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Review

Artificial Intelligence in Swimming Biomechanics and Fluid Dynamics: A Structured Narrative Review Towards Mechanistically Interpretable Models

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Abstract

Artificial intelligence is increasingly used in sport performance analysis, but its contribution to swimming biomechanics and fluid dynamics remains fragmented across wearable sensing, computer vision, predictive analytics and computational modelling. This structured narrative review synthesises current applications and evaluates how artificial intelligence can progress from describing movement to supporting mechanistically defensible interpretations of hydrodynamic propulsion, drag and performance. Evidence was identified through PubMed and Google Scholar (last search: 28 July 2026) and organised around inertial sensing, markerless pose estimation, training analytics, computational fluid dynamics, explainability and validation. Swimming cycle recognition, lap segmentation and temporal event detection are more extensively studied, but they lack adequate external validation, and direct validation of force- and flow-related outputs is weaker. Machine learning surrogates, physics-informed models and multimodal fusion offer promising routes to connect kinematics with hydrodynamic mechanisms, although small homogeneous datasets, data leakage and insufficient reporting constrain generalisability. The central contribution is the explicit distinction between kinematic observations, validated biomechanical estimates and hydrodynamic inferences. Artificial intelligence can extend biomechanical reasoning in swimming when predictions remain traceable to measurement quality, physical principles and the intended decision context.

Keywords: artificial intelligence; swimming biomechanics; fluid dynamics; propulsion; drag; inertial sensors; computer vision; computational fluid dynamics; explainable artificial intelligence; performance analysis

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1. Introduction

Swimming performance emerges from the interaction between propulsive actions, resistive forces, body alignment, coordination and the capacity to preserve effective mechanics as velocity and fatigue change [1,2]. Although this formulation is conceptually straightforward, its measurement is unusually demanding. The swimmer is partly or fully immersed, the body deforms continuously and the surrounding flow changes within and between cycles. Breathing, body roll, limb recovery and underwater actions alter the geometry exposed to the water, while propulsion and drag cannot be separated experimentally without assumptions. Consequently, swimming analysis has developed through several complementary traditions, including race analysis, video-based kinematics, tethered and

semi-tethered force assessment, active- and passive-drag methods, inertial sensing and computational fluid dynamics [3–7]. Each tradition provides important information, but no single method captures the complete swimmer–water interaction.

Therefore, the contemporary problem is not simply a shortage of data. Elite and developmental programmes can produce synchronised or near-synchronised streams from above- and underwater videos, inertial measurement units, speedometers, pressure sensors, electromyography, physiological monitoring and competition analysis. The difficulty lies in converting these heterogeneous signals into reliable biomechanical information at a timescale useful for researchers, analysts and coaches. Reviews of inertial sensing in swimming have consistently recognised its portability and ecological value, but have also described persistent problems of calibration, sensor placement, drift, phase definition and validation [8,9]. More recent mapping of artificial intelligence (AI) applications indicates that swimming systems remain dominated by narrow tasks such as swimming technique classification, lap detection and fatigue monitoring rather than integrated swimmer-centred recommendations [10].

AI may help address this integration problem and, in the current review, is used as an umbrella term covering machine learning, deep learning, computer vision, explainable AI and physics-informed learning. Throughout the current review, mechanistic interpretability is distinguished from explainable artificial intelligence, since the first concerns the transparency of how a model reaches an output, whereas the latter requires the output to be traceable to physically or biomechanically meaningful quantities (such as propulsion, drag or coordination). The general growth of AI in sport biomechanics has exposed a persistent tension between prediction and mechanistic understanding [11,12]. These approaches can automate feature extraction, identify temporal events, classify movement patterns, model nonlinear associations and combine multiple data modalities. Explainable and multimodal methods are particularly relevant when several data sources contribute to a decision [13,14], but accuracy alone is not sufficient for biomechanical decision-making. A model may predict race performance or classify a swimming cycle with high accuracy while providing little evidence about propulsion, drag, coordination or efficiency. In swimming, this tension is amplified because plausible kinematic associations can easily be misinterpreted as hydrodynamic mechanisms.

The purpose of this structured narrative review is to synthesise the current and emerging roles of AI in swimming biomechanics and fluid dynamics. Previous reviews have separately addressed swimming sensor technology [8,9], AI-based recommendation systems [10] and AI in sports biomechanics more broadly [11]. The current review extends this work by focusing specifically on swimming, by separating swimming-specific empirical evidence from general machine learning and fluid-mechanics methods, and by organising the field around an explicit hierarchy of hydrodynamic claims. The scope covers competitive and developmental swimmers across the main techniques and training environments (pool, flume and competition) and includes wearable sensing, video and markerless analysis, multimodal integration, performance prediction, fluid-dynamics inference and coach-facing feedback. Generative AI and digital twins are included because they are increasingly proposed for coaching and decision support, even though their biomechanical validity remains largely untested. The review also evaluates the principal limitations of the available evidence and proposes a framework for mechanically interpretable, independently validated and practically useful models. The central position is that AI should extend biomechanical reasoning rather than replace it, by identifying which movement features changed, quantifying the certainty of that finding, relating the change to defensible mechanical consequences and communicating what can reasonably be modified.

2. Narrative Review Approach

A structured narrative review was adopted rather than a systematic review because the topic spans heterogeneous research designs, measurement systems and computational methods that are not suited to a single pooled estimate. Accordingly, no pre-registered protocol, PRISMA flow diagram or independent duplicate screening was performed. The literature was identified through targeted searches of PubMed and Google Scholar from database inception to 28 July 2026, complemented by searches of publisher and journal websites, reference list screening and citation tracking. Representative search strings combined swimming-related terms ("swimming" OR "swimmer") with artificial-intelligence terms ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network") and domain-specific terms including "computer vision", "pose estimation", "inertial measurement unit", "wearable sensor", "classification", "explainable artificial intelligence", "computational fluid dynamics", "propulsion", "active drag", "passive drag" and "physics-informed". The dedicated repository of the International Symposium on Biomechanics and Medicine in Swimming, which indexes the symposium proceedings from 1970 onwards, was also searched, with searches being limited to English-language records. Both authors screened retrieved records against the inclusion criteria described below, resolving disagreements by discussion, and ~60 peer-reviewed sources were retained and cited. Backward-and-forward citation checking identified additional methodological and foundational studies that were not retrieved through the principal search-term combinations.

Peer-reviewed original studies, reviews and methodological papers were prioritised when they addressed competitive swimming or directly informed the interpretation of swimmer-centred biomechanical and hydrodynamic models. Conference papers were included selectively where they represented early or technically distinctive AI, sensing or computer-vision developments not yet available as journal articles. General AI and fluid-mechanics sources were retained only when they established concepts directly relevant to explainability, physics-informed learning, validation or reporting. Studies focused solely on recreational activity recognition, drowning detection or clinical aquatic exercise were outside the central scope unless they provided transferable methodological information. Because this was a narrative rather than systematic review, no claim of exhaustive retrieval or formal risk-of-bias grading is made. The evidence was instead organised according to measurement modality, computational task, mechanical interpretation, validation strategy and practical relevance.

3. Biomechanical and Hydrodynamic Foundations

3.1. What Must an Artificial Intelligence Model Explain?

The fundamental output of competitive swimming is forward velocity, but velocity alone does not reveal how it was produced. Mean velocity reflects the balance between propulsive and resistive forces, whereas instantaneous velocity fluctuates in response to the timing and magnitude of limb actions, changes in projected frontal area and inertial effects. Intra-cycle velocity variation can expose aspects of sprint front crawl mechanics that mean velocity conceals [2], yet it should not be interpreted automatically as a direct measure of efficiency. Similar caution applies to stroke length, stroke frequency and stroke index. These are useful descriptors, but the same value may arise from different combinations of force production, coordination, body position and energy expenditure.

The measurement of velocity variation is itself method-dependent. Studies remain heterogeneous in their definitions and in the procedures used to normalise velocity, and lower intra-cycle velocity variation is not consistently associated with faster swimming [15]. Moreover, the coefficient of variation should not be used as a standalone measure of intra-cycle velocity fluctuation because the assumed positive linear association between mean

velocity and its standard deviation may not be satisfied [16]. Therefore, mean velocity, standard deviation and the selected normalisation procedure should be reported explicitly. A more mechanically grounded approach has recently expressed velocity variation relative to the power required to overcome hydrodynamic drag [17], and this formulation may improve interpretation, but its drag estimates and underlying assumptions must remain visible when it is incorporated into AI models.

In fact, a mechanically informative system must distinguish description, association and inference. Video may directly describe segment positions within the limits of camera calibration and reconstruction, and a speedometer may directly record the motion of its attachment point (although cable dynamics and anatomical placement affect interpretation). An inertial sensor records acceleration and angular velocity at the sensor location, not joint angles or propulsive force unless these variables are estimated by a validated model. Computational fluid dynamics estimates pressure and shear distributions under specified geometries, boundary conditions and turbulence assumptions. AI adds another inferential layer, with the validity of its output depending on the quality and relevance of the criterion data used during training and testing.

3.2. Propulsion, Resistance and Coordination

Propulsion in swimming results from the interaction between moving body segments and the surrounding water. Hand and forearm orientation, segmental acceleration, foot motion, trunk rotation and the timing of upper- and lower-limb actions contribute to the generation and redirection of fluid momentum [5,7]. The visible trajectory of a segment is consequently informative but incomplete: the same trajectory may have different consequences depending on local flow conditions, segment orientation and velocity and interactions with previously generated vortices. Passive drag is particularly relevant to starts, turns and gliding, whereas active drag concerns the resistance encountered during swimming actions. Both are velocity-dependent and sensitive to body alignment and morphology, but active drag is additionally affected by technique and the method used to separate propulsion from resistance [3,4,6]. Direct comparisons at matched velocities also indicate that front crawl and backstroke differ in their trunk rotation patterns and in the mechanics used to generate propulsion [18], emphasising that technique-specific mechanics must be retained when defining targets for AI.

Coordination links these forces across time: (i) in alternating techniques, AI may help quantify the relationship between body roll, breathing and the timing of the different phases of the upper- and lower-limb phases, and (ii) in simultaneous techniques, it may help identify how upper- and lower-limb phases interact with glide duration and velocity peaks. Coordination analyses have shown that breaststroke strategies vary with competitive level [19], supporting the need for models that retain event- and technique-specific meaning. A generic movement classifier may detect a cycle correctly while missing the temporal feature that explains why the cycle is effective.

4. Artificial Intelligence Applications in Swimming

4.1. Wearable Inertial Sensing

Wearable inertial sensing is the most mature entry point for AI in swimming. Accelerometers and gyroscopes can be positioned on the trunk, sacrum, wrist, limbs or head and can record repeated cycles with minimal disruption to training. Earlier reviews established the feasibility of extracting stroke frequency, lap duration, turns and technique-specific signals [8,9]. Machine learning models extend this work by learning combinations of temporal, spectral and statistical features that discriminate swimming techniques or phases. In elite swimmers, supervised models trained on lumbar inertial data achieved very

high classification performance across swimming techniques, while also demonstrating that intra-cycle segmentation and conventional sliding windows influence prediction and computational cost [20].

Deep learning can reduce dependence on hand-crafted features, as a single sacrum-mounted inertial measurement unit has been used to recognise swimming activities and estimate lap times against video reference data [21]. Other systems have integrated upper- and lower-limb actions and breathing on an inter-cycle basis [22], or used functional clustering of inertial-derived variability to profile sprint front crawl abilities [23]. Deep-learning approaches have also been proposed for swimming cycle recognition in wearable-assisted applications [24]. Collectively, these studies show that inertial signals can support automated temporal analysis, but they do not establish that sensor-derived outputs are equivalent to biomechanical criterion measures.

This distinction is illustrated by validation studies of accelerometer-derived instantaneous velocity, in which agreement with reference velocity profiles varied with stroke and with individual swimming characteristics [25]. The implication for AI is important: a model trained on one device may learn its filtering, placement and signal-processing characteristics rather than the underlying mechanics. Calibration transfer, sensor replacement and differences in attachment can create domain shifts that reduce performance outside the original dataset. Thus, future wearable models should report sensor specifications, placement, calibration, sampling frequency, pre-processing and the consequences of swimmer-independent testing [26].

4.2. Video, Computer Vision and Markerless Pose Estimation

Video remains central to swimming biomechanics because it preserves spatial information about body and limb motion, but manual digitisation is labour-intensive and sensitive to operator decisions. Computer vision can automate swimmer detection, tracking, phase identification and pose estimation. Early systems used swimmer detection and pose models to determine stroke rate continuously, while subsequent deep architectures derived key frames and kinematic parameters from competitive swimmers recorded through a flume window [27,28]. These studies highlighted conditions that remain problematic: bubbles, splashes, reflections, refraction, self-occlusion and partial visibility.

Recent video-sequence models have classified conventional swimming techniques using convolutional neural networks [29], and underwater pose-estimation research has begun to evaluate model configurations specifically for swimmer images rather than relying only on terrestrial benchmarks [30]. This specificity is essential since general-purpose pose estimators are trained predominantly on upright terrestrial activities and may force anatomically plausible but incorrect joint configurations when limbs disappear behind the body or water surface. Two-dimensional keypoint accuracy can also obscure errors in depth, camera calibration and refraction correction. For biomechanical use, the relevant endpoint is not only whether a keypoint is detected, but whether derived joint angles, phase timings and segment velocities agree with criterion measurements within an acceptable error. The distinction between landmark-detection accuracy and biomechanical validity is illustrated by comparisons between hip- and centre-of-mass-derived kinematics in front crawl. Although hip motion provided similar mean horizontal velocity and displacement, it introduced measurable errors and overestimated intra-cycle velocity variation [31]. Thus, even an accurately detected anatomical landmark may constitute an imperfect proxy for the mechanical variable that an artificial intelligence model is intended to estimate.

Markerless analysis is attractive because it may permit rapid assessment in training and competition, but an automated skeleton is not a biomechanical explanation. The transformation from pixels to joint centres, joint angles and mechanical variables requires

calibrated geometry and a clearly defined model. Above- and underwater views must be synchronised if the movement crosses the waterline, and refraction should be modelled rather than treated as random noise. This requirement is particularly important in underwater three-dimensional analysis, where image deformation and light refraction may compromise the coordinates used for reconstruction. In a large swimming calibration volume, planar homography reduced the reconstruction error of both surface and underwater views, demonstrating that image rectification and calibration procedures materially affect the accuracy of the resulting trajectories [32]. Accordingly, computer-vision models should not be validated solely against manually digitised points without first establishing the geometric accuracy of those reference coordinates. Two-dimensional video approaches can extend the field of view in applied settings, but their validity depends on the software used, the calibration of the image space and the raters involved [33]. Therefore, validation against known coordinates and distances is required before the reconstructed trajectories are used as labels for computer-vision models. Reporting should include camera characteristics, frame rate, shutter settings, calibration volume, annotation protocol, model training data and performance stratified by view, technique, sex, body size and visibility conditions.

Deep neural networks provide substantial opportunities for swimming kinematic analysis by automating procedures that traditionally require laborious frame-by-frame digitisation. During model development, representative video frames are manually annotated by identifying anatomical landmarks, such as the head, shoulders, elbows, wrists, hips, knees and ankles. The network learns the visual features and spatial patterns associated with these landmarks and subsequently estimates their two-dimensional coordinates in previously unseen images [30]. When tracked across consecutive frames, these coordinate trajectories can support the identification of key events and cycle phases and the automated derivation of temporal and spatial kinematic parameters [27,30]. Nevertheless, the accuracy of these outputs depends strongly on the size, diversity and annotation quality of the training dataset. Underwater applications introduce additional difficulties associated with image distortion, refraction, bubbles, turbulence, self-occlusion and changes in lighting, camera position or swimmer morphology. Consequently, anatomically implausible landmark estimates and limited generalisation across swimmers and acquisition settings remain important concerns requiring biomechanical quality control and external validation [34].

4.3. Intelligent Analytics, Performance Prediction and Training Monitoring

Early swimming-specific applications also explored neural networks for signal reconstruction and velocity-profile identification. A proof-of-concept system combined a low-cost incremental-encoder device with a radial basis function neural network optimised through generalised extremal optimisation to estimate front-crawl velocity profiles [35]. Although this work anticipated the integration of sensing and nonlinear modelling, its limited validation means that it should be interpreted as an early technical demonstration rather than evidence of swimmer-independent biomechanical accuracy.

Swimming-specific predictive modelling predates the recent expansion of explainable AI. Linear models, multilayer perceptron neural networks and radial basis function neural networks have been compared for predicting centre-of-mass horizontal velocity from combined physiological and biomechanical inputs across low-to-severe swimming intensities [36]. Nonlinear models were particularly informative at heavy and severe intensities, demonstrating the potential of artificial neural networks to integrate multidimensional swimming data. Nevertheless, the small and homogeneous sample used in this early study also illustrates why contemporary models require swimmer-independent testing and external validation.

AI has also been used to connect practical tests and training variables with competitive performance. An intelligent analytics framework can combine Internet-of-Things devices, cloud processing and feedback components [37], but the scientific value of such a framework depends on the variables and validation embedded within it. Explainable models using Shapley additive explanation values have identified the magnitude and direction of contributions from training duration, countermovement-jump impulse, fat mass, and other variables to World Aquatics points [38]. Longitudinal work has extended this logic to heart-rate-variability-derived inputs during an overload period, linking model outputs with training and perceived-load variation [39].

Digital twins provide a broader architecture for connecting a swimmer's physical measurements with a continuously updated virtual representation, analytical services and decision-support outputs. A systematic review of digital twins in sport identified potential applications in real-time monitoring, personalised training and scenario simulation, while also concluding that many implementations remain experimental or at prototype maturity [40]. In elite swimming, an applied digital-twin approach has combined inertial measurement units, hand-mounted differential pressure sensors and underwater video to examine streamline, underwater lower-limb actions and race-specific technical scenarios [41]. This example illustrates how multimodal data may be translated into individualised recommendations and simulated time gains, but the evidence is primarily descriptive and case-based, without independent validation of the estimated forces, drag or performance effects.

Generative AI has also been evaluated as a direct training-prescription tool. Weekly programmes produced by ChatGPT-4 for elite distance and sprint swimmers received neutral-to-positive ratings from experienced coaches, whereas athletes were more critical and frequently requested major modifications [42]. The plans were more acceptable for simple low-intensity work but contained inappropriate repetition structures, recovery periods and session frequencies in moderate-intensity and anaerobic zones. This evidence supports the use of large language models as preliminary planning aids, but not as autonomous recommendation systems for complex periodisation.

These applications are valuable because they move beyond univariate associations and present variables in a form that coaches can interrogate. However, feature importance is not causality: Shapley additive explanations values describe how a fitted model used its inputs for prediction, but they do not prove that changing a feature will produce the predicted improvement. Related variables may share or redistribute importance, and results may change across model classes, samples and validation schemes [13,14]. Performance models should be framed as decision-support tools, with explicit separation between prediction, explanation and intervention.

The practical endpoint is not a universal recommendation engine, and evidence mapped in a recent swimming-focused review indicates that complete swimmer-centred systems are still lacking [10]. Current tools typically solve isolated tasks, while coaches make decisions by integrating training phase, event demands, fatigue, history and technical priorities. AI should support this integration by presenting uncertainty, trends and mechanically plausible alternatives, rather than convert a probabilistic association into a prescriptive technical correction without experimental or longitudinal evidence. The principal AI application domains in swimming, including their typical tasks, potential contributions, main limitations and supporting examples, are summarised in Table 1.

Table 1. Principal artificial intelligence application domains in swimming.

Data Domain	Typical Task	Potential Contribution	Principal Limitation	Examples
Wearable IMU	Technique, phase or lap classification; temporal features	Automated repeated monitoring in training	Sensor placement, drift, device-specific signals and limited external validation	[8,9,20–26]
Video/computer vision	Swimmer detection, tracking, key frames and pose	Spatial analysis with reduced manual digitisation	Refraction, bubbles, occlusion, depth ambiguity and dataset bias	[27–30]
Multimodal analytics	Fusion of sensor, video, training and physiological data	Integrated athlete profiles, digital twins and longitudinal monitoring	Synchronisation, missing data, prototype maturity and unclear causal interpretation	[37–41,43]
Generative AI	Training plan generation and conversational decision support	Rapid preliminary planning and accessible synthesis of training principles	Prompt sensitivity, incomplete individualisation and unsafe or suboptimal prescriptions	[42]
Explainable prediction	Performance and training-load modelling	Directional feature contributions and transparent model interrogation	Feature importance is not causality and correlated predictors complicate interpretation	[13,14,38,39]
CFD/physics-informed AI	Surrogate simulation, parameter estimation and constrained learning	Faster exploration of hydrodynamic scenarios with physical constraints	Scarce swimmer-specific validation and sensitivity to geometry and boundary conditions	[3,7,44–50]

5. Artificial Intelligence, Propulsion and Fluid Dynamics

5.1. From Kinematic Cues to Hydrodynamic Inference

The largest conceptual risk in this field is the conversion of visible motion into unsupported hydrodynamic claims. A lower head position, narrower lower-limb action or altered hand path may be associated with performance, but the sign and magnitude of its effect on resistance or propulsion depend on the complete movement and flow state. Even if AI can learn associations between kinematic patterns and experimentally derived forces, its outputs should be described as estimates or inferences unless the target variable was measured directly. This terminology is especially important for active drag, where criterion methods rely on assumptions and may not agree.

A defensible development pathway begins with synchronised data; for instance, kinematics from calibrated video or inertial sensors can be paired with force, pressure, velocity or validated computational outputs. Then, models may identify which features contain information about a defined mechanical target. Cross-validation must occur at the swimmer level, because cycle-level random splitting allows near-duplicate observations from the same swimmer to enter training and testing sets. Apparent accuracy can consequently reflect individual signatures rather than generalizable mechanics. External testing across swimmers, velocities, techniques and acquisition sites is required before a model can support hydrodynamic decisions.

5.2. Computational Fluid Dynamics and Machine Learning

Computational fluid dynamics has provided detailed estimates of pressure, shear, flow separation and vortical structures around swimmers and body segments. Comparisons of computational and inverse-dynamics methods in breaststroke glide positions have shown both the potential and the method dependence of passive-drag estimation [3]. Simulations of hand and forearm acceleration have likewise demonstrated how local motion affects estimated propulsive forces [7]. Computational analyses of finger spreading, thumb abduction, angle of attack and sweepback angle further show that apparently small changes in segment configuration can alter estimated hand and forearm hydrodynamic coefficients [51]. Underwater undulatory swimming research has linked kinematic organisation with trunk- and wake-related vortices [52,53]. These findings supply mechanistic targets for AI, but they also show that fluid-dynamics outputs are conditional on geometry, mesh resolution, boundary conditions, turbulence treatment and prescribed motion.

Machine learning can contribute to computational fluid dynamics in three broad ways: (i) surrogate models may approximate expensive simulations after training on a carefully sampled parameter space; (ii) machine learning may assist numerical solvers or estimate unresolved terms; and (iii) physics-informed models can incorporate governing equations, initial and boundary conditions or conservation constraints into learning [44–48]. In swimming, a surrogate could allow rapid exploration of posture, joint timing or segment orientation after an adequate high-fidelity simulation set has been generated. The advantage would be computational speed, not freedom from the assumptions of the original simulations.

Physics-informed learning is particularly attractive where labelled experimental data are limited. Neural networks can be constrained by governing equations or by softer biomechanical relationships, such as non-negative drag, plausible force–velocity behaviour and continuity across phases [44,45]. Yet, physics-informed does not automatically mean physiologically or biomechanically valid, as a model can satisfy simplified equations while using unrealistic swimmer geometry or boundary conditions. Human swimming includes a deforming free surface, intermittent segment emergence and complex turbulence, making direct transfer from canonical fluid-mechanics benchmarks inappropriate without validation.

Reinforcement learning studies of self-propelled bodies and vortex-mediated collective swimming demonstrate that artificial agents can discover energetically favourable flow interactions [49]. These studies are conceptually relevant because they show how learning can exploit fluid structures, but they should not be cited as direct evidence for human technique. The nearer-term application in competitive swimming is likely to be hybrid modelling: AI used to accelerate, interpolate or interrogate validated biomechanical and computational models rather than to infer complete hydrodynamics from a single uncalibrated video.

Swimming-specific applications of machine learning to computational fluid dynamics remain comparatively rare. Classical CFD studies have computed drag and propulsion for swimmer postures and limb configurations [3,6,7,51], whereas the deep-learning surrogates, physics-informed neural networks and operator-learning methods that now dominate general fluid mechanics [44,46–48,54] have only begun to be transferred to swimming. Reviews of physics-informed neural networks for fluid mechanics [54] outline the conservation-law constraints, data requirements and uncertainty quantification that swimming-specific surrogates would need to satisfy before they could replace or accelerate high-fidelity swimmer simulations.

5.3. A Hierarchy of Hydrodynamic Claims

Hydrodynamic outputs should be interpreted through a hierarchy of evidential strength: (i) AI identifies a kinematic feature associated with a measured performance variable; (ii) that feature is associated with an independently measured mechanical variable such as force, pressure or drag; (iii) a model predicts the mechanical variable in swimmers not used for development; (iv) the prediction generalises across techniques, velocities or centres; and (v) an intervention based on the model changes technique and produces the expected mechanical and performance consequences. Most current swimming applications remain at the first or second level, meaning that claims about optimisation should be reserved for evidence reaching the later levels.

6. Explainability and Mechanistic Interpretability

Explainable AI encompasses methods that make model behaviour more accessible, whereas mechanistic interpretability requires correspondence with a plausible causal or mechanical process (the two concepts overlap but are not identical). Feature-attribution methods can show that stroke frequency or body roll influenced a prediction, but they do not establish why or through which force pathway. A mechanically interpretable model should relate its inputs to a defined chain: movement or morphology changes projected geometry or segment–water interaction, which changes propulsion or resistance, which changes velocity or energy cost. The chain may remain probabilistic, but its assumptions must be visible.

Post hoc explanations can be useful for auditing complex models [13,14], particularly when they reveal dependence on implausible features. However, there is a risk that a convincing explanation is accepted even when the underlying model is unstable. In high-stakes settings, inherently interpretable models may be preferable to opaque models accompanied by explanations [55]. This does not imply that simple models are always sufficient. Rather, model complexity should be justified by a meaningful improvement in swimmer-independent performance and accompanied by sensitivity analysis, calibration and uncertainty.

Mechanistic interpretability can be strengthened through feature design and model architecture. Inputs may be organised according to known phases, bilateral actions or mechanical domains instead of supplying an unrestricted array of signals. Temporal models may preserve the order of the different upper- and lower-limb phases and breathing rather than classifying isolated windows. Hybrid architectures may include differentiable biomechanical relations or penalties for mechanically impossible outputs. Explanations should be expressed in swimming terms and retain direction and magnitude, for example, that a predicted reduction in velocity was associated with longer deceleration after hand exit and increased trunk oscillation, rather than with an abstract latent feature.

To make the distinction concrete, consider a model that recognises front crawl phases from inertial-sensor data. An explainable-AI analysis might report that the model relies on the medio-lateral accelerometer channel during the transition between phases, which will clarify the model's behaviour but does not, by itself, establish a mechanical consequence. A mechanistic interpretation would test whether that feature corresponds to a physically meaningful event (such as hand entry or body-roll reversal) by relating it to an independently measured kinematic or kinetic criterion. Swimming studies that apply explainable methods to performance and training variables [38,39] illustrate the first step, whereas studies that pair model outputs with force, pressure, drag or computational criteria [3,44,51] demonstrate the additional step required for mechanistic interpretation.

7. Validation, Generalisability and Reporting

7.1. Validation Design

Validation is the central requirement separating a useful analytical model from a technically impressive demonstration. Random division of cycles or frames can produce severe information leakage when observations from the same swimmer, trial or video appear in both sets. The preferred minimum is grouped validation by swimmer, with a fully independent test set when sample size permits. Multicentre external validation is required when a system is intended for broad use, and models should also be tested under realistic sources of variation (including sex, age, body size, competitive level, technique, velocity, breathing pattern, fatigue, camera view and sensor placement).

Performance metrics must match the task, and classification studies should provide class-specific precision, recall, F1 scores (representing the harmonic mean of precision and recall) and confusion matrices rather than accuracy alone. Continuous biomechanical outcomes require absolute and relative error, bias, limits of agreement and calibration across the observed range. Timing outputs should report error in meaningful units and relative to cycle duration. For hydrodynamic inference, comparison with a single computational model is not independent validation if the AI model was trained from that same simulation family. Experimental force, pressure or drag data, or simulations generated under substantively different assumptions, are needed to test transfer.

7.2. Dataset Size, Diversity and Reproducibility

Swimming datasets are typically small because synchronised underwater acquisition is expensive and technically demanding. Deep models trained on limited participants can overfit individual morphology, technique and recording conditions. Data augmentation may improve robustness to image or signal perturbations, but it does not create new swimmers or new mechanical strategies. Transfer learning from terrestrial images may help initialise pose estimation, although domain-specific fine-tuning remains necessary. Reporting the number of swimmers, trials, cycles and frames separately is essential because a large number of frames from a small number of individuals does not represent a large independent sample.

Reproducibility would benefit from shared benchmark datasets, common event definitions and transparent preprocessing. Data sharing in elite sport is constrained by privacy, competitive sensitivity and ownership, but de-identified signals, annotations, model code and synthetic benchmark tasks can still be made available. The Findable, Accessible, Interoperable and Reusable (FAIR) principles provide a useful foundation for managing data and metadata [56]. When data cannot be shared, authors should provide sufficiently detailed pipelines, locked test protocols and executable code or pseudocode to permit independent replication.

7.3. Minimum Reporting Recommendations

Machine learning guidance in human movement biomechanics emphasises alignment between the research question, dataset, validation and interpretation [57]. For swimming, reporting should additionally describe aquatic acquisition conditions, i.e., studies should identify swimming pool or flume settings, water depth (where relevant), camera relationship to the waterline, calibration and refraction procedures, sensor attachment, synchronisation and the operational definition of each phase. Model selection and hyperparameter tuning should be confined to development data, and the test set should remain untouched until the final model is locked. These reporting recommendations are intended as guidance for future studies and were not applied retrospectively as a formal

quality-appraisal instrument for the studies reviewed here. The minimum information that should be reported across these domains is summarised in Table 2.

Table 2. Minimum reporting elements for artificial intelligence studies in swimming biomechanics.

Domain	Recommended Information
Participants	Number of independent swimmers, sex, age, anthropometry, competitive level, technique specialisation and inclusion criteria
Acquisition	Pool/flume context, velocity, breathing condition, fatigue state, camera and sensor specifications, placement, calibration and synchronisation
Ground truth	Definition, measurement method, annotator training, inter-rater reliability and known criterion error
Dataset structure	Numbers of swimmers, trials, cycles and frames; missing data; class balance; grouping and nesting
Model development	Preprocessing, features, architecture, hyperparameters, augmentation, software and random seeds
Validation	Swimmer-independent splits, internal versus external testing, leakage prevention and subgroup analyses
Performance	Task-appropriate metrics, confidence intervals, calibration, bias and error in biomechanically meaningful units
Interpretation	Direct measurement versus inference, uncertainty, plausible mechanism, failure cases and limits of use
Reproducibility	Code, model version, data or metadata availability and sufficient detail for replication

8. Translation into Coaching and Performance Support

Coaches require information that is timely, reliable and connected to an intervention [58], and a system that produces numerous metrics after a long processing delay may add less value than a simple measure available during the session. AI can reduce this delay by automating event detection and prioritising meaningful changes. The output should answer four questions: What changed? How certain is the change? What mechanical consequence is plausible? What response can be tested, and what indicates when the data are insufficient? Transparent coach-centred feedback is increasingly recognised as a design requirement for multimodal swimming systems [43].

Generative systems require an additional distinction between fluent output and valid prescription. A plausible weekly plan may reproduce familiar terminology and broadly appropriate intensity categories while still misallocating volume, repetition duration, recovery or session frequency [42]. The discrepancies identified when coaches and athletes evaluated ChatGPT-4-generated plans for elite swimmers show that acceptability varies by training zone and evaluator perspective [42]. Therefore, human review must assess both physiological coherence and compatibility with the swimmer's technical status, competition programme, recovery and longitudinal response.

Individual baselines are often more useful than universal thresholds, with swimmers' technique depending on morphology, event, velocity and training objective [59], so a deviation from a population mean is not necessarily an error. Longitudinal models can learn the normal variation in an individual swimmer and flag departures that exceed measurement noise. In this sense, these alerts may direct video review or targeted testing. The coach and biomechanist retain responsibility for deciding whether a change reflects fatigue, adaptation, pacing, intentional technique or poor measurement.

Real-time feedback should be used cautiously since immediate cues may support phase timing or pacing, but repeated external feedback can alter attention and learning. In fact, the shortest computational latency is not always the optimal pedagogical strategy [60]. Systems should allow coaches to select the variable, timing and frequency of feedback and to compare technical changes with performance and effort. The effectiveness of AI-supported feedback should ultimately be evaluated in longitudinal intervention studies rather than inferred from classification accuracy.

9. Research Gaps and Priorities

The first priority is the development of benchmark datasets that combine calibrated above- and underwater videos, inertial signals, velocity curves and criterion mechanical measurements. These datasets should represent multiple techniques, sexes, ages, performance levels and velocities. Standardised annotations for phases, breathing and turns would permit meaningful comparison among models. A benchmark should preserve swimmer-level grouping and include an inaccessible or independently managed test set to reduce optimistic reporting.

The second priority is direct validation of mechanically important outputs. AI research in swimming has progressed faster in activity recognition than in propulsion and resistance. Future studies should pair models with pressure, force, active-drag, passive-drag or validated computational measurements, and uncertainty from the criterion method must be incorporated into interpretation. If two drag methods disagree beyond the desired model error, it is misleading to present one as error-free ground truth.

The third priority is hybrid and physics-informed modelling. Surrogate computational fluid dynamics, constrained temporal networks and differentiable biomechanical components may help reduce data requirements and improve plausibility [50]. These models should be compared with unconstrained alternatives to determine whether the added physics improves external generalisation rather than merely fitting the development data. Sensitivity analyses are needed to establish which constraints drive predictions and when they fail.

The fourth priority is prospective evaluation. Since most evidence is cross-sectional and technical, prospective studies are urgently needed. This limitation is longstanding: a systematic review of longitudinal interventions in elite swimming showed that prospective evidence remains scarce and concentrated on a limited set of physiological and biomechanical variables [61], reinforcing the need for prospective studies. Longitudinal studies should test whether model-informed feedback produces repeatable changes in mechanics, whether those changes transfer to race performance and whether benefits persist without continuous feedback. Digital twins should progress beyond descriptive virtual replicas by demonstrating reliable updating, predictive calibration and measurable benefit relative to established analysis [40]. Pragmatic studies should also quantify analyst time, coach acceptance, false alerts and the consequences of incorrect recommendations. Practical usability is an empirical outcome, not an assumed property of an interface.

The fifth priority is governance: As swimmer data may reveal health, fatigue, training and performance information with competitive and personal sensitivity, data ownership, consent, retention, access and secondary use should be defined before collection. The continuous and multimodal data flows required by digital twins intensify concerns regarding interoperability, data integrity, privacy and unauthorised reuse [40]. Research involving generative AI should additionally preserve human accountability, disclose substantive uses of the technology, verify generated information and bibliographic references and protect confidential or personal data included in prompts or uploaded materials [62]. Models trained across clubs or nations may reproduce systematic differences in equipment,

coaching and selection, and subgroup evaluation and transparent documentation are scientific and ethical requirements. These priorities, their underlying limitations, required developments and evaluation endpoints are summarised in Table 3.

Table 3. Priority roadmap for mechanistically interpretable artificial intelligence in swimming.

Priority	Current Limitation	Required Development	Evaluation Endpoint
Benchmark multimodal datasets	Fragmented, small and laboratory-specific datasets	Synchronised video, IMU, velocity and mechanical criteria across diverse swimmers	Open or independently tested benchmark with swimmer-level splits
Mechanically validated outputs	Classification dominates; propulsion and drag are inferred indirectly	Pair models with force, pressure, drag and high-fidelity CFD	Predefined acceptable error and independent criterion comparison
Hybrid models	Black-box associations with limited transfer	Embed phase structure, conservation principles and plausible constraints	External generalisation and ablation of each constraint
Longitudinal interventions	Technical accuracy without evidence of performance benefit	Test model-informed feedback across training blocks	Technique, performance, retention and coach-use outcomes
Transparent deployment	Limited uncertainty and subgroup reporting	Calibrated uncertainty, failure detection and governance	Prospective monitoring of errors and unintended consequences

Some limitations should be acknowledged: (i) since the search was intentionally narrative rather than systematic, relevant studies may have been missed, and selection and publication bias cannot be excluded; (ii) no formal methodological quality assessment of the included studies was performed, meaning that the relative strength of the evidence rests on narrative appraisal rather than a standardised risk-of-bias tool; and (iii) the field is developing rapidly, and several of the most promising directions discussed here (including generative AI, digital twins and coach-facing decision-support systems) remain emergent, with limited prospective or external validation evidence. Therefore, the framework proposed below is a structuring device for reasoning about the literature, not an empirically validated model of swimming performance.

10. Conceptual Framework

Figure 1 summarises the proposed pathway from data acquisition to decision support, with the framework deliberately separating biomechanical interpretation from hydrodynamic inference. AI may process and fuse data, but a second layer must establish whether the output corresponds to coordination, body roll, cycle mechanics, propulsion, drag or flow-related cues. The final decision-support layer should integrate the evidence, uncertainty and individual context. This structure prevents a direct and unjustified transition from a sensor signal to a technical prescription. Moreover, it is a proposed conceptual framework for mechanistically interpretable AI in swimming biomechanics and fluid dynamics. Multimodal acquisition and AI-based processing require explicit biomechanical interpretation and separately validated hydrodynamic inference, with criterion measurement and swimmer-independent validation connecting each level, before outputs are translated into coach-centred decisions (model feedback then updates the biomechanical interpretation as new evidence accumulates). This framework is proposed as a structuring device and has not yet been validated as an integrated system.

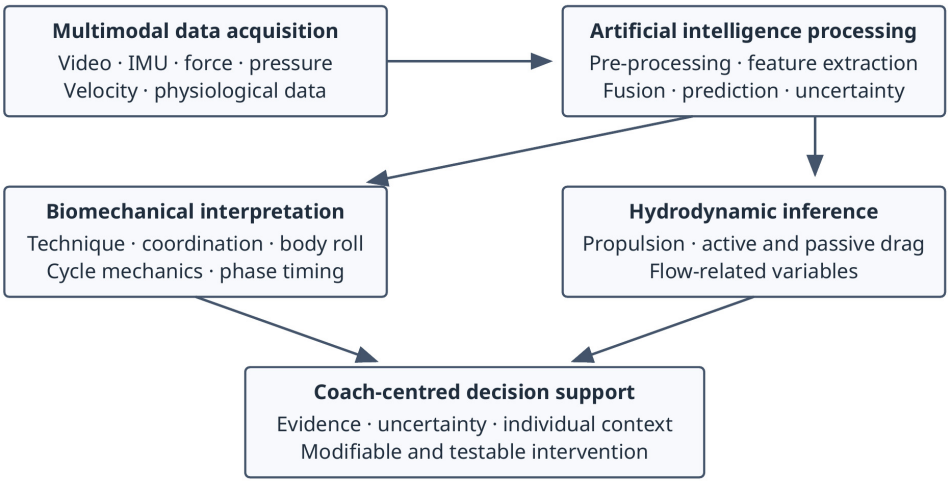


Figure 1. Conceptual framework for mechanistically interpretable AI in swimming biomechanics and fluid dynamics. Multimodal acquisition and AI-based processing require explicit biomechanical interpretation and separately validated hydrodynamic inference before outputs are translated into coach-centred decisions.

11. Conclusions

AI can substantially improve the scale, speed and integration of swimming analysis in established applications, although prospective and external validation evidence remains limited for more ambitious systems.

The strongest current evidence concerns automated recognition of techniques, laps and phases, inertial-sensor processing, video-based pose estimation and multivariable performance or training monitoring. These applications reduce manual workload and reveal patterns that are difficult to observe in isolated signals. By contrast, the anticipated benefits of physics-informed, hydrodynamic and coach-facing systems, including generative AI and digital twins, remain largely prospective and should be treated as directions rather than established capabilities. The established applications do not by themselves explain propulsion, resistance or efficiency, and the direct application of AI to swimmer-specific fluid dynamics remains at an early stage.

Progress requires a shift from task accuracy to mechanically meaningful validation. Models should be tested on swimmers not used for development, compared with appropriate criterion measures and evaluated across techniques, velocities and populations. Hydrodynamic variables should be reported as estimates when they are inferred indirectly. Explainability should clarify model behaviour, while mechanistic interpretation should connect movement to plausible force and flow consequences. Physics-informed and hybrid models offer a promising route, provided that their assumptions and external validity are tested. AI should ultimately function as an extension of biomechanical reasoning. The most useful systems will not simply classify a movement or predict a race score. They will identify what changed, quantify uncertainty, distinguish observation from inference and help coaches test an appropriate intervention. This orientation can transform AI from a technological novelty into a rigorous component of swimming science and performance support.

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References

1. Barbosa, T.M.; Barbosa, A.C.; Simbaña Escobar, D.; Mullen, G.J.; Cossor, J.M.; Hodierne, R.; Arellano, R.; Mason, B.R. The role of the biomechanics analyst in swimming training and competition analysis. *Sports Biomech.* **2023**, *22*, 1734–1751. [CrossRef] [PubMed]
2. Tella, V.; Toca-Herrera, J.L.; Gallach, J.E.; Benavent, J.; González, L.M.; Arellano, R. Effect of fatigue on the intra-cycle acceleration in front crawl swimming: A time–frequency analysis. *J. Biomech.* **2008**, *41*, 86–92. [CrossRef] [PubMed]
3. Costa, L.; Mantha, V.R.; Silva, A.J.; Fernandes, R.J.; Marinho, D.A.; Vilas-Boas, J.P.; Machado, L.; Rouboa, A. Computational fluid dynamics vs. inverse dynamics methods to determine passive drag in two breaststroke glide positions. *J. Biomech.* **2015**, *48*, 2221–2226. [CrossRef] [PubMed]
4. Havriluk, R. Variability in measurement of swimming forces: A meta-analysis of passive and active drag. *Res. Q. Exerc. Sport* **2007**, *78*, 32–39. [CrossRef] [PubMed]
5. Arellano, R. Vortices and propulsion. In *Swimming: Applied Proceedings of the XVII International Symposium on Biomechanics in Sports*; Sanders, R., Linsten, J., Eds.; School of Biomedical and Sports Science: Perth, Australia, 1999; pp. 53–66.
6. Marinho, D.A.; Reis, V.M.; Alves, F.B.; Vilas-Boas, J.P.; Machado, L.; Silva, A.J.; Rouboa, A.I. Hydrodynamic drag during gliding in swimming. *J. Appl. Biomech.* **2009**, *25*, 253–257. [CrossRef] [PubMed]
7. Rouboa, A.; Silva, A.; Leal, L.; Rocha, J.; Alves, F. The effect of swimmer's hand/forearm acceleration on propulsive forces generation using computational fluid dynamics. *J. Biomech.* **2006**, *39*, 1239–1248. [CrossRef] [PubMed]
8. Mooney, R.; Corley, G.; Godfrey, A.; Quinlan, L.R.; ÓLaighin, G. Inertial sensor technology for elite swimming performance analysis: A systematic review. *Sensors* **2016**, *16*, 18. [CrossRef] [PubMed]
9. de Magalhães, F.A.; Vannozzi, G.; Gatta, G.; Fantozzi, S. Wearable inertial sensors in swimming motion analysis: A systematic review. *J. Sports Sci.* **2015**, *33*, 732–745. [CrossRef] [PubMed]
10. Patil, M.; Goudar, R.H.; Hukkeri, G.S. AI for swimming recommendation systems: Exploring the current landscape and research opportunities. *Discov. Appl. Sci.* **2026**, *8*, 156. [CrossRef]
11. Souaifi, M.; Dhahbi, W.; Jebabli, N.; Ceylan, H.I.; Boujabli, M.; Muntean, R.I.; Dergaa, I. Artificial intelligence in sports biomechanics: A scoping review on wearable technology, motion analysis and injury prevention. *Bioengineering* **2025**, *12*, 887. [CrossRef] [PubMed]
12. Xu, D.; Zhou, H.; Jie, T.; Zhou, Z.; Yuan, Y.; Jemni, M.; Quan, W.; Gao, Z.; Xiang, L.; Gusztáv, F.; et al. Data-Driven Deep Learning for Predicting Ligament Fatigue Failure Risk Mechanisms. *Int. J. Mech. Sci.* **2025**, *301*, 110519. [CrossRef]
13. Tjoa, E.; Guan, C. A survey on explainable artificial intelligence (XAI): Toward medical XAI. *IEEE Trans. Neural Netw. Learn. Syst.* **2021**, *32*, 4793–4813. [CrossRef] [PubMed]
14. Rodis, N.; Sardianos, C.; Radoglou-Grammatikis, P.; Sarigiannidis, P.; Varlamis, I.; Papadopoulos, G.T. Multimodal explainable artificial intelligence: A comprehensive review of methodological advances and future research directions. *IEEE Access* **2024**, *12*, 159794–159820. [CrossRef]
15. Pinto, M.P.; Marinho, D.A.; Neiva, H.P.; Morais, J.E. Relationship between swimming speed, intra-cycle variation of horizontal speed, and Froude efficiency during consecutive stroke cycles in adolescent swimmers. *PeerJ* **2023**, *11*, e16019. [CrossRef] [PubMed]
16. Pinto, M.P.; Marinho, D.A.; Neiva, H.P.; Barbosa, T.M.; Morais, J.E. Insights on the selection of the coefficient of variation to assess speed fluctuation in swimming. *J. Funct. Morphol. Kinesiol.* **2024**, *9*, 129. [CrossRef] [PubMed]

17. Fernandes, A.; Vilas-Boas, J.P.; Fernandes, R.J.; Mezêncio, B. Relative power to velocity variation: A new quantification method for assessing swimming kinematics. *J. Biomech.* **2025**, *192*, 112970. [CrossRef] [PubMed]
18. Nikodelis, T.; Gourgoulis, V.; Lola, A.; Ntampakis, I.; Kollias, I. Front crawl and backstroke sprint swimming have distinct differences along with similar patterns regarding trunk rotations. *Int. J. Kinesiol. Sports Sci.* **2023**, *11*, 1–7. [CrossRef]
19. Leblanc, H.; Seifert, L.; Chollet, D. Arm–leg coordination in recreational and competitive breaststroke swimmers. *J. Sci. Med. Sport* **2009**, *12*, 352–356. [CrossRef] [PubMed]
20. Worsey, M.T.O.; Pahl, R.; Espinosa, H.G.; Shepherd, J.B.; Thiel, D.V. Is machine learning and automatic classification of swimming data what unlocks the power of inertial measurement units in swimming? *J. Sports Sci.* **2021**, *39*, 2095–2114. [CrossRef] [PubMed]
21. Delhaye, E.; Bouvet, A.; Nicolas, G.; Vilas-Boas, J.P.; Bideau, B.; Bideau, N. Automatic swimming activity recognition and lap time assessment based on a single IMU: A deep learning approach. *Sensors* **2022**, *22*, 5786. [CrossRef] [PubMed]
22. Fantozzi, S.; Coloretti, V.; Piacentini, M.F.; Quagliarotti, C.; Bartolomei, S.; Gatta, G.; Cortesi, M. Integrated timing of stroking, breathing and kicking in front-crawl swimming: A novel stroke-by-stroke approach using wearable inertial sensors. *Sensors* **2022**, *22*, 1419. [CrossRef] [PubMed]
23. Bouvet, A.; Pla, R.; Delhaye, E.; Nicolas, G.; Bideau, N. Profiling biomechanical abilities during sprint front-crawl swimming using IMU and functional clustering of variabilities. *Sports Biomech.* **2025**, *24*, 1844–1864. [CrossRef] [PubMed]
24. Chen, L.; Hu, D. An effective swimming stroke recognition system utilizing deep learning based on inertial measurement units. *Adv. Robot.* **2023**, *37*, 467–479. [CrossRef]
25. Clément, J.; Charbonneau, M.; Thompson, M. Instantaneous velocity estimation for the four swimming strokes using a 3-axis accelerometer: Validation on paralympic athletes. *J. Biomech.* **2021**, *117*, 110261. [CrossRef] [PubMed]
26. Guignard, B.; Rouard, A.; Chollet, D.; Seifert, L. Behavioral dynamics in swimming: The appropriate use of inertial measurement units. *Front. Psychol.* **2017**, *8*, 383. [CrossRef] [PubMed]
27. Zecha, D.; Eggert, C.; Lienhart, R. Pose estimation for deriving kinematic parameters of competitive swimmers. *Electron. Imaging* **2017**, *29*, 21–29. [CrossRef]
28. Zecha, D.; Greif, T.; Lienhart, R. Swimmer detection and pose estimation for continuous stroke-rate determination. *Proc. SPIE* **2012**, *8304*, 830410. [CrossRef]
29. Hamid, A.H.A.; Othman, Z.; Suhaimi, S. Swimming style recognition for video sequences using deep learning. In Proceedings of the 2023 International Conference on Electrical Engineering and Informatics, Bandung, Indonesia, 10–11 October 2023; pp. 1–6. [CrossRef]
30. Caputo, A.; Scocco, A.; Castellini, P. Problem-related performance metrics of deep learning models: Application to swimmer pose estimation in underwater environments. *Meas. Digit.* **2026**, *6*, 100029. [CrossRef]
31. Fernandes, R.J.; Ribeiro, J.; Figueiredo, P.; Seifert, L.; Vilas-Boas, J.P. Kinematics of the Hip and Body Center of Mass in Front Crawl. *J. Hum. Kinet.* **2012**, *33*, 15–23. [CrossRef] [PubMed]
32. de Jesus, K.; de Jesus, K.; Figueiredo, P.; Vilas-Boas, J.P.; Fernandes, R.J.; Machado, L. Reconstruction Accuracy Assessment of Surface and Underwater 3D Motion Analysis: A New Approach. *Comput. Math. Methods Med.* **2015**, *2015*, 269264. [CrossRef] [PubMed]
33. Matúš, I.; Vadašová, B.; Eliáš, T.; Rydzik, Ł.; Ambroży, T.; Czarny, W. Validity and reliability of 2D video analysis for swimming kick start kinematics. *J. Funct. Morphol. Kinesiol.* **2025**, *10*, 184. [CrossRef] [PubMed]
34. Cronin, N.J. Using deep neural networks for kinematic analysis: Challenges and opportunities. *J. Biomech.* **2021**, *123*, 110460. [CrossRef] [PubMed]
35. Ferreira da Cruz, L.; Freire, R.Z.; Coelho, L.S. Low-cost prototype development and swim velocity profile identification using neural network associated to generalised external optimisation. In *Proceedings of the XIIth International Symposium on Biomechanics and Medicine in Swimming, Canberra, Australia, 28 April–2 May 2014*; Mason, B., Ed.; Australian Institute of Sport: Canberra, Australia, 2014; pp. 566–572.
36. de Jesus, K.; de Jesus, K.; Ayala, H.V.H.; dos Santos Coelho, L.; Vilas-Boas, J.P.; Fernandes, R.J.P. Predicting centre of mass horizontal speed in low to severe swimming intensities with linear and non-linear models. *J. Sports Sci.* **2019**, *37*, 1512–1520. [CrossRef] [PubMed]
37. Costa, J.; Silva, C.; Santos, M.; Fernandes, T.; Faria, S. Framework for intelligent swimming analytics with wearable sensors for stroke classification. *Sensors* **2021**, *21*, 5162. [CrossRef] [PubMed]
38. Carvalho, D.D.; Goethel, M.F.; Silva, A.J.; Vilas-Boas, J.P.; Pyne, D.B.; Fernandes, R.J. Swimming performance interpreted through explainable artificial intelligence (XAI)—Practical tests and training variables modelling. *Appl. Sci.* **2024**, *14*, 5218. [CrossRef]
39. Carvalho, D.D.; Goethel, M.F.; Erblang, M.; Vilas-Boas, J.P.; Pyne, D.B.; Fernandes, R.J.; Lopes, P. Impact of an overload period on heart rate variability, sleep quality, motivation and performance in high-level swimmers: Use of explainable artificial intelligence to assess training load variations. *Sports Med.* **2026**, *56*, 1235–1254. [CrossRef] [PubMed]
40. Hliš, T.; Fister, I.; Fister, I., Jr. Digital twins in sport: Concepts, taxonomies, challenges and practical potentials. *Expert Syst. Appl.* **2024**, *258*, 125104. [CrossRef]

41. Douglass, K.; Lamb, A.; Lu, J.; Ono, K.; Tenpas, W. Swimming in data. *Math. Intell.* **2024**, *46*, 145–155. [CrossRef]
42. Puce, L.; Żmijewski, P.; Cotellessa, F.; Schenone, C.; Ceylan, H.I.; Bragazzi, N.L.; Trompetto, C. The role of artificial intelligence in sports training: Opportunities, challenges and future applications for competitive swimming. *Biol. Sport* **2026**, *43*, 355–367. [CrossRef] [PubMed]
43. Camilleri, V.; Camilleri, R.Y.; Fialovszky, M.; Pace, D.; Seychell, D.; Montebello, M. Towards explainable multimodal sensing for swimming analysis: Early findings from the SWIM-360 project. *Sensors* **2025**, *25*, 7047. [CrossRef] [PubMed]
44. Karniadakis, G.E.; Kevrekidis, I.G.; Lu, L.; Perdikaris, P.; Wang, S.; Yang, L. Physics-informed machine learning. *Nat. Rev. Phys.* **2021**, *3*, 422–440. [CrossRef]
45. Raissi, M.; Perdikaris, P.; Karniadakis, G.E. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *J. Comput. Phys.* **2019**, *378*, 686–707. [CrossRef]
46. Brunton, S.L.; Noack, B.R.; Koumoutsakos, P. Machine learning for fluid mechanics. *Annu. Rev. Fluid Mech.* **2020**, *52*, 477–508. [CrossRef]
47. Vinuesa, R.; Brunton, S.L. Enhancing computational fluid dynamics with machine learning. *Nat. Comput. Sci.* **2022**, *2*, 358–366. [CrossRef] [PubMed]
48. Aly, A.M. Machine learning reshaping computational fluid dynamics: A paradigm shift in accuracy and speed. *Fluids* **2025**, *10*, 275. [CrossRef]
49. Verma, S.; Novati, G.; Koumoutsakos, P. Efficient collective swimming by harnessing vortices through deep reinforcement learning. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 5849–5854. [CrossRef] [PubMed]
50. Willard, J.; Jia, X.; Xu, S.; Steinbach, M.; Kumar, V. Integrating physics-based modeling with machine learning: A survey. *arXiv* **2022**, arXiv:2003.04919. [CrossRef]
51. Marinho, D.A.; Barbosa, T.M.; Reis, V.M.; Kjendlie, P.L.; Alves, F.B.; Vilas-Boas, J.P.; Machado, L.; Silva, A.J.; Rouboa, A.I. Swimming propulsion forces are enhanced by a small finger spread. *J. Appl. Biomech.* **2010**, *26*, 87–92. [CrossRef] [PubMed]
52. Veiga, S.; Lorenzo, J.; Trinidad, A.; Pla, R.; Fallas-Campos, A.; de la Rubia, A. Kinematic analysis of the underwater undulatory swimming cycle: A systematic and synthetic review. *Int. J. Environ. Res. Public Health* **2022**, *19*, 12196. [CrossRef] [PubMed]
53. Tanaka, T.; Hashizume, S.; Kurihara, T.; Isaka, T. The large and strong vortex around the trunk and behind the swimmer is associated with great performance in underwater undulatory swimming. *J. Hum. Kinet.* **2022**, *84*, 64–73. [CrossRef] [PubMed]
54. Cai, S.; Mao, Z.; Wang, Z.; Yin, M.; Karniadakis, G.E. Physics-informed neural networks (PINNs) for fluid mechanics: A review. *Acta Mech. Sin.* **2021**, *37*, 1727–1738. [CrossRef]
55. Rudin, C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nat. Mach. Intell.* **2019**, *1*, 206–215. [CrossRef] [PubMed]
56. Wilkinson, M.D.; Dumontier, M.; Aalbersberg, I.J.; Appleton, G.; Axton, M.; Baak, A.; Blomberg, N.; Boiten, J.-W.; da Silva Santos, L.B.; Bourne, P.E.; et al. The FAIR Guiding Principles for scientific data management and stewardship. *Sci. Data* **2016**, *3*, 160018. [CrossRef] [PubMed]
57. Halilaj, E.; Rajagopal, A.; Fiterau, M.; Hicks, J.L.; Hastie, T.J.; Delp, S.L. Machine learning in human movement biomechanics: Best practices, common pitfalls and new opportunities. *J. Biomech.* **2018**, *81*, 1–11. [CrossRef] [PubMed]
58. Phillips, E.; Davids, K.; Renshaw, I.; Portus, M. Expert performance in sport and the dynamics of talent development. *Sports Med.* **2010**, *40*, 271–283. [CrossRef] [PubMed]
59. Seifert, L.; Chollet, D.; Rouard, A. Swimming constraints and arm coordination. *Hum. Mov. Sci.* **2007**, *26*, 68–86. [CrossRef] [PubMed]
60. Winstein, C.J.; Schmidt, R.A. Reduced frequency of knowledge of results enhances motor skill learning. *J. Exp. Psychol. Learn. Mem. Cogn.* **1990**, *16*, 677–691. [CrossRef]
61. Costa, M.J.; Bragada, J.A.; Marinho, D.A.; Silva, A.J.; Barbosa, T.M. Longitudinal interventions in elite swimming: A systematic review based on energetics, biomechanics, and performance. *J. Strength Cond. Res.* **2012**, *26*, 2006–2016. [CrossRef] [PubMed]
62. European Commission; Directorate-General for Research and Innovation. *Living Guidelines on the Responsible Use of Generative AI in Research*, 3rd ed.; European Commission: Brussels, Belgium, 2026. Available online: https://research-and-innovation.ec.europa.eu/document/download/2b6cf7e5-36ac-41cb-aab5-0d32050143dc_en (accessed on 29 July 2026).

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