE Symposium on Computational Intelligence in Multi-Criteria Decision-Making(MCDM)*. ; 2009:66-73. doi:10.1109/MCDM.2009.4938830

21. Cichanowski HR, Schmitt JS, Johnson RJ, Niemuth PE. Hip Strength in Collegiate Female Athletes with Patellofemoral Pain. *Medicine & Science in Sports & Exercise*. 2007;39(8):1227-1232. doi:10.1249/mss.0b013e3180601109

22. Scott DA, Bond EQ, Sisto SA, Nadler SF. The intra- and interrater reliability of hip muscle strength assessments using a handheld versus a portable dynamometer anchoring station. *Archives of Physical Medicine and Rehabilitation*. 2004;85(4):598-603. doi:10.1016/j.apmr.2003.07.013

23. Stirn I, Strmecki J, Strojnik V. The Examination of Different Tests for the Evaluation of the Efficiency of the Eggbeater Kicks. *Journal of Human Kinetics*. 2014;41(1):215-226. doi:10.2478/hukin-2014-0049

24. Yanagi H, Amano K, Sakai T, Hara A. Vertical Force Exerted during Eggbeater Kick in Water Polo. In: ; 1995:1016-1017.

25. Bernards JR, Sato K, Haff GG, Bazyler CD. Current Research and Statistical Practices in Sport Science and a Need for Change. *Sports*. 2017;5(4):87. doi:10.3390/sports5040087

26. Carter JEL, Ackland TR. *Kinanthropometry in Aquatic Sports: A Study of World Class Athletes*. Human Kinetics; 1994.

27. Grimston SK, Hay JG. Relationships among anthropometric and stroking characteristics of college swimmers. *Medicine & Science in Sports & Exercise*. 1986;18(1):60-68.

28. Yamamura C, Zushi S, Takata K, Ishiko T, Matsui N, Kitagawa K. Physiological Characteristics of Well-Trained Synchronized Swimmers in Relation to Performance Scores. *Int J Sports Med*. 1999;20(04):246-251. doi:10.1055/s-2007-971125

29. Oliveira N, Fernandes R, Sarmento M, et al. Muscle Activity During the Typical Water Polo Eggbeater Kick. *International Journal of Aquatic Research and Education*. 2010;4(2). doi:https://doi.org/10.25035/ijare.04.02.07