

# Peaking for the Olympic Games. An Integrated Approach Developed With the French National Swimming Team for Paris 2024

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## Abstract

Bosquet, L, Bretonneau, Q, Pla, R, Vachon, A, and Morales-Artacho, A. Peaking for the Olympic games: an integrated approach developed with the French national swimming team for Paris 2024. *J Strength Cond Res* 38(11): 1981–1986, 2024—In energy-dominant disciplines, such as swimming, performance depends largely on the difference between the levels of fatigue and physical fitness: the greater this difference, the higher the probability of reaching a peak performance. The main challenge before major events such as the Olympic games is therefore in identifying the most efficient strategies to reduce the fatigue accumulated during previous mesocycles, while maintaining, or even improving the level of physical fitness. The most widespread strategy relies in the manipulation of training load parameters. This is the taper period, which has been shown to improve performance by  $\approx 2\%$  in elite athletes. However, tapering may not be sufficient for the most tired athletes. In this case, the strategy commonly used consists in combining the manipulation of training load with the implementation of recovery methods. Regardless of the strategy, we perceive that the challenge for athletes, coaches, and sport scientists is to estimate the level of cumulative fatigue as precisely as possible to individualize the recommendations. This relies not only on the identification of valid markers but also on the ability to interpret their variations over time. The objective of this article is to present the method initially developed in a European champion professional rugby team and now implemented with the French swimming team as part of its preparation for the Paris 2024 Olympic and Paralympic Games. More specifically, this article provides some details about the conception of the monitoring dashboard, and the method used to interpret changes over time to categorize the level of fatigue.

**Key Words:** taper, performance, fatigue, recovery, training load, interpreting change

## Introduction

In energy-dominant disciplines such as cycling, running, rowing, or swimming, performance depends largely on the difference between fatigue levels and physical fitness: the greater this difference, the greater the probability to achieve maximum performance is high (3). The main challenge before major events like the Olympic Games therefore consists of identifying the most effective strategies to reduce the fatigue accumulated during previous mesocycles, while maintaining, or even improving the level of physical fitness. The most widespread strategy, designed as the taper period, relies in the manipulation of training load parameters (14). In their meta-analysis, Bosquet et al. (4) established that the optimal strategy to achieve peak performance in high-level athletes was a gradual 40–60% reduction in training volume over a two-week period, while maintaining exercise intensity and frequency. The weighted average performance gain was  $\approx 2\%$ , which is considerable in the context of elite sport, because the smallest enhancement of performance that has a substantial effect on the probability to win a medal has been estimated to about one-third of the typical variation of performance in competition (12), which is approximately 0.5–1% in swimming (28).

Nevertheless, Bosquet et al. (4) also reported an important interindividual variability, the benefits being occasionally very different between athletes. According to the model by Banister and Fitz-Clark (3), the key factor to consider in individualizing this strategy is the level of fatigue: the higher it is, the greater the reduction in training load should be to obtain a peak performance. This hypothesis has been confirmed in mathematical modeling studies (29) as in interventional studies (2,5,32). In this context, we understand the necessity of disposing a training load monitoring system that allows to estimate as precisely as possible the level of cumulative fatigue before major events, to individualize the taper period.

The monitoring of athletes' training load, and more generally the monitoring of their adaptation to this training load, has received the attention of many research teams over the past 3 decades, as evidenced by the exponential rise of scientific publications on this topic (15,20). The question to date is no longer related to the identification of markers that make it possible to monitor readiness to perform or avoid maladaptation, even if there is always room for innovation and debate around existing solutions. The challenge is rather to integrate these measures into a longitudinal follow-up, allowing a more precise monitoring of an athlete's adaptation over time, to individualize the training load. This raises the question of the interpretation of change: from which threshold should we consider that change in

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a particular marker falls within random error or reflects a true change? This question is paramount for the teams involved in the monitoring of elite athletes. Indeed, the more accurate the interpretation, the more relevant the decision will be. This problem is also at the heart of the D-Day project.

Funded by the French National Research Agency as part of the preparation for the Olympic and Paralympic Games of Paris 2024, the aim of this project is to provide national teams with specific tools and recommendations to estimate the level of fatigue several weeks before the Games, to help individualizing recovery, tapering, and peaking strategies. The purpose of this opinion article is to introduce the approach that has been adopted and the issues associated with it. This framework should not be considered as definitive or as a synthesis of existing approaches, but rather as a contribution to the monitoring of athletes' adaptation, to encourage the debate within the scientific community, and eventually to set up studies that will make it possible to refine monitoring methodologies. The approach we have developed is based on 3 distinct steps. The first one concerns the elaboration of the monitoring dashboard, and more specifically the tests and measures to be integrated to estimate the level of accumulated fatigue. The second step refers to the interpretation of changes observed over time, whereas the third one focuses on the categorization of fatigue from the interpretation of these changes. Each specific step is described below.

**The First Step: Choosing Tests and Measures to be Included in the Monitoring Dashboard**

As already mentioned, considerable efforts have been made since the early work of Manfred Lehmann et al. (18) to identify the most sensitive markers of fatigue and overreaching. Systematic reviews discussing the pros and cons of each of them are available (24), and several methodological frameworks have been proposed to guide their integration into a monitoring systems (23,30). Three criteria were used to choose the tests and measures to be included in our monitoring dashboard. The first was the absence of a pathognomonic sign of overreaching. In fact, overreaching is a complex diagnosis based on the interpretation of changes in athletes' physiological, psychological, and neuromuscular profiles (10,21,26). Specific measures are therefore needed in each of these 3 categories to obtain the most accurate estimate of their respective

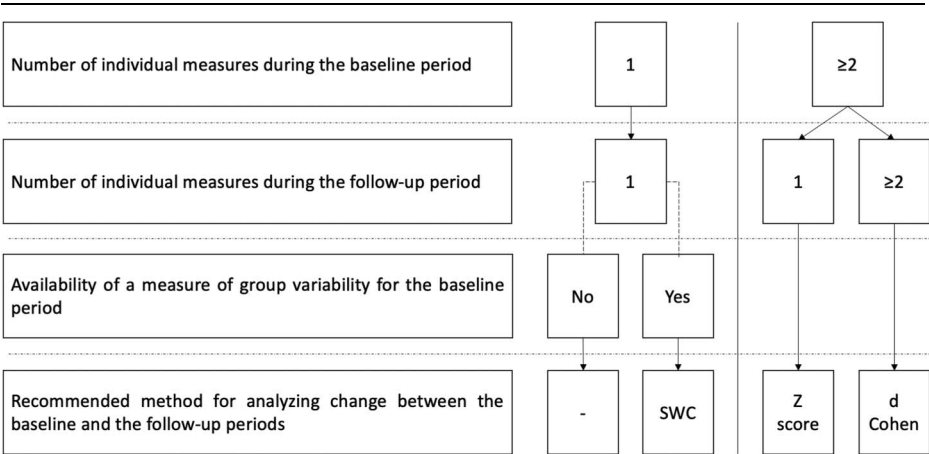
level. The second was the need to minimize random error to provide the most precise interpretation of changes over time. Tests and measures were therefore selected based on their reliability. The third criterion, and probably the most important, was a systematic application of Occam's razor principle (8). In fact, it is counter-productive to choose the most valid and reliable measures if athletes and coaches do not adhere to the approach because they consider that the level of constraint is too high. In the end, even if the monitoring dashboard included the same profile categories for all athletes, specific tests and measures varied between training groups, so that our approach would adapt to their training model, not the other way around. Therefore, this approach requires checking the validity, reproducibility, and accessibility of the measures, as well as a consultation with the athlete support staff to define the testing periods and their specific objectives (i.e., preventing overreaching, reaching a peak performance, etc).

In the context of the D-Day project, several periods of measures were identified with coaches and athletes.

- A 10-day reference period scheduled 2–3 weeks after athletes resume training in the early season, to collect as much information as possible about each of the markers integrated into the dashboard. The aim was to define the reference level of these measures. Two scenarios were considered: (a) each new reference period replaces the previous one in young athletes (first Olympic cycle), considering their potential progression from one year to the other; and (b) each new reference period is added to the previous one in more experienced athletes (second or third Olympic cycle) because their physical fitness is quite stable. The number of measurements collected during this period could range from 1 to 10 (psychological profile: 1; neuromuscular profile: 3; and physiological profile: 7–10).
- A 3-day follow-up period, scheduled after an overload period or before a taper period. The number of measurements collected during this follow-up could range from 1 to 3 (psychological profile: 1; neuromuscular profile: 1–3; and physiological profile: 3).

**The Second Step: Interpreting Change**

The key point of this step is to identify the threshold beyond which we can reasonably consider a change to be real, regardless of whether it is positive or negative. Several approaches have been



**Figure 1.** Decision tree used within the D-Day project to determine the change analysis method to be employed based on the number of measurements made during the baseline and the follow-up periods. SWC = smallest worthwhile change.

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**Table 1****Thresholds used for each statistical procedure to determine the magnitude of the difference.\***

Interpretation	Cohen's <i>d</i>	Z score	SWC*
Trivial negative change	$ d  < 0.2$	$ Z \text{ score}  < 0.67$	$ \Delta  < 1 \text{ SWC}$
Small negative change	$\geq 0.2$ and $< 0.5$	$\geq 0.67$ and $< 0.96$	$\geq 1 \text{ SWC}$ and $< 3 \text{ SWC}$
Moderate negative change	$\geq 0.5$ and $< 0.8$	$\geq 0.96$ and $< 1.34$	$\geq 3 \text{ SWC}$ and $< 6 \text{ SWC}$
Large negative change	$\geq 0.8$ and $< 1.2$	$\geq 1.34$ and $< 2.33$	$\geq 6 \text{ SWC}$ and $< 10 \text{ SWC}$
Very large negative change	$\geq 1.2$	$\geq 2.33$	$\geq 10 \text{ SWC}$

\*SWC = smallest worthwhile change.

proposed in the literature. Hecksteden et al. (11) proposed to define this threshold using a Bayesian approach, comparable to that used in the athlete's biological passport. Verboon and Peeters (33) suggested a different approach based on applying general logistics models to single-case designs. For their part, Hopkins et al. (13) and Buchheit (6) promoted a simple and accessible approach based on magnitude-based inference. Each of these methods, along with others that have not been presented, because the list is not exhaustive, has pros and cons. If we consider that accessibility is a central parameter in the implementation of this type of monitoring in an elite setting, then the method proposed by Hopkins et al. (13) and Buchheit (6) seems quite suitable. As interesting and relevant as the method is within the context of elite athletes' follow-up, this approach suffers some limitations (34). Although it may be useful in athletes' monitoring to compare individual values with group means (25), it is for example questionable to define the smallest worthwhile change (SWC, equation 3) from the data of the group when individual data are available, especially when we unanimously consider that individualization is the rule with this population. Therefore, we developed an adaptation of this approach first with professional rugby players (32) and thereafter with tier 4 and tier 5 swimmers (19) within the D-Day project. The following decision tree, illustrated in Figure 1, was used:

However, it requires the tests to be repeated on several occasions to obtain a mean and a *SD*.

$$d = (\bar{x}_{\text{follow-up}} - \bar{x}_{\text{baseline}}) / \text{sd}_{\text{pooled}}, \quad (1)$$

where *d* is Cohen's *d*,  $\bar{x}$  is the mean value at baseline or during the follow-up, and  $\text{sd}_{\text{pooled}}$  is the pooled standard deviation, calculated as follows:

where  $\text{SD}_{\text{pooled}}$  is the pooled standard deviation, *SD* is the standard deviation at baseline or during the follow-up, and *n* is the number of measurements at baseline or during the follow-up.

Scenario #2: a mean and a *SD* are available for the reference period, but there is only a single measure for the follow-up. The magnitude of the difference is estimated from the *Z* score (equation 2) and interpreted according to the scale presented in Table 1. Like Cohen's *d*, the advantage of this approach is that it provides a reference measure specific to each athlete. However, it requires a normal distribution of the reference value and relies on a single value for the follow-up. Although the first limit can be easily controlled by collecting enough data, the second one necessitates to choose the most reproducible measures, otherwise, the risk of overestimating or underestimating the actual change is important.

$$Z = (\bar{x}_{\text{follow-up}} - \bar{x}_{\text{baseline}}) / \text{sd}_{\text{baseline}}, \quad (2)$$

$$\text{sd}_{\text{pooled}} = \sqrt{((\text{sd}_{\text{baseline}}^2 \times (n_{\text{baseline}} - 1) + \text{sd}_{\text{follow-up}}^2 \times (n_{\text{follow-up}} - 1)) / (n_{\text{baseline}} + n_{\text{follow-up}} - 2))},$$

Scenario #1: a mean and a *SD* are available for the reference period and the follow-up. The magnitude of the difference is estimated from Cohen's *d* (equation 1) and interpreted according to the scale presented in Table 1. The advantage of this approach is that it provides a reference measure that is specific to each athlete.

where *Z* is the *Z* score,  $\bar{x}$  is the mean value at baseline or during the follow-up, and *sd* is the standard deviation of individual measures at baseline.

Scenario #3: there is only one measure for the baseline and during the follow-up, then we use the group variability to

**Table 2****Individual variations of physiological, psychological, and biomechanical parameters between the baseline and the follow-up periods calculated with the specific method.\*†**

Measure	Physiological profile			Psychological profile				Biomechanical profile	
	HR rest	HR exercise	HR recovery	POMS fatigue	POMS vigor	POMS EI	POMS EI* <0	TS force	TS impulsion
N measure baseline	7 to 10	7 to 10	7 to 10	1	1	1		3	3
N measure follow-up	3	3	3	1	1	1		1	1
Statistical method	Cohen's <i>d</i>	Cohen's <i>d</i>	Cohen's <i>d</i>	SWC	SWC	SWC	—	Z score	Z score
Athlete 1	—	—	1.55	1.87	−5.04	−4.34	Yes	—	—
Athlete 2	—	−2.68	0.88	—	—	—	Yes	−2.75	—
Athlete 3	—	−2.15	—	2.81	−16.38	−11.71	Yes	−3.96	—

\*HR = heart rate; POMS = profile of mood states; EI = energy index; EI\* = energy index during the follow-up period; TS = tethered swimming; SWC = smallest worthwhile change.

†Cells in emdash: a positive change or a trivial negative change, cells in bold: a small negative change, cells in italic: a large or a very large negative change.

**Table 3****Individual variations of physiological, psychological, and biomechanical parameters between the baseline and the follow-up periods calculated with the SWC method.\*†**

Measure	Physiological profile			Psychological profile				Biomechanical profile	
	HR rest	HR exercise	HR recovery	POMS fatigue	POMS vigor	POMS EI	POMS EI* <0	TS force	TS impulsion
N measure baseline	1	1	1	1	1	1		1	1
N measure follow-up	1	1	1	1	1	1		1	1
Statistical method	SWC	SWC	SWC	SWC	SWC	SWC	—	SWC	SWC
Athlete 1	—	<b>-1.49</b>	—	<b>1.87</b>	<i>-5.04</i>	<i>-4.34</i>	Yes	—	—
Athlete 2	—	—	—	—	—	—	Yes	<b>-1.05</b>	—
Athlete 3	—	—	<i>6.30</i>	<b>2.81</b>	<i>-16.38</i>	<i>-11.71</i>	Yes	<b>-1.33</b>	—

\*HR = heart rate; POMS = profile of mood states; EI = energy index; EI\* = energy index during the follow-up period; TS = tethered swimming; SWC = smallest worthwhile change.

†Cells in emdash: a positive change or a trivial negative change, cells in bold: a small negative change, cells in italic: a large or a very large negative change.

estimate the magnitude of the difference, as recommended by Buchheit (equation 3), and we use the appropriate scale for the interpretation of SWC (Table 1). The advantage of this method is that it allows an estimation of change, even if there is only one measure at baseline and during the follow-up. However, as already mentioned, its main disadvantage is that the interpretation criterion (i.e., SWC) is defined based on the group's values, which remains an important limit when the objective is to individualize the taper period.

$$SWC = 0.2 \times \text{between-athlete } SD_{\text{baseline}}, \quad (3)$$

where SWC is the smallest worthwhile score, and sd is the standard deviation of the group at baseline.

This approach is illustrated in Table 2, which presents calculations made with these 3 methods using data collected from 3 swimmers of international level (tier 4), whereas Table 3 presents calculations made with the SWC method only, irrespective of the scenario of the decision tree. It should be noted that pros and cons of these statistics are more deeply discussed in the review by Thornton et al. (30).

### The Third Step: Categorizing Fatigue

The monitoring of an athlete's adaptation to training load can be used to ensure that previously determined development goals are being achieved or are in the process of being achieved, or more generally to estimate the readiness to perform in competition. As part of the D-Day project, the objective is rather to categorize the level of fatigue before taper periods to individualize training and recovery strategies during the final 2–3 weeks before the main competitions. Therefore, it is a matter of considering the variations of all the markers

integrated into the dashboard to estimate the level of cumulative fatigue. Depending on the context, 2 to 3 categories of fatigue are proposed to the coach (Table 4), and the training and recovery recommendations obviously depend on the category. A standard taper model may be recommended if the cumulative level of fatigue is moderate (4); a taper with a larger decrease in training volume or a longer taper duration if the level of fatigue is high (29); or a taper with the addition of proactive recovery methods if the level of fatigue is very high or the athlete is diagnosed as overreached (17,32). In this latter scenario, recovery methods are chosen according to the expected effect on the most altered parameters of the dashboard and according to prior implementation with each athlete (16). This general approach is refined over time (i.e., successive competitive seasons), to simplify the process as much as possible (Occam's razor principle), by focusing on fatigue markers and recovery methods that work best for each athlete. This type of strategy requires time to be effective and underlines the importance of education of young athletes in the high-performance structures, which should enable them to experiment this kind of tools so that they can use them routinely during their careers.

### Perspectives

A next step should be the identification of the variables that could alter the interpretation of changes and to integrate them into the monitoring dashboard. This is the case, for example, of resilience. Indeed, Goss (9) showed that swimmers who have been participating in the same period of overload training and were facing a similar decrease in performance capacity could have diametrically opposite results to the profile of mood states (POMS) depending on their level of resilience. Therefore, it is important to evaluate this personality trait to define the level of confidence that one can have in the results of the other questionnaires of the monitoring dashboard. This is what is done in the D-Day project with the CD-RISC questionnaire (7).

It is also necessary to refine the decision-making algorithm presented in Table 4 to improve the estimation of level of fatigue. Robertson et al. (23) provide a very interesting framework in that purpose. Some computational possibilities like statistical clustering methods, deep learning, or other artificial intelligence (AI) approaches may be used in this purpose. These tools could be relevant not only at the fatigue-classification level but also in the selection of the measures to be included in the monitoring dashboard and the criteria used to interpret their changes (steps 1 and 2 of our approach). If the interest of AI seems obvious in this context, it remains associated with several limitations that must

**Table 4****Criteria used for the categorization of fatigue.\***

Criteria	Scenario	Category
Algorithm 1		
Multiple small to moderate negative changes and no more than 1 large negative change in 2 distinct profiles	1	NF
At least 1 large negative change in 2 distinct profiles	2	OR
Algorithm 2		
Multiple small negative changes and no more than 1 moderate negative change in 2 distinct profiles	1	NF
At least one moderate negative change and no more than 1 large negative change in 2 distinct profiles	2	AF
At least 1 large negative change in 2 distinct profiles	3	OR

\*NF = normal fatigue; OR = overreaching; AF = acute fatigue.



**Table 5****Decision making of the level of fatigue with the specific method and the SWC method.\***

Athlete	Specific method					SWC method				
	Physiological profile	Psychological profile	Biomechanical profile	Scenario (algorithm 1 see Table 4)	Group	Physiological profile	Psychological profile	Biomechanical profile	Scenario (algorithm 1 see Table 4)	Group
1	1 large negative change	1 moderate negative change and 3 large negative changes	Nothing to report	2	OR	1 moderate negative change	1 moderate negative change and 3 large negative changes	Nothing to report	1	AF
2	2 large negative changes	1 large negative change	1 large negative change	2	OR	Nothing to report	1 large negative change	1 moderate negative change	1	AF
3	1 large negative change	1 moderate negative change and 3 large negative changes	1 large negative change	2	OR	1 large negative change	1 large negative change	1 moderate negative change	2	OR

\*SWC = smallest worthwhile change, OR = overreaching; AF = acute fatigue.

be kept in mind before producing a model. Beyond requiring high-quality data and secure databases, which is an essential condition for athletes' monitoring, whether AI is used or not, one of the main limitations is that these models do not provide an explanatory link between the proposed solutions and the underlying mechanisms. This means that AI does not exempt interventional studies with elite athletes to understand the mechanisms involved and ultimately to polish the model.

Although it was developed with and for elite athletes, the approach presented in this article is also suitable for other populations, such as patients with chronic diseases or those who are prone to professional burnout. In both cases, the level of evidence on the benefits of physical activity and more generally of lifestyle habits is well established (1,22,27,31). However, physical exercise professionals are faced with the same difficulty as coaches: having tools enabling them to adjust exercise prescription to the level of cumulated fatigue. This is a key point for the effectiveness of exercise programs, but it is also for the long-term adherence of subjects, which is probably one of the most important determinants of health. The general principles presented above also apply in this context, especially Occam's razor. The next step is to integrate them in a systematic way into physical activity programs, to adapt the interpretation scale and the decision tree to the specificities of each population.

### Practical Applications

As already mentioned, the fundamental idea that must guide the implementation of this approach is the Occam's razor principle. First, this requires identifying all the markers collected daily, weekly, or monthly by the support staff to identify those that can be integrated into the monitoring dashboard without adding new tests. This is very important for athlete buy-in and more generally for their physical integrity. Indeed, it is not necessarily a good idea to add new tests (either maximal or submaximal) to an already very high training load, especially if they require the acquisition of new equipment, new skills by the staff, or they lengthen the time spent at the training site. Therefore, the challenge lies in testing in a relevant way without disrupting the usual schedule or being too time consuming or physically demanding. One of the difficulties of this approach is that the level of cumulated fatigue can be estimated differently according to the method

used to interpret changes (Table 5) or the method used to categorize the level of fatigue (Table 4). Specific methodological studies are probably needed to clarify this point. Nevertheless, according to the data we collected during the D-Day project, it seems that the SWC method is more conservative than the others, which decreases its sensitivity to small but clinically significant changes. One of the explanations probably relies on the use of the group *SD* to compute this statistic, instead of the individual one. This would not be a problem if groups were homogeneous. However, the groups we monitored were made up of men and women of different age, swimming style, and swimming distance. This heterogeneity is associated with a high *SD*, which ultimately reduces the magnitude of the differences observed over time. From an empirical point of view, it seems therefore that the approach based on the specific methods should be preferred to the method using only the SWC (Table 5), at least in tier 4 and tier 5 swimmers of different gender and swimming styles.

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