Dynamic Quadrant Model: A Practical Framework for Monitoring and Decision-Making in Soccer Training

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Training load | Monitoring | Decision-Making | Football | Readiness | Adaptation

Headline

Human beings have an inherent need to exert control over their actions, seeking to understand and manage their environment through continuous feedback from multiple indicators. Naturally, football was never going to be the exception. In recent years, we have witnessed a technological revolution in the tracking and analysis of player movement. This evolution has provided a more precise and detailed understanding of both competitive contexts (Bradley et al., 2018; Chena et al., 2021; Hader et al., 2019; Lobo-Triviño et al., 2024; Piñero et al., 2023) and training environments (Chena et al., 2020; Chena et al., 2022; Clemente et al., 2019).

Advanced technologies have unlocked the ability to conduct fine-grained analyses of athletes' individual needs, enabling the identification of personalized performance profiles (Chena et al., 2020; Hader et al., 2019). Capturing as much real-time information as possible has become a priority in the pursuit of competitive success. The dynamic nature of team performance and injury epidemiology has highlighted the need for effective tools to support practical decision-making throughout the training process (Ekstrand et al., 2022; Hägglund et al., 2013; Impellizzeri et al., 2020).

However, despite technological advances and the growing volume of available data, much of the current research continues to rely on reductionist approaches, where interpretation is based on the isolated analysis of individual variables (Verhagen & Gabbett, 2019). Ignoring the complex interactions between contributing factors may lead to a fragmented and limited understanding of what is truly happening.

Only through the strategic integration of goal-sensitive variables and a logical sequencing of events can we generate meaningful knowledge that is useful for decision-making in real-world performance settings (Campos-Vázquez & Jiménez-Iglesias, 2024; Gabbett, 2020; Verhagen & Gabbett, 2019).

Aim

Therefore, the aim of this study was to propose a practical and visual framework designed to support coaches and fitness coaches professionals in making context-driven decisions based on monitored data and real-world performance needs.

Why is training load monitoring important in football?

The evolving nature of football has made it increasingly necessary to accurately control the physical demands imposed by the game (Lago-Peñas et al., 2023). Over the past few decades, the systematic description of metrics related to match load has provided practitioners with essential tools to evaluate players' physical performance, taking into account multiple contextual variables (Bradley et al., 2018; Castellano et al., 2022; Lago et al., 2010).

This body of knowledge has emerged as a key reference point for designing and prescribing weekly training loads (Campos-Vázquez & Jiménez-Iglesias, 2024; Chena et al., 2020; Martín-García et al., 2018; Owen et al., 2017). The training process must ensure a sufficient stimulus to elicit the desired adaptations. Inappropriate or excessive loads compromise the individual physical condition, increase injury risk, and affect team performance (Gabbett, 2016).

In this context, monitoring training load variables becomes a crucial strategy to optimize performance while respecting the player's individual limits of tolerance (Gabbett, 2016; Vanrenterghem et al., 2017). Regular monitoring of selected load variables enables practitioners to identify patterns and trends in the training model, facilitating the comparison between imposed training loads and actual competitive demands. This also allows the establishment of workload ratios and exposure percentages relative to each player's competitive profile (Chena et al., 2020; Owen et al., 2017). Based on this information, practitioners can implement short- and long-term load management strategies that respect individualization and support the adaptation process (Ravé et al., 2020).

One of the primary goals of load monitoring is to prevent or reduce the negative consequences of training: excessive fatigue, overtraining, or injury. The relationship between training load and injury incidence has been widely debated in the scientific literature (Ehrmann et al., 2016; Delecroix et al., 2018; Gabbett et al., 2016; Howle et al., 2020; Malone et al., 2017), especially given the growing concern among health professionals and sport scientists working with footballers (Ekstrand et al., 2022).

Training load, therefore, is considered a modifiable risk factor. While high training loads have been associated with increased injury risk, it has also been demonstrated that inadequate or poorly structured training can negatively impact player health (Colby et al., 2018; Gabbett, 2020; Malone et al., 2017). At the same time, solid evidence suggests that adequate exposure to optimal loads may have a protective effect, derived from the adaptations triggered by the training process itself (Colby et al., 2018; Gabbett, 2020; Malone et al., 2017).

In summary, training load monitoring stands out as an essential tool for optimizing performance and minimizing injury risk. However, in the ongoing pursuit of excellence, managing the increasing volume of data remains a complex challenge for coaches and support staff.

In the following sections, we will present practical criteria aimed at transforming raw data into meaningful information, and information into knowledge-facilitating interventions that integrate the key objectives of all stakeholders (players, coaches, strength and conditioning staff, and medical personnel).

Perhaps the most useful starting point when analyzing and interpreting data is to ask: What are we trying to achieve through athlete monitoring?

How can training load data be interpreted?

The optimal distribution of training loads, in line with the athlete's physiological adaptation principles, is a complex process influenced by factors that often fall outside of our control. However, there are useful strategies to guide the monitoring process through sound management of the metrics we can control (Gabbett, 2020; Impellizzeri et al., 2020). As previously mentioned, a well-structured distribution of load can enhance athletic performance, while poor planning may lead to overtraining, injury, or mechanical and functional decline (Gabbett, 2016). Therefore, information management should follow a methodological process that includes data collection, storage, transformation, analysis, interpretation, visualization, and communication—ultimately facilitating practical and contextualized decision-making (Lacome et al., 2018).

Nevertheless, interpreting data goes beyond numbers. It requires a deep understanding of the specific context surrounding each athlete and situation.

One key concept in this process is the dose-response relationship, which reflects the interaction between training load and the resulting physical and physiological responses (Clemente et al., 2019). This relationship is modulated by several factors, including an athlete's load tolerance, the appropriateness of the stimulus, the moment within the season, and the individual level of adaptation to the prescribed activities.

Since the player is the central figure in this process, it becomes necessary to connect external load variables with internal load measures to better understand the dose-response relationship (Jeffries et al., 2022). Training outcomes depend on the psychophysiological stress (internal load) experienced by the player, which in turn is shaped by the imposed external load and the individual's characteristics (Gabbett et al., 2017; Impellizzeri et al., 2005).

So, what levels of training load should we target to ensure that players or teams reach optimal readiness? How much is too little, sufficient, or excessive—especially in terms of safeguarding player health?

These questions are often approached from a reductionist perspective, where factors are examined in isolation without accounting for their interactions (Gabbett et al., 2017; Verhagen & Gabbett, 2018). However, achieving a positive training effect requires finding the right balance between applied load and the athlete's capacity to tolerate it. It's not just about managing the workload, but adapting it to individual tolerance. When this balance is disrupted, the risk of adverse effects on health and performance increases significantly (Verhagen & Gabbett, 2018).

Moreover, both training load and load capacity are dynamic—constantly fluctuating based on contextual factors. A training dose that is appropriate today may not be suitable tomorrow, depending on variables that shift this balance (Verhagen & Gabbett, 2018).

Evidence suggests that many non-contact lower limb injuries are linked to excessive exposure to high-speed running. However, several studies have overlooked the potential protective effect of chronic load accumulation (Malone et al., 2017). It is this progressive and sustained exposure that fosters adaptations and increases tolerance to training stress. In contrast, sudden spikes in workload over short periods are often responsible for soft-tissue injuries (Gabbett, 2018). In other words, the difference between "poison" and "antidote" lies in the dose.

One of the most common strategies for estimating appropriate load is to compare what is being done to what has previously been done. Gabbett (2018) showed that players with higher chronic training loads had up to five times less injury risk compared to those with low chronic exposure. Similarly, Colby et al. (2018) found that minimal exposure to high-speed running was associated with the highest risk of injury.

Foundational training principles—such as progressive overload and tapering—are key to promoting adaptation. In football, where matches occur once or more per week, a wavelike distribution of training load is essential to maximize physical performance (Chena et al., 2020; Ravé et al., 2020). The real challenge lies in identifying which load fluctuations deserve attention, particularly given the variability across microcycles and competitive calendars (Ravé et al., 2020). Players with optimal chronic loads are better prepared to tolerate these fluctuations than those with suboptimal preparation levels (Gabbett, 2018).

Within this context, other fundamental questions arise: Are players tolerating their training loads appropriately? Are they truly ready to train or compete under optimal conditions?

The relationship between objective load variables and subjective wellness measures can offer valuable insights (Gabbett et al., 2017). It is important to remember that low perceived wellness is not always exclusively caused by physical load—highlighting the need to consider complementary and contextual factors.

Finally, incorporating objective data on player readiness is crucial. It is well established that residual fatigue from intense matches or training can impair functional capacity (Silva et al., 2018). Practitioners often use performance tests to assess recovery kinetics (Nédélec et al., 2012). Combining these results with wellness assessments provides actionable insights into whether players are ready to train or compete—or whether recovery strategies or workload modifications are needed (Gabbett et al., 2017).

Considering that coaches must navigate daily decisions to help their players perform at their best, the following section introduces the Dynamic Quadrant Model—a tool designed to optimize the decision-making process. While this model is inspired by the monitoring cycle proposed by Gabbett et al. (2017), it incorporates specific contextual elements from the world of football (Buchheit et al., 2024), making it highly relevant for real-world application.

What is the Dynamic Quadrant Model and how does it support decision-making?

In a sport like football, where players face numerous matches over short recovery periods, the efficient management of information has become a top priority. Considering that each player is, in essence, a "data factory," the overwhelming volume of recorded metrics can quickly become a source of confusion for coaching and performance staff if not properly structured.

The Dynamic Quadrant Model emerges as a practical tool designed to facilitate decision-making based on monitored data. Its purpose is to transform information into action, enabling interventions that are both context-sensitive and performance-oriented.

Football is a long-season sport in which every match counts equally. Training must prepare players to perform optimally with limited recovery time throughout an extended competitive period. This means that coaching interventions are constantly shaped by the residual effects of the previous match and the specific demands of the next.

To ensure optimal stimulus assimilation, training priorities must be sequenced in accordance with the players' psychophysiological state. However, not all microcycles follow the same structure, as the competitive calendar introduces significant variability. This reality demands a model that can dynamically adapt to the weekly context while still respecting the biological principles of adaptation and the individual needs of each player.

The following section presents the step-by-step structure of the Dynamic Quadrant Model, broken down into a series of quadrants (Figure 1) that provide a visual and operational guide for each phase of the planning, intervention, and adjustment process.

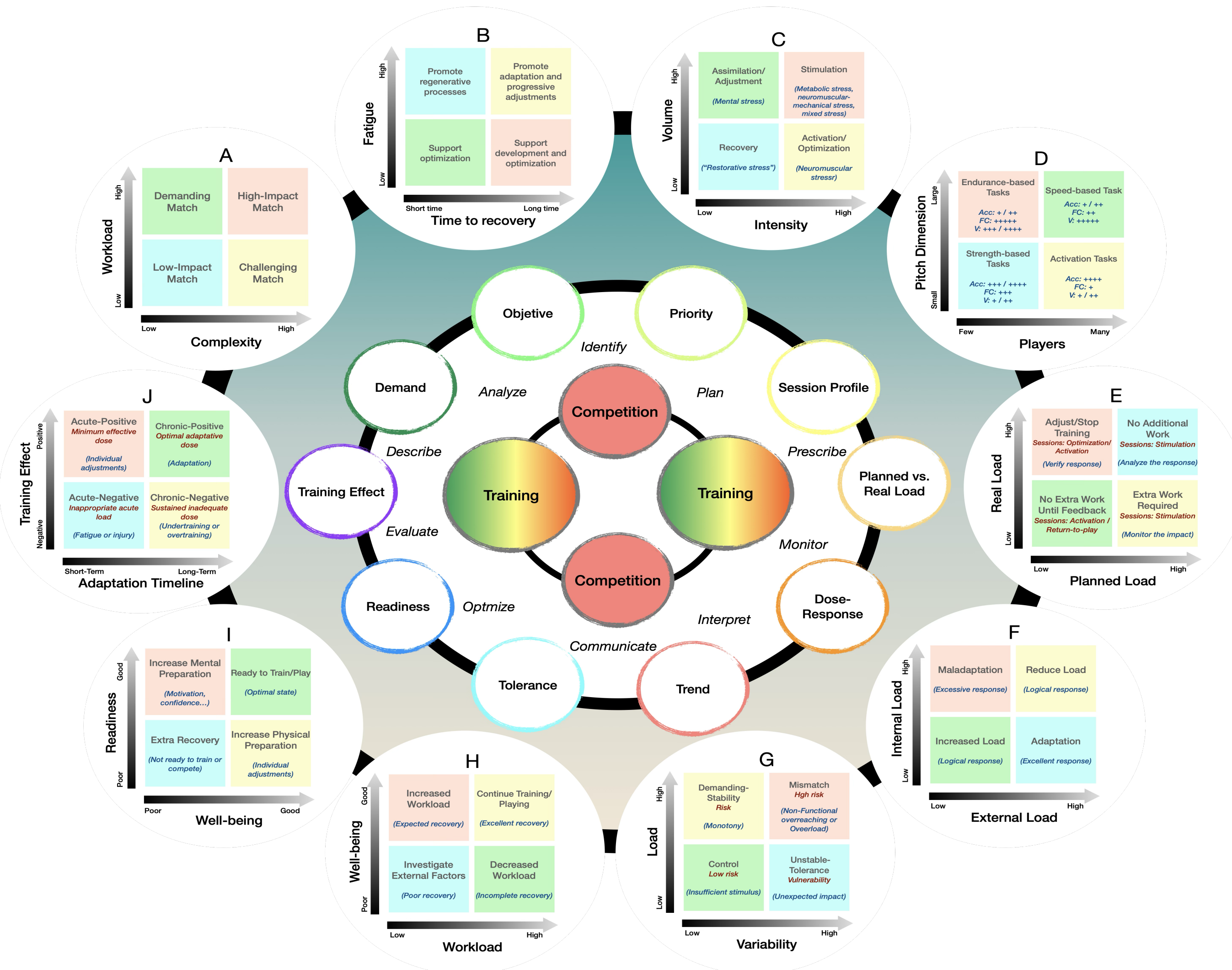

Fig. 1. **Dynamic Quadrant Model for Decision-Making in Soccer Training.**

Quadrant 1A - Match Demands and Competitive Context

Fatigue resulting from a football match is characterized by a temporary decline in physical performance during the hours and days following competition (Nédélec et al., 2012). This fatigue directly affects the scope of training interventions in the early stages of the microcycle, where recovery-focused content or compensatory work for non-starters should be prioritized (Buchheit et al., 2024).

To anticipate the week's planning, the first step of the model involves evaluating the demand of the previous match, understood as the result of the interaction between the workload and the athlete's response (i.e., the internal load or stress experienced), as well as the competitive complexity (external contextual factors that may influence match demands—e.g., travel, match outcome, red cards, opponent level, league ranking, home vs. away status, etc.).

This integrated view allows the categorization of match demands on an individual basis, offering a first-layer interpretation of the type of match each player experienced. This foundation enables more accurate anticipation of player needs and informs the early stages of training week design.

Quadrant 1B - Time to Next Match and Prioritization of Objectives

The second step in the model builds on a fundamental premise: the available recovery time until the next match, taking into account the residual effects of the previous one. The shorter the turnaround, the greater the need to prioritize regenerative content; the longer the time available, the greater the opportunity to include adaptive training stimuli. By relating the player's fatigue status (assessed via wellness questionnaires or objective indicators) with the number of days until the next match, practitioners can establish appropriate training priorities. This enables a coherent weekly periodization that aligns with team objectives while maintaining individualization.

This quadrant not only guides the weekly training progression, but also serves to connect recent past and near future—bridging the influence of the last match with the demands of the upcoming one. It respects the biological principle of recovery-adaptation, and supports a balanced approach between performance optimization and player health.

Quadrant 1C - Training Load Distribution

Once the microcycle objectives have been established—based on players' psychophysiological state and the competitive schedule—the next step in the model is to distribute the training load across the week.

According to scientific evidence, this planning should follow a periodized logic that respects the principles of biological adaptation. Traditionally, training sessions are grouped into three phases: recovery, acquisition, and tapering. However, the irregular nature of the competitive calendar often makes strict adherence to these phases challenging, requiring practitioners to prioritize and adjust planning according to the specific needs of each context (Buchheit et al., 2024).

To guide this process, the model suggests defining the tendency of each session based on the interaction between volume and intensity. This combination allows for a more precise classification of the session profile (Campos-Vázquez & Jiménez-Iglesias, 2024). It is important to note that the interpretation of what constitutes "high" or "low" load must be individualized, using each player's competitive profile as the primary reference.

Within this framework, we introduce the concept of "restorative stress" to describe recovery sessions. Although these sessions are characterized by lower loads, they are not "empty" or "passive." Their purpose is to provide a sufficient stimulus to promote regeneration and rebalancing of systems altered by the previous match or demanding sessions. This active stimulation supports the recovery process, sustains the adaptive rhythm, and gradually prepares the player for the next training load.

Quadrant 1D - Training Task Profile

Once the weekly load and its distribution have been defined, the next step is to determine what type of training tasks will be included in each session. In modern football—where technical and tactical priorities often dominate—the true challenge lies in designing tasks that simultaneously achieve physical and tactical goals, without compromising either.

Scientific evidence has shown that well-structured technical-tactical training can significantly enhance physical conditioning while also reducing perceived fatigue (Castellano & Casamichana, 2016; Chena et al., 2022). This makes it a strategic tool for optimizing overall performance.

According to the literature, the physical demands of drills can vary depending on numerous variables. However, to simplify the process, the model proposes a quadrant based on two key variables in task design: the size of the playing area and the number of players involved.

This classification allows coaches to align training task design with pre-established objectives, maintaining coherence between tactical content and the desired physical load. It is particularly useful for managing intra-week load progression, upholding the principles of individualization and specificity, and targeting specific physical parameters. Ultimately, this quadrant acts as a bridge between tactical and physical domains, helping coaches make more informed decisions and design tasks that are consistent with the overall training plan (Chena et al., 2022).

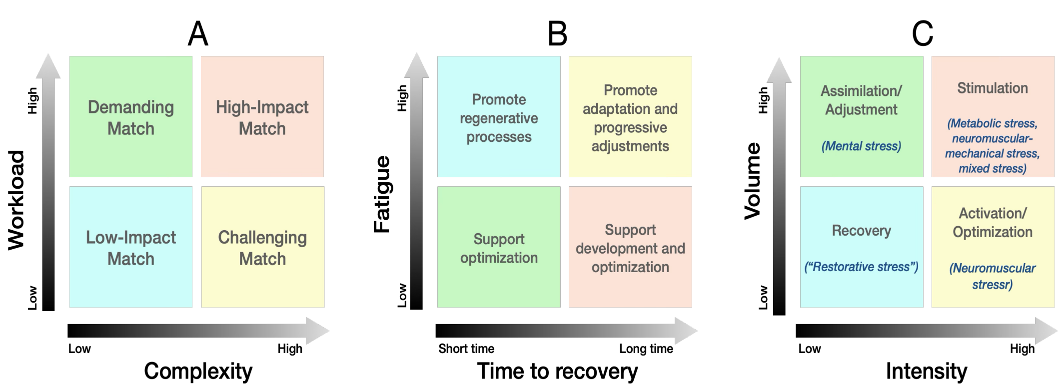

Fig. 2. Quadrants A, B, and C of the Dynamic Quadrant Model.

Quadrant 1E - Internal Player Response to the External Load Applied

Once the training sessions have been designed and delivered, it becomes essential to analyze how each player responded to the applied stimulus. Regardless of session profile, the key lies in linking the external load performed with the internal load perceived, in order to interpret the actual impact of training on the athlete.

This quadrant recommends selecting session-specific metrics to ensure meaningful analysis. For example, if the session was focused on neuromuscular or mechanical demands, it is logical to analyze variables such as accelerations, decelerations, or changes of direction that reflect mechanical load.

Combining these data with subjective ratings of perceived exertion (RPE), or other physiological internal markers, allows for a more comprehensive profile of the athlete's individual response (Gabbett et al., 2017; Impellizzeri et al., 2020; Jeffries et al., 2022).

This quadrant becomes a key tool for identifying whether a player's response is logical and expected based on the applied load. It can also help flag excessive responses, which may indicate poor tolerance or increased injury risk, and identify optimal responses, which signal good adaptation and potential readiness to increase future training demands. Additionally, current technology enables real-time monitoring of the load being performed. This gives rise to a new scenario: sometimes, what was planned does not match what is actually executed. This leads to practical questions that performance coaches must answer on the fly:

- Should extra work be added at the end of the session to increase the load?
- Should the final volume be reduced to protect certain players?
- Is it better to wait and analyze the athlete's response the following day before intervening?

These decisions are addressed in the next quadrant, which evaluates the relationship between planned and actual load, enabling a more precise and dynamic adjustment of the training process.

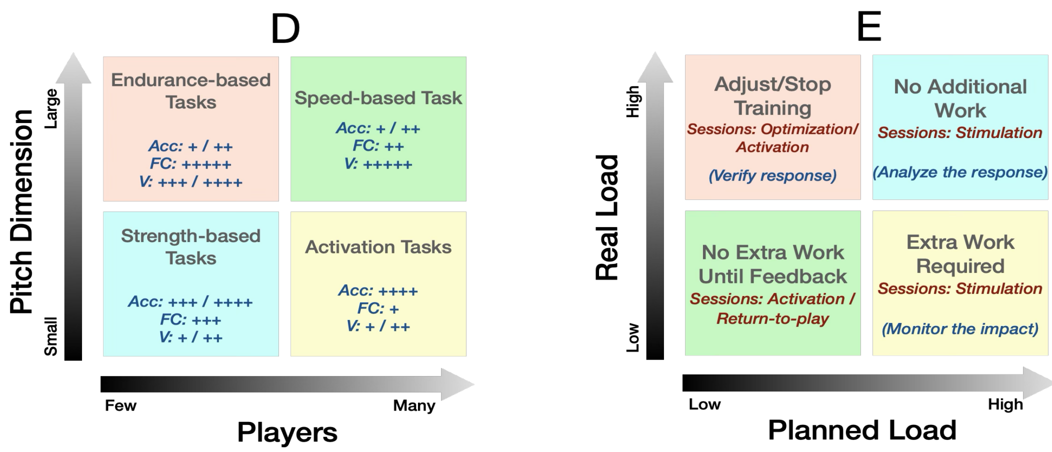

Fig. 3. Quadrants D and E of the Dynamic Quadrant Model.

Quadrant 1F - Planned Load vs. Real Load

In day-to-day training environments, it is common for the planned training load to differ from the real load actually completed. Factors such as the true intensity of drills, team dynamics, or in-session tactical decisions made by the coach may cause substantial deviations from the original plan.

Quadrant 1F is designed to support coaching staff in making real-time decisions when meaningful discrepancies are identified between what was planned and what was executed.

A range of responses may be considered in this scenario:

- If the real load is lower than the planned load, the staff should evaluate whether it is necessary to include additional work at the end of the session (e.g., individualized compensatory drills or targeted small-sided games).
- If the real load exceeds the planned load, it may be necessary to reduce or modify the remaining activities to protect certain players.
- In other cases, the most prudent strategy may be to wait until the following day, analyze the athlete's response (see Quadrants 1E and 1H), and then decide whether to apply an acute intervention or simply adjust upcoming training loads.

This quadrant encourages a dynamic and flexible approach to load management, enabling immediate adjustments when required by the context. It also facilitates microdosing strategies for underrepresented stimuli in the team session (e.g., high-speed running), and helps safeguard at-risk players based on accumulated load or individual tolerance.

However, to make this tool meaningful, it is crucial to select load variables that are aligned with the specific objectives of the session. The analysis loses relevance if metrics unrelated to the intended conditional target are evaluated. Therefore, this quadrant must be applied with careful consideration of what was intended to be trained versus what was actually trained.

This step concludes the execution block and transitions into the next phase: evaluating the variability of the applied stimulus in relation to each player's previous training history. In other words, not only examining what was done, but how much it differs from the athlete's individual baseline.

Quadrant 1G. Stimulus Variability

Once the session has concluded and the player's immediate response has been interpreted, the next step involves contextualizing that load within their recent training history. This quadrant evaluates the variability of the training load in comparison to previous sessions of similar profile, enabling the identification of potential risk, adaptation, or vulnerability scenarios.

The underlying logic is straightforward: the same load value can lead to very different outcomes depending on what the player has been previously exposed to. A high training load, if part of a progressive trend, may be beneficial. However, that same load—if it represents a sudden spike compared to the player's usual pattern—may result in maladaptation or overload.

This quadrant suggests comparing the current session's load with the average load of similar session types. While some degree of variability is expected, it is essential to determine how different the load truly is, using statistical indicators such as the smallest worthwhile change or z-scores. This approach helps identify:

- Normal stimuli, where the load aligns with the player's recent history.
- Acute overloads, where the applied stimulus is unusually high and may warrant follow-up.

- Understimulated sessions, which could lead to maladaptation or detraining.
- Vulnerability scenarios, where the athlete shows an unexpected negative response to a low load—often observed when exposed to unfamiliar or novel training stimuli.

This quadrant may also be used to analyze the planned training load across a microcycle in relation to previous weeks, using the well-known ACWR (Acute:Chronic Workload Ratio) (Chena et al., 2020; Gabbett, 2016, 2020; Malone et al., 2017). However, due to the inherent variability of the professional football calendar, this indicator must be interpreted cautiously, with context-sensitive time windows (Carey et al., 2017).

In summary, this quadrant allows practitioners to better understand athletes' responses to the load applied during a session and to anticipate potential declines in well-being. It does so not only based on the absolute value of the load but also in relation to its variation compared to the athlete's recent context. As such, it serves as a proactive strategy to identify and mitigate issues before they manifest.

Quadrant 1H. Individual Load Tolerance

Before initiating a new training session, it is essential to assess how the player tolerated the previous day's workload. This quadrant proposes a relationship between two key dimensions: the training load performed during the previous session and the perceived well-being reported by the player the following day (e.g., general fatigue, sleep quality, muscle soreness, stress levels, etc.).

Cross-referencing this information enables practitioners to anticipate potential maladaptive responses to recent stimuli and, more importantly, to adjust the dose of the upcoming session based on the athlete's recovery status. When a player reports high well-being after a demanding session, this may be interpreted as a positive sign of adaptation. Conversely, poor well-being following a similar session may suggest incomplete recovery or an elevated risk of overload, which should be considered before administering another high-intensity session.

Beyond expected scenarios, this quadrant becomes especially valuable when atypical responses emerge. For instance, if a player reports poor well-being following a low-load session, it is advisable to investigate additional contributing factors such as poor sleep, emotional stress, suboptimal nutrition, or exposure to novel or unfamiliar stimuli. As highlighted by Gabbett et al. (2017), elevated workloads are not the only reason athletes may experience compromised well-being.

This analysis supports practical decision-making prior to each session—whether to maintain, adjust, or even redesign the planned training load depending on the player's condition. In the days leading up to a match, this quadrant is particularly useful in determining whether an athlete is in optimal condition to complete the final training session, or whether a modified training dose may better facilitate match readiness. If the player responds positively to this adjusted session, they may be deemed available for competition. However, a negative response may indicate insufficient readiness, requiring further intervention before returning to full availability.

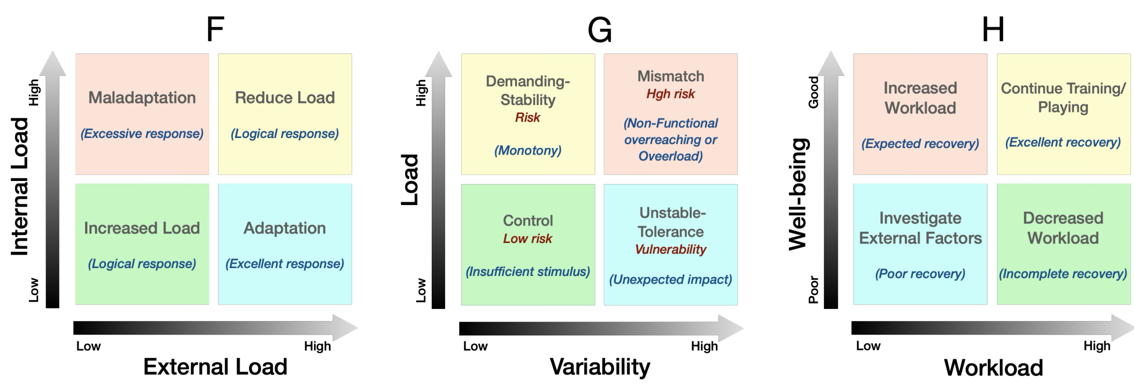

Fig. 4. **Quadrants F, G and H of the Dynamic Quadrant Model.**

Quadrant 1I. Validation of Training and Match Readiness

Although subjective well-being assessments are useful and operationally effective for guiding decisions, certain professional environments provide the material and human resources to take one step further—validating whether subjective perception aligns with the athlete's physiological reality.

This quadrant proposes cross-referencing perceived well-being with objective functional markers, such as countermovement jumps (CMJ), sprint tests, isometric strength evaluations, or modified reactive strength index (RSI). This triangulation enables a more precise judgment of the athlete's true readiness, by combining what they say they feel with how their neuromuscular system actually responds.

When both subjective and objective indicators are aligned in positive values, the player's availability for training or competition is reinforced. On the contrary, if both indicators are poor, the need for a recovery-oriented or risk-prevention intervention becomes evident.

However, the most interesting—and often most complex—scenario arises when there is discordance between the two dimensions. For example, an athlete may report feeling well emotionally and motivationally, yet display neuromuscular disturbances in functional tests. In such cases, caution is warranted, as the player may not be fully aware of their physiological condition. Similarly, negative subjective reports may stem from contextual or personal factors, while stable objective markers indicate physical readiness.

This integrated analysis enhances decision-making precision, as it does not rely on a single indicator but rather the convergence of multiple sources. Ultimately, this quadrant adds a layer of safety, enabling more individualized interventions, minimizing the risk of error, and optimizing load management.

Quadrant 1J. Training Effect and Temporal Horizon

After planning, executing, and tailoring the training process, the final step is to evaluate whether the applied stimulus has yielded the intended outcome—that is, whether the intervention contributed to a functional improvement or, conversely, triggered a physiological disruption.

This quadrant analyzes training impact across two dimensions: the direction of the physiological response (positive or negative) and the timeframe in which it manifests (acute or chronic). The combination of these axes allows practitioners to determine whether the stimulus has led to short-term adaptation, sustained improvements, or, alternatively, to maladaptation, either through overload or underload.

A positive acute response may indicate a successful stimulus for a short-term objective, but it may not be sufficient to drive long-lasting adaptations. On the other hand, sustained progression over several weeks signals that the training was functional, coherent, and adaptive.

Conversely, if the stimulus leads to a transient drop in performance or temporary fatigue that later resolves, it may be considered a predictable deregulation. However, if negative effects persist, leading to reduced load tolerance and compromised performance, this constitutes a clear warning sign of poor adaptation.

This analysis closes the model's cycle—not only by reflecting on what has been done but by validating whether the training process is aligned with the team's goals. Ultimately, training must be a means to stimulate adaptation without compromising availability or player health. This quadrant, therefore, completes the practical framework of the Dynamic Quadrant Model, encouraging professionals to adopt a critical and longitudinal perspective on the effects of their interventions.

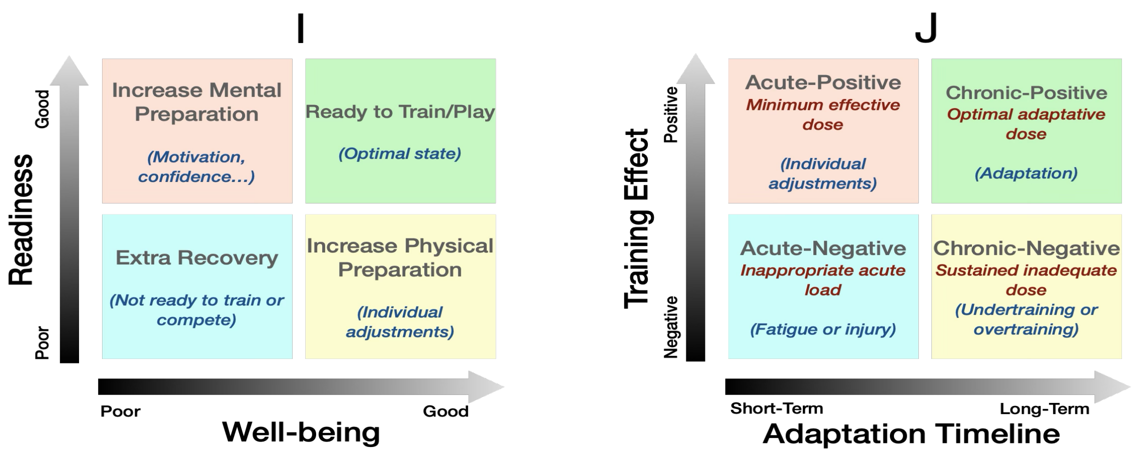

Fig. 5. Quadrants I and J of the Dynamic Quadrant Model.

How Can We Help Coaches Make Practical Decisions from the Numbers?

The implementation of monitoring systems has become a widely accepted practice in professional football. In many environments, their use is no longer optional but an expected standard. However, the true value of these systems does not lie in the accumulation of data, but rather in the ability to translate that information into practical, contextualized, and actionable decisions for the coaching staff.

The Dynamic Quadrant Model is not intended to replace the coach's intuition, experience, or situational awareness, but to complement them with a clear framework that helps better interpret what is happening and anticipate what might happen. Numbers alone do not carry predictive power unless they are understood within the framework of the game, the competitive context, the player's emotional state, and the week's strategic plan.

This model, therefore, is proposed as an integrative tool that supports professional judgment—reinforcing decisions and reducing uncertainty. For the model to have real-world impact, physical coaches and sport scientists must act as knowledge facilitators, and its implementation should be accompanied by effective education and communication strategies targeting coaches and technical staff. It is not just about showing numbers, but about sharing insight, translating data into action, and turning monitoring into a trustworthy decision-support tool.

Another key aspect to consider is that not all quadrants within the model are designed to be applied with the same frequency. Some of them —such as those related to the match demands (Quadrant A), weekly objectives (Quadrant B), or load distribution (Quadrant C)— are typically applied once per microcycle, as they reflect strategic planning points. However, others —especially Quadrants F, G, H, and I— are intended to be used daily, immediately after each training session, as they provide key information regarding the actual load performed, the variability of the stimulus, the athlete's tolerance, and their readiness to train or compete. Finally, Quadrant J, which evaluates the training effect and adaptation timeline, is more likely to be applied periodically or at key moments of the season, when assessing the long-term efficacy of the training process.

Understanding this distinction allows practitioners to integrate the model naturally into their daily and weekly workflow, applying it where and when it matters most, and reinforcing its value as a practical, dynamic framework for real-time decision-making in elite football.

Key points

- The dynamic nature of team performance and injury epidemiology highlights the need for effective tools to support practical decision-making.
- Bridging the gap between data collection and short- and long-term decision-making requires the integration of con-

textual factors, physiological responses, and player availability.
- The Dynamic Quadrant Model is a visual, dynamic, and coach-friendly framework designed to transform complex data into actionable processes of interpretation, planning, intervention, and monitoring.

References

1. Bradley PS, Ade JD. Are Current Physical Match Performance Metrics in Elite Soccer Fit for Purpose or Is the Adoption of an Integrated Approach Needed? Int J Sports Physiol Perform. 2018 May 1;13(5):656-664. doi: 10.1123/ijspp.2017-0433.

2. Buchheit M, Douchet T, Settembre M, Mchugh D, Hader K, Verheijen R. The 11 Evidence-Informed and Inferred Principles of Microcycle Periodization in Elite Football. Microcycle Periodization in Elite Football. 2024 Sport Performance & Science Report. 2024 Feb 218, 1-23.

3. Campos-Vázquez MA, Jiménez-Iglesias J. Periodización Integral. Un Modelo Holístico Para El Fútbol Actual: De La Sala al Campo. 2024, Granada

4. Carey DL, Blanch P, Ong KL, Crossley KM, Crow J, Morris ME. Training loads and injury risk in Australian football-differing acute: chronic workload ratios influence match injury risk. Br J Sports Med. 2017 Aug;51(16):1215-1220. doi: 10.1136/bjsports-2016-096309. Epub 2016 Oct 27. PMID: 27789430; PMCID: PMC5537557.

5. Castellano J, Casamichana, D. El arte de planificar en fútbol. Fútbol De Libro. 2016. Barcelona

6. Castellano J, Errekagorri I, Los Arcos A, Casamichana D, Martín-Garcia A, Clemente FM, López-Del Campo R, Resta R, Echeazarra I. Tell me how and where you play football and I'll tell you how much you have to run. Biol Sport. 2022 Sep;39(3):607-614. doi: 10.5114/biolsport.2022.106155. Epub 2021 Jul 28. PMID: 35959318; PMCID: PMC9331352.

7. Chena M, Morcillo JA, Rodríguez-Hernández ML, Zapardiel JC, Owen A, Lozano D. The Effect of Weekly Training Load across a Competitive Microcycle on Contextual Variables in Professional Soccer. Int J Environ Res Public Health. 2021 May 11;18(10):5091. doi: 10.3390/ijerph18105091. PMID: 34064978; PMCID: PMC8151593.

8. Chena M, Morcillo-Losa JA, Rodríguez-Hernández ML, Asín-Izquierdo I, Pastora-Linares B, Carlos Zapardiel J. Workloads of Different Soccer-Specific Drills in Professional Players. J Hum Kinet. 2022 Nov 8;84:135-147. doi: 10.2478/hukin-2022-000075. PMID: 36457458; PMCID: PMC9679172.

9. Chena Sinovas M, Morcillo Losa JA, Rodríguez Hernández ML, Zapardiel JC. Multivariable Training Planning Model in Professional Soccer. Revista Internacional de Medicina y Ciencias de la Actividad Física y el Deporte vol. 2020; inpress

10. Clemente FM, Clark C, Castillo D, Sarmento H, Nikolaidis PT, Rosemann T, Knechtle B. Variations of training load, monotony, and strain and dose-response relationships with maximal aerobic speed, maximal oxygen uptake, and isokinetic strength in professional soccer players. PLoS One. 2019 Dec 4;14(12):e0225522. doi: 10.1371/journal.pone.0225522. PMID: 31800617; PMCID: PMC6892557.

11. Colby MJ, Dawson B, Peeling P, Heasman J, Rogalski B, Drew MK, Stares J. Improvement of Prediction of Noncontact Injury in Elite Australian Footballers With Repeated Exposure to Established High-Risk Workload Scenarios. Int J Sports Physiol Perform. 2018 Oct 1;13(9):1130-1135. doi: 10.1123/ijspp.2017-0696. Epub 2018 Oct 19. PMID: 29543079.

12. Delecroix B, McCall A, Dawson B, Berthoin S, Dupont G. Workload and non-contact injury incidence in elite football players competing in European leagues. Eur J Sport Sci. 2018 Oct;18(9):1280-1287. doi: 10.1080/17461391.2018.1477994.

13. Ehrmann FE, Duncan CS, Sindhusake D, Franzsen WN, Greene DA. GPS and Injury Prevention in Professional Soccer. J Strength Cond Res. 2016 Feb;30(2):360-7. doi: 10.1519/JSC.0000000000001093. PMID: 26200191.

14. Ekstrand J, Bengtsson H, Waldén M, Davison M, Khan KM, Hägglund M. Hamstring injury rates have increased during recent seasons and now constitute 24% of all injuries in men's professional football: the UEFA Elite Club Injury Study from 2001/02 to 2021/22. Br J Sports Med. 2022 Dec 6;57(5):292-8. doi: 10.1136/bjsports-2021-105407. Epub ahead of print. PMID: 36588400; PMCID: PMC9985757.

15. Gabbett TJ. The training-injury prevention paradox: should athletes be training smarter and harder? Br J Sports Med. 2016 Mar;50(5):273-80. doi: 10.1136/bjsports-2015-095788.

16. Gabbett TJ. Debunking the myths about training load, injury and performance: empirical evidence, hot topics and recommendations for practitioners. Br J Sports Med. 2020 Jan;54(1):58-66. doi: 10.1136/bjsports-2018-099784. Epub 2018 Oct 26. PMID: 30366966.

17. Gabbett TJ, Kennelly S, Sheehan J, Hawkins R, Milsom J, King E, Whiteley R, Ekstrand J. If overuse injury is a 'training load error', should undertraining be viewed the same way? Br J Sports Med. 2016 Sep;50(17):1017-8. doi: 10.1136/bjsports-2016-096308. Epub 2016 Jun 1. PMID: 27251895.

18. Gabbett TJ, Nassis GP, Oetter E, Pretorius J, Johnston N, Medina D, Rodas G, Myslinski T, Howells D, Beard A, Ryan A. The athlete monitoring cycle: a practical guide to interpreting and applying training monitoring data. Br J Sports Med. 2017 Oct;51(20):1451-1452. doi: 10.1136/bjsports-2016-097298. Epub 2017 Jun 23. PMID: 28646100.

19. Hader K, Rumpf MC, Hertzog M, Kilduff LP, Girard O, Silva JR. Monitoring the Athlete Match Response: Can External Load Variables Predict Post-match Acute and Residual Fatigue in Soccer? A Systematic Review with Meta-analysis. Sports Med Open. 2019 Dec 9;5(1):48. doi: 10.1186/s40798-019-0219-7.

20. Hägglund M, Waldén M, Magnusson H, Kristenson K, Bengtsson H, Ekstrand J. Injuries affect team performance negatively in professional football: an 11-year follow-up of the UEFA Champions League injury study. Br J Sports Med. 2013 Aug;47(12):738-42. doi: 10.1136/bjsports-2013-092215. Epub 2013 May 3. PMID: 23645832.

21. Howle K, Waterson A, Duffield R. Injury Incidence and Workloads during congested Schedules in Football. Int J

Sports Med. 2020 Feb;41(2):75-81. doi: 10.1055/a-1028-7600.

22. Impellizzeri FM, Menaspà P, Coutts AJ, Kalkhoven J, Menaspà MJ. Training Load and Its Role in Injury Prevention, Part I: Back to the Future. J Athl Train. 2020 Sep 1;55(9):885-892. doi: 10.4085/1062-6050-500-19. PMID: 32991701; PMCID: PMC7534945.

23. Impellizzeri FM, Rampinini E, Marcora SM. Physiological assessment of aerobic training in soccer. J Sports Sci. 2005 Jun;23(6):583-92. doi: 10.1080/02640410400021278.

24. Jeffries AC, Marcora SM, Coutts AJ, Wallace L, McCall A, Impellizzeri FM. Development of a Revised Conceptual Framework of Physical Training for Use in Research and Practice. Sports Med. 2022 Apr;52(4):709-724. doi: 10.1007/s40279-021-01551-5. Epub 2021 Sep 14. PMID: 34519982.

25. Lacome M, Simpson B, Buchheit M. Monitoring training status with player-tracking technology. Still on the road to Rome. Part 1. ASPETAR Sports Medicine Journal. 2018; 7(1):55-63.

26. Lago C, Casais L, Dominguez E, Sampaio J, The Effects of Situational Variables on Distance Covered at various Speeds in Elite Soccer. European Journal of Sport Science. 2010;10(2):103-109. doi.org/10.1080/17461390903273994.

27. Lago-Peñas C, Lorenzo-Matínez M, López-Del Campo R, Resta R, Rey E. Evolution of physical and technical parameters in the Spanish LaLiga 2012-2019. Sci Med Footb. 2023 Feb;7(1):41-46. doi: 10.1080/24733938.2022.2049980. Epub 2022 Mar 7. PMID: 35243954.

28. Lobo-Triviño D, García-Calvo T, Manzano-Rodríguez D, Nevado F, Chena M, Piñero-Madrona JÁ, et al. (2024) Examining tactical sprint actions and distribution among playing positions attending to match status in soccer: Implications for specific training. PLoS ONE 19(6): e0301925. https://doi.org/10.1371/journal.pone.0301925

29. Malone S, Owen A, Newton M, Mendes B, Collins KD, Gabbett TJ. The acute:chonic workload ratio in relation to injury risk in professional soccer. J Sci Med Sport. 2017 Jun;20(6):561-565. doi: 10.1016/j.jsams.2016.10.014.

30. Martín-García A, Gómez Díaz A, Bradley PS, Morera F, Casamichana D. Quantification of a Professional Football Team's External Load Using a Microcycle Structure. J Strength Cond Res. 2018 Dec;32(12):3511-3518. doi: 10.1519/JSC.0000000000002816. PMID: 30199452.

31. Nédélec M, McCall A, Carling C, Legall F, Berthoin S, Dupont G. Recovery in soccer: part I - post-match fatigue and time course of recovery. Sports Med. 2012 Dec 1;42(12):997-1015. doi: 10.2165/11635270-000000000-00000. PMID: 23046224.

32. Owen A, Djaoui L, Newton M, Malone S, Mendes B. A contemporary multi-modal mechanical approach to training monitoring in elite professional soccer. Sci. Med. Footb. 2017 1:216-221. doi: 10.1080/24733938.2017.1334958.

33. Piñero JÁ, Chena M, Zapardiel JC, Roso-Moliner A, Mainer-Pardos E, Lampre M, Lozano D. Relative Individual Sprint in Most Demanding Passages of Play in Spanish Professional Soccer Matches. Sports (Basel). 2023 Mar 23;11(4):72. doi: 10.3390/sports11040072. PMID: 37104146; PMCID: PMC10141546.

34. Ravé G, Granacher U, Boullosa D, Hackney AC, Zouhal H. How to Use Global Positioning Systems (GPS) Data to Monitor Training Load in the "Real World" of Elite Soccer. Front Physiol. 2020 Aug 20;11:944. doi: 10.3389/fphys.2020.00944. PMID: 32973542; PMCID: PMC7468376.

35. Silva JR, Rumpf MC, Hertzog M, Castagna C, Farooq A, Girard O, Hader K. Acute and Residual Soccer Match-Related Fatigue: A Systematic Review and Meta-analysis. Sports Med. 2018 Mar;48(3):539-583. doi: 10.1007/s40279-017-0798-8.

36. Vanrenterghem J, Nedergaard NJ, Robinson MA, Drust B. Training Load Monitoring in Team Sports: A Novel Framework Separating Physiological and Biomechanical Load-Adaptation Pathways. Sports Med. 2017 Nov;47(11):2135-2142. doi: 10.1007/s40279-017-0714-2.

37. Verhagen E, Gabbett T. Load, capacity and health: critical pieces of the holistic performance puzzle. Br J Sports Med. 2019 Jan;53(1):5-6. doi: 10.1136/bjsports-2018-099819. Epub 2018 Sep 25. PMID: 30254049.