The role of the biomechanics analyst in swimming training and competition analysis

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ABSTRACT
Swimming analysts aid coaches and athletes in the decision-making by providing evidence-based recommendations. The aim of this narrative review was to report the best practices of swimming analysts that have been supporting high-performance athletes. It also aims to share how swimming analysts can translate applied research into practice. The role of the swimming analyst, as part of a holistic team supporting high-performance athletes, has been expanding and is needed to be distinguished from the job scope of a swimming researcher. As testing can be time-consuming, analysts must decide what is needed to test and when to conduct the evaluation sessions. Swimming analysts engage in the modelling and forecast of the performance, that in short- and mid-term can help set races target-times, and in the long-term provide insights on talent and career development. Races can be analysed by manual, semi-automatic or fully automatic video analysis with single or multi-cameras set-ups. The qualitative and quantitative analyses of the swim strokes, start, turns, and finish are also part of the analyst job scope and associated with race performance goals. Land-based training is another task that can be assigned to analysts and aims to enhance the performance, prevent musculoskeletal injuries and monitor its risk factors.

Introduction
Swimming research has increased since the inception of the series ‘International Symposium in Biomechanics and Medicine in Swimming’ in the 1970s. Ever since, studies about swimming typically comprise physiology and biomechanics analyses...
Research helped to improve technology and better understand the principles that underpin human swimming performance, and can be classified as basic (fundamental) or field-oriented (applied). In sport sciences, basic research is usually published and has specific academic purposes, whereas field research aims to produce an outcome that can be applied to enhance performance or reduce the incidence of injury and eventually may result in a publication (Bishop et al., 2006). Field research is based on performance analysis, which can be defined as the provision of objective feedback to athletes and coaches through the use of different technologies and statistical analyses. Basic researchers aim to share ground-breaking publications, based mostly on their own research questions; conversely, field researchers in sport sciences aim to answer questions addressed by coaches, athletes and support staff (Buchheit, 2016). In tandem, the end-goal of research tailored towards the practitioner needs does not aim at being just disseminated in the form of a research paper (Buchheit, 2017a). Instead, it aims to give a step further, being the findings explored and providing guidance to key actors in the sports ecosystem (coaches, athletes and support staff).

Regardless of being basic or field-oriented, swimming research is strongly performance-oriented. Performance analysis can be used to: (1) improve performance; (2) monitor progress over time; (3) track changes in performance-related variables; and (4) identify strengths and weaknesses of the athlete and other competitors. Force platform, tethered swimming, speedometer, video-based analysis and inertial sensors are the most common technologies used for performance and biomechanics assessments in competitive swimming. These technologies should be combined with other domains such as physiology, psychology, nutrition or strength and conditioning to backup the decision-making (Mooney et al., 2016). Notwithstanding, swimming is a sport where the interdisciplinary and multidisciplinary approaches are standard frameworks and that the ultimate vision is to move on and become transdisciplinary.

Analysts are expected to collect, analyse and interpret data, and also have good communication and visualisation skills to aid coaches and athletes’ decision-making (Buchheit, 2017b). Coaches frequently conduct qualitative analysis themselves by eyeballing (based on educated guess) and video-based analyses (Wilson, 2008). Analysts should be open to this practical knowledge based on the coaches’ background and past experience. As such, a good balance between qualitative and quantitative analyses is advisable.

A source of concern and one of the main challenges for analysts is the translation of some research into practice. Multiple research is conducted in laboratory settings with costly and time-consuming set-ups, which are hard to replicate in day-to-day testing by analysts. Also, research projects that recruited low-calibre swimmers may fail to have external and ecological validity if applied to high-performance counterparts. Therefore, academic researchers are encouraged to present a detailed description of the competitive level within their articles (e.g., percentage of World Record, FINA points, race time plus SD, minimum and maximum values) and interpret the results and potential applications accordingly. Swimming researchers can design highly controlled testing procedures, whereas analysts quite often must compromise the control of confounding factors, feasibility, minimum disruption of the training schedule and delivering recommendations in a timely manner.
Table 1. Comparison of the tasks carried out between swimming researchers and swimming analysts.

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<tr>
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Even though some overlap, the tasks carried out by swimming researchers and swimming analysts are different (Table 1). Time is needed for the development of research tools, validating new technologies, or new training methods. Conversely, analysts need to work faster to aid decision-making (Coutts, 2016), have a holistic view of performance determinants (Groom & Cushion, 2004; Williams & Kendall, 2007) and advise where athletes can improve. The main goal of a swimming researcher is to gather evidence-based knowledge, whereas an analyst is to deliver evidence-based recommendations to swimmers. Swimming researchers design case–control studies, cross-over studies or randomised control trials to address a research question. Conversely, swimming analysts are more focused on case studies, addressing the swimmers concerns. Researchers deliver the findings of their studies to peers and analysts by publishing research papers, dissertations and thesis, or presentations at scientific meetings. On the other hand, analysts aim to provide recommendations to aid the decision-making of swimmers and coaches by delivering reports, infographics, video clips or hands-on lectures to peers, coaches, support staff and swimmers. The specific tasks of a swimming analyst are set in collaboration with coaches and remaining team staff. The job scope includes: (1) to be updated on scientific literature and translate it into short reports for coaches peruse; (2) to determine the different areas of evaluation (e.g., analysis
of starts, turns and swim stroke by different techniques, race analysis, dryland measurement of muscular strength and power); (3) to design, plan and implement testing sessions; (4) to communicate with coaches and swimmers; (5) to handle data, results and deliver reports; (6) to collaborate with research teams. Therefore, the job scope of a swim analyst requires multiple skills, bridging research and practice.

From what was above mentioned, one can argue that the job scope, practices, tasks and deliverables of swimming analysts are different from swimming researchers. However, we failed to find in the literature any sharing of standard procedures and daily practices carried out by swimming analysts. Swimming analysts engage in the modelling and forecast of the performance, analysts must decide what to test and when to conduct the evaluation sessions. They also conduct race analysis, qualitative and quantitative analyses of the swim strokes, start, turns, and finish. Land-based training is another task that can be assigned to analysts. The aim of this narrative review was to report the best practices of swimming analysts that have been supporting high-performance athletes. It also aims to share how swimming analysts can translate applied research into practice.

**Modelling and forecast of performance**

One important role of an analyst is to run retrospective and prospective studies on a swimmer’s race performance. The tracking, follow-up and forecast of the race time can be carried out based on univariate or multivariate analyses. Univariate analysis consists of the study of performance time-series. It aims to describe or forecast how performance changes over time without considering the influence of determinant factors. For instance, it is possible to assess the stability of the performance from childhood to adulthood (Costa et al., 2011), in an Olympic cycle (Costa et al., 2010) or a competitive season (Costa et al., 2012). Long-term analysis can provide insightful benchmarks for talent development (Allen et al., 2014). Whereas, mid- and short-term analyses can aid swimmers to set target-times at major international competitions (Allen et al., 2015). It was possible to create a tool to easily evaluate the progress of any swimmer between the ages of 12 and 30 years by plotting the age-related performance progression towards the 2012 Olympic gold medal winning time, as showcased with Katie Ledeck and Ryan Lochte (Allen et al., 2014). Another example is the forecast if Adam Peaty would be able to swim the 100 m Breaststroke under 57 s (Barbosa & Hodierne, 2018), which happened one year later, in 2019 (forecast in 2018: 56.83 s, World Record in 2019: 56.88 s).

Conversely, multifactorial analysis aims to describe, explain, and forecast the performance based on the changes of determining factors. These are models where the performance is set as the dependent variable and key-factors that can determine it as independent variables. An analyst must take note of the dependent variable (e.g., race time, time trial, swim velocity) and collect data on the determinant factors (independent variables) by experimental testing or analytical models within days from the competitive event. Biomechanics, energetics, and motor control seem to be the main performance determinants in competitive swimming (Barbosa et al., 2010). Thus, split times, duration of each race phase, stroke kinematics, limb and body kinematics, drag force, thrust are some of the independent variables that can be input in the model. For example, multilevel modelling can be run to determine the speed achieved during each arm-pull (dependent
variable) having as independent variables the arm length, forearm length, hand surface area, handgrip strength, peak swim speed, speed fluctuation, underwater stroke time, mean thrust of the arm-pull, peak thrust and thrust fluctuation (Morais et al., 2020a).

Multivariate models enable the analyst to understand (Morais et al., 2014, 2017; Silva et al., 2007): (1) what are the main independent variables affecting the swimmer’s performance; (2) how dependent and independent variables change over time; (3) what is the partial contribution of each independent variable and how these change over time; (4) how much each independent variable explains the performance at a given point in time. These analyses are mostly underpinned by complex and dynamical systems, making use of data science, large data sets and analytics. An example is the modelling and prediction of an elite female swimmer in the final of the 200 m backstroke at the 2000 Olympic Games by neural network (Edelmann-Nusser et al., 2002). The prediction error was 0.05 s in a final race time of 2:12.64, having as input 19 races and training data in the 4 weeks prior to each race.

The computation of standardised effect sizes is a practical tool on day-to-day tasks of an analyst, provided it is possible to collect more than two measures or population variability is known. Thus, an analyst can run several trials, or compute the variability of a cohort of swimmers of similar profile or performance level. Standardised effect sizes yield the magnitude and direction of difference between two testing moments. In elite sports, effect sizes greater than 0.2 are deemed as meaningful (Buchheit, 2016). Alternatively, standardised effect sizes can also be converted into percentile gains (Barbosa et al., 2020a). Everything else being equal, the percentile gain can provide insight on how much a swimmer will improve if benchmarked against a hypothetical group of 100 peers.

One of the challenges is determining the significance of any differences observed and sharing this significance to coaches and swimmers. Same challenge has been reported in clinical settings and in this field it was put forward the concept of ‘minimum clinically important difference’, which aims at identify the clinically important and meaningful effects of treatments in patients (Jaeschke et al., 1989). Likewise, some analysts believe it can also be insightful to learn the smallest important effect, or smallest worthwhile change of their athletes (Hopkins et al., 2009). For instance, to stay in contention for a medal, an Olympic swimmer should improve performance by 1% within a competition and by 1% within the year leading up to the Olympics but an extra 0.4% improvement will substantially increase the chances of a medal (Pyne et al., 2004).

In summary, analysts have at their disposal several tools to model and forecast performance. In the short- and mid-term, it can help set target-times at major competitions. In the long-term, it provides insights on talent and career development.

**Training and testing**

Biomechanical testing can provide valid and reliable assessments in both dry-land and in-water environments and assist in understanding the relationship between training load and the induced adaptations. A primary task of an analyst is to decide which variables should be measured. Changes in swimming speed mainly relate to the forces acting on the swimmer in the direction of motion, which are propulsion and drag (Toussaint & Truijens, 2005). Propulsion depends on dry-land strength and power abilities and...
technique, i.e., mechanical power and Froude efficiency (Toussaint, 1990; Toussaint & Truijens, 2005); whereas, drag relates to body size and dimensions (Kjendlie & Stallman, 2011) and technique (drag coefficient, Havriluk, 2006). As shown in Figure 1, other variables can be related to propulsion and drag and, therefore, are also worth monitoring in any swimming programme. Although many, some of them are of common interest for other staff members and can be obtained in cooperation. For instance, mechanical power can also be relevant for the strength and conditioning coach and physiotherapist practices. Besides, as the testing can be time-consuming and demanding, analysts should combine practical and affordable measurements with technological ones to cover a wider range of variables and, in a viable manner, get a better view of the swimmer’s actual status. For instance, Barbosa et al. (2019) combined simple (anthropometry and maximal strength) and more complex measurements (tethered force, speedometer and video analysis) to provide insights on how an Olympic sprinter improved the 50 m freestyle performance. In this sense, short duration and in-water protocols may be preferred as they are specific, time-saving, have a low injury risk and hardly produce residual fatigue and delayed onset muscle soreness. Hence, they can be used during taper and even one day before the competition, as performed by Barbosa et al. (2021) with speedometer plus video analysis.

The timing of the evaluation session is the next major decision to be made by the analyst. Interpreting the relationship between training load and the induced adaptations requires synchronising the testing schedule with coaches’ planning so that ideally swimmers are evaluated at the beginning and end of every intensification and taper periods (Hellard et al., 2013). The frequency of distinct tests may differ and should be adjusted according to the response time of each variable (Figure 2). For instance, technique (measured by the drag coefficient) can be highly responsive in the short-term (e.g., one week, Havriluk, 2006). Conversely, strength and power abilities may require 6–12 weeks to elicit positive results (Aspenes & Karlsen, 2012).

![Figure 1. A model for understanding the relevant variables that affect speed and forces in swimming.](image)
Although not directly related to biomechanics, the quantification of internal and external training loads within intensification and taper periods is critical for understanding training effects (Barbosa et al., 2019; Hellard et al., 2019, 2017; Impellizzeri et al., 2019). For instance, the volume prescribed in different training intensities is a well-known method for quantifying external load (Barbosa et al., 2019; Hellard et al., 2017), whereas the internal load can be assessed by the session RPE method (Foster et al., 2001; Wallace et al. 2009; Barbosa et al., 2020c). These parameters should be of interest to the analyst as they can considerably affect drag and propulsion-related variables. When systematically repeated, the analysis of load–response relationship can reveal training trends, provide recommendations within and between cycles, improve performance forecast, and assess the actual athlete’s status for competition (Smith et al., 2002).

**Race analysis**

Swimming race analysis is a tool to evaluate competitive performance of a swimmer and provide information for specific race pace training. Data collection has evolved over the past decades from manual (Pai et al., 1984) to fully automated real-time image recognition technologies (Arellano et al., 2018; Balius et al., 2008). Until these days, race analysis encompasses exclusively the description of the swimmer’s kinematics. Research has been conducted lately to make available simple and yet valid models to estimate swim kinetics (drag, power, propulsion) in competition settings, similar to the models used in other sports (Barbosa et al., 2015).
A swimming race can be broken into the start, swim stroke (also called clean swimming), turn and finish phases (Figure 2). In each phase, the analyst can consider several sub-phases (Mason & Cossor, 2000). For instance, the start analysis can include the block time, flight time, underwater time and distance (Garcia-Hermoso et al., 2013; McGibbon et al., 2018; Saavedra et al., 2012). The swim stroke is broken into different sections in each lap (e.g., 15 m, 25 m, 35 m, 45 m and 50 m marks in a long course pool). Stroke frequency, count, length and index are measured in each of these sections (Morais, Marinho, Arellano, & Barbosa, 2019). The analyst calculates the average values over each stretch of the race, or alternatively cycle-by-cycle variations, notably in sprint events (Simbaña-Escobar et al., 2018). It can help to adjust race strategy from heats to semi-final and final, and provide guidance for training within and between macrocycles. A detailed race analysis is conducted in short- and middle-distances (50 m to 400 m); whereas, a less detailed analysis is carried out in long-distance events (800 and 1500 m) (Morais et al., 2020b).

Currently race analysis is conducted mostly by video-analysis using digital video cameras (Morais et al., 2019). The simpler set-up comprises one single panning camera that tracks the swimmers over the race. Alternatively, a set of fixed cameras at different distances can also be set-up. The cameras are connected to a video selector and the film is saved to a digital storage system. The pool sections are calibrated using external references or the lane rope marks (Morais et al., 2019). Dedicated softwares can be selected to analyse the change in swimmer’s position and time over the race. The analysis can be manual, semi-automatic or fully automatic. In manual analysis, the analyst must track the swimmer frame-by-frame and record the position and/or time-stamp over different events of the race. In semi-automatic analysis, the software can shift from one event to another, with no need for the analyst to move the video clip frame-by-frame. Therefore, the semi-automatic analysis is quicker than the manual alternative. More recently, fully automated analysis has been implemented, and without human intervention the process can be ten times faster than the manual procedure (Arellano et al., 2018). It allows splitting the race into smaller sections (e.g., every 5 m) and provides even more details on the race performance.

Upon collection, raw data (position and time-stamps) are processed and saved to databases. Reports are shared with coaches and athletes in the form of spreadsheets that include graphs and numerical data. The same data can be displayed differently among analysts, according to individual and institutional report layout preferences. The reports may present within- and between-subject comparisons and/or comparisons against modelled performances or forecasts.

**Swim stroke**

It has been proposed in the swimming literature that swimmers should be deemed as non-linear, complex and dynamic systems (T. M. Barbosa et al., 2016) and indicated that there may exist different ways to reach the same goal. This suggests that stroke technique and its relationship to performance is individual to each athlete, as there exists many varying and successful stroke models in elite performance we seek to understand. The use of different tools and devices improve our understanding of swim technique and its contribution to performance. Using cameras from different angles through specific software provides the necessary visual feedback within a kinaesthetic sport/environment,
drawing the connection between ‘feel’ (Dekerele, 2020) and visual (i.e., qualitative) feedback to accelerate the learning process and enhance the effectiveness of the technical intervention.

Evaluating body shape and its impact on passive (i.e., gliding in the streamline positions) and active (i.e., propelling the body by limbs’ actions) drag measures can provide an initial understanding of the athlete’s swimming form and streamline ability (Naemi et al., 2010). Papic et al. (2020a) argued that digitising body landmarks manually from video clips seems outdated. Another alternative is the use of mechanical speedometers (Vilas-Boas et al., 2010). With use of a more recent alternative of 2D body landmark digitisation by neural networks, one can determine an athlete’s glide factor, relating to the athletes’ in-water body form and also provides an objective means to race suit selection. This method has been calculated to digitise body landmarks up to 233 times faster than manual operators and relative errors are within the bounds of manual digitisation (Papic et al., 2021). Such method can be widely available in the near future to swim analysts because it significantly decreases the amount of time spent on set-up, data collection and data handling. Set-up is quite straightforward as all it is required is an underwater camera to capture the underwater glide and a calibration frame. A dedicated software is used for neural network training of the anatomical landmarks to be tracked. Then, neural network training outputs are transferred to a local laptop to digitise the body landmarks of all tested swimmers. As far as the end-user is concerned, the main difference in comparison to conventional manual tracking is the need to train the neural network beforehand.

Regarding athlete free swim ability, Ganzevles et al. (2019) demonstrated the usefulness of a tri-axial accelerometer for quantifying jerk cost and swimmer smoothness where findings offer insight into refined flow and coordination patterns of elite swimmers. Intra-stroke velocity and intra-cyclic stroke variations measured with inertial measurement units provide promising possibilities into body segment coordination and sequence timing (Worsey et al., 2018).

Stroke cycle propulsion can be derived from experimental data or analytical procedures, both having advantages and disadvantages. Current experimental methods to assess propulsion are obtrusive and more practical to measure using hand paddles (Tsunokawa et al., 2019). Instrumenting a swimmer may constrain the technique because it can affect the range of motion, hydrodynamic drag and propelling efficiency, among other swimming determinants. Thus, an alternative is relying on indirect extrapolation measures that infer power output (Barbosa et al., 2015). To date there is no approach that clearly outweighs the other. Swim analysts should consider both and select the most feasible procedure based on testing goals and settings. For instance, analytical procedures can yield insights at competing settings because it is not possible to instrument the swimmer. Conversely, experimental evaluation is an interesting method in dedicated testing sessions or during regular training sessions.

One of the biggest challenges for swimmers is how to enhance the stroke technique. Most of the times they rely on watching it (e.g., from video clips) or feeling it (kinaesthetic awareness). From an unconventional approach, Hermann et al. (2020) poses an insightful means of understanding the swimmer’s interaction with water through the sonification of pressure changes during free swimming. This ability to combine multiple data channels into a single sound stream provides an alternative
method for swimmers to listen to their stroke (i.e., bio-feedback) as opposed to mainstream means of visual and kinaesthetic feedback.

Testing and analysing free swim technique should be associated with race performance goals. The protocol design should align with race requirements, rather than capturing measures from detached efforts in isolation. We need to adapt testing to refine foundational and fundamental motor skill requirements for swimming by measuring and understanding already known factors correlated to swim performance. Through generative conversations with coaches, analysts need to align testing protocols to athlete priorities to be better positioned to facilitate the path to performance enhancement.

**Starts, turns & finish**

The final piece of the puzzle for biomechanists working with swimmers is the skill components of starts, turns, and finishes. Evaluation of the importance of the starts and turns has been measured during international swimming competitions (Cossor & Mason, 2001; Mason & Cossor, 2000; Morais et al., 2019; Veiga & Roig, 2017). Distances vary slightly between researchers but tend to be from the gun signal to the 15 m for a start, 5–7.5 m into the wall and then 7.5–15 m out from the wall in a turn, and 5 m for the finish. Success in these skills comes from maximising the power produced when leaving the block/wall and maintaining the velocity through drag reduction and optimal underwater undulatory technique (Arellano et al., 2002).

The aquatic environment limits equipment available for kinetic analysis within the sport of swimming. However, over the last 20 years kinetic analysis has become more feasible, particularly for starts and turns (Figure 2). Technology used by analysts to determine kinematic and kinetic measures of the starts and turns include instrumented starting blocks and turning platforms, as well as inertial sensors (Mooney et al., 2015; Slawson et al., 2010). With the cost of these systems beyond the reach of many swimming programmes, researchers have developed a reliable system that is cost effective (De Jesus et al., 2020). Links have been made between forces produced in starts and turns with simple land measures and techniques as an alternative, and affordable option, to pool testing (Cuenca-Fernández et al., 2018; Keiner et al., 2019). Regardless of the technology it is important to break the skill into different phases to determine the strengths and weaknesses for the individual.

Whilst researchers and biomechanists can determine the cause of the technical limitations to the skill phases within swimming, if they are unable to change the current behaviour of the swimmer then the skill will remain a problem. Krause (2017) recommended the use of augmented feedback to improve skill performance using both video and time information. This is in contrast to skill acquisition researchers who recommend a constraints led approach to adapt performances (Otte et al., 2020). Coaches and biomechanists understand the importance of ‘feel’ within swimming which is why there is a need to enable swimmers to develop a kinaesthetic awareness that allows them to adapt when external feedback is provided (Dekerle, 2020). The timing, type, and quality of feedback will vary depending on the phase of skill adaptation that the swimmer is in. Intrinsic mechanisms should enable the athlete to learn behaviours that result in permanent skill improvements.
The ability to provide feedback in a timely manner assists practitioners working within the daily training environment. Qualitative feedback tends to be used more frequently than quantitative feedback but the frequency of the interaction with the coach-athlete partnership can have an impact on the start and turn skill enhancement from one major competition to the next.

**Land-based training**

Numerous studies have shown positive correlations between swimming speed and dry-land strength and power abilities (Beretić et al., 2013; Dopsaj et al., 1999; Garrido et al., 2012; Gola et al., 2014; Weston et al., 2015). Assessing variables which the literature supports, presenting these to the coaching staff, tracking them over time, and making training recommendations is the main role of an analyst.

The start is the aspect of swimming most correlated with strength training. Research suggested the time taken to reach predetermined set distances of 5, 10 and 15 m, was more highly related to vertical squat jump and countermovement jump than muscle strength and other parameters (Mason & Cossor, 2000). The correlations of dry-land strength and in-water performance seems to vary with swimming distance (Gola et al., 2014). The relative importance of strength increases as the distance decreases. Several dryland strength interventions reported positive effects on sprint swimming performance (Aspenes & Karlsen, 2012; Girold et al., 2007; Weston et al., 2015). However, the wide variety of the protocols and the diversity of results make it necessary to examine the existing evidence to reach a consensus of the most effective dryland strength practices. Moreover, few studies have assessed non-front crawl strokes and endurance events. Most studies utilise traditional strength and conditioning exercises, bench press, back squat, and deadlift. Other studies have used elbow flexion and extension as their corollary with swimming performance (Gola et al., 2014). However, there is not a standard parameter or test for analysing overall strength enhancements.

Land-based analysis also aims to prevent musculoskeletal injuries and monitor its risk factors (Figure 2). Swimmers frequently develop shoulder pain. The shoulder is the most frequently injured joint in swimming (McMaster & Troup, 1993). The prevalence of shoulder pain varies from 3% to 91% (Tessaro et al., 2017). Biomechanics, training volume, and repetitive sport stresses are the biggest contributors to shoulder injury (Grote et al., 2004; Johnson, 2003; Keskinen et al., 1980; McFarland & Wasik, 1996; Rovere & Nichols, 1985; Stocker et al., 1995; Vizsolyi et al., 1987). Risk factors that were only investigated by a single study assigned a low level of certainty as there is insufficient evidence to make a conclusion and requires future investigation to aid an evidence-based practice by analysts. These risk factors include the triceps length (Tate et al., 2012), latissimus length (Tate et al., 2012) and internal/external rotation endurance (Beach et al., 1992). The trunk and knee are also common sites for injuries in swimmers (Kerr et al., 2015). Notwithstanding, measurable risk factors have not been specifically assessed in swimmers.

In summary, more research is needed to quantify variables which correlate swimming performance with strength and conditioning and those which may predict injuries in swimmers. Until this occurs, strength and conditioning and injury prevention programmes must be individualised. Stroke specialities, training history, injury history, flexibility, body composition, and swimming biomechanical flaws are factors to consider when developing an
individualised strength and conditioning and injury prevention programme. The level of education of coaches, communication, procedures for field effectiveness have also been put forward as some of the hypothetical key-factors (Cossor et al., 2014; Hellard, 2014).

Conclusions

Swim analysts provide insightful information to athletes and coaches that aids their decision-making (Figure 2). Swim analysts can forecast performances and target-times in different time frames. They should also do on regular basis race analysis at official competitions and run testing sessions on underlying performance determinants of the swim stroke, start, turns and finish. Besides in-water testing, on-land assessment of strength and conditioning and injury prevention are part of the job scope.

These days, one large portion of the time is spent setting-up tests, collecting and handling data. Machine learning, big data, automatic evaluation tools and systems enable streaming information to athletes on the go. As this technology becomes readily available to most analysts, the job scope will shift more towards the analysis and interpretation of the data, being more engaged in the recommendation exercise to athletes and coaches.

Increasingly, the analyst is seen as part of the swim team, supporting athletes, and delivering quality recommendations to help coaches in the decision-making. Coaches, analysts and researchers must continue to strive to work in synergy supporting athletes to excel, serving the analyst the role of hinge between the former and the latter. Ultimately, the analyst should be able to address the challenges shared by the swimmer, providing insightful solutions that are evidence-based on cutting-edge research.

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