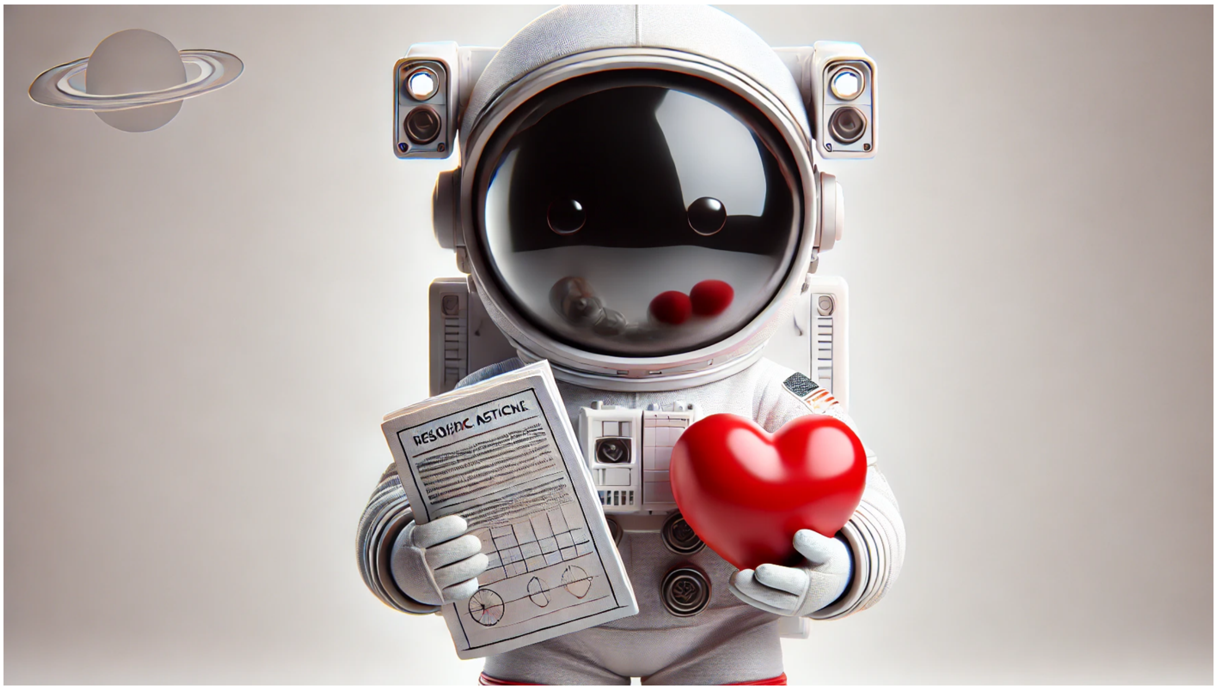
Sports Science 3.0 Series



AI-Assisted HRV Monitoring: Enhancing Training Load Response and Decision-Making

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Sports Science 3.0 | Artificial intelligence (AI) | Response-guided training | Athlete performance | Athlete readiness | Training load management | Evidence-informed practices

Headline

Sports Science 3.0 represents a pivotal shift in how technology and artificial intelligence (AI) are applied to training and performance. While Sports Science 1.0 focused on establishing fundamental principles, and Sports Science 2.0 utilized technology for monitoring, these advancements often lacked sufficient contextual grounding. Sports Science 3.0 bridges this gap by integrating cutting-edge AI with foundational sports science knowledge, creating a holistic approach to optimizing athlete performance (Buchheit & Laursen, 2024).

Aim

The aim of this paper is to explore the practical application of heart rate variability (HRV) and resting heart rate (RHR) in response-guided training. By leveraging AI within the Sports Science 3.0 framework, we seek to enhance the utility of these metrics in everyday practice, making them more accessible and actionable for athletes and coaches.

Integrating AI and Foundational Knowledge in Sports Science

This paper responds to the call made in the Sports Science 3.0 framework by seeking to bridge the gap between foundational knowledge and advanced technology. Specifically, it focuses on heart rate variability (HRV) and resting heart rate (RHR) as tools for deepening our understanding of athletes' responses to training load. By offering a structured interpretation and application of these metrics, we aim to make response-informed training more accessible and actionable, aligning with Sports Science 3.0's principles.

In athletic training, the process is relatively straightforward: a stimulus (training load) is applied, and a response (training load response) is monitored. While the training load is generally well-planned and understood, the challenge lies in accurately assessing and leveraging an individual's unique response to that stimulus (Laursen & Buchheit, 2018). Training is not one-size-fits-all; athletes exhibit significant variability in their responses due to factors like physical abilities, genetics, lifestyle, and mental state (Figure 1). Although the stimulus side is well-controlled, the response side often remains underutilized. Maximizing an athlete's potential requires better insight into and application of their individualized responses (Buchheit, 2014).

HRV and RHR have emerged as valuable metrics for monitoring training load responses (Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, 1996). These day-to-day variations provide a practical, non-invasive, and cost-effective window into the autonomic nervous system's (ANS) response to training-induced stress (Plews et al., 2012). This HRV-guided approach allows for dynamic adjustments to training loads based on an athlete's physiological state, helping to optimize performance outcomes (Kiviniemi et al., 2004; 2007).

Resting, exercise, and recovery heart rates are increasingly recognized as tools for assessing fatigue, fitness, and endurance performance. Their practical significance lies in their ability to inform daily adjustments to training loads during specific blocks and competitive seasons (Plews et al., 2013a). However, widespread adoption of HRV and RHR in practice remains limited. To be effective, these metrics must be interpreted within the right context, accounting for measurement error, the smallest meaningful changes, and the specifics of the training phase, load, and intensity distribution. The choice to use these measures should be based on the athlete's needs, the metric's sensitivity to training status, and practical considerations of measurement (Buchheit, 2014).

It's also important to recognize that heart rate metrics alone cannot capture the full spectrum of an athlete's wellness, fatigue, and performance. A comprehensive monitoring system should combine these physiological measures with training logs, psychometric assessments, and non-invasive performance tests. This multi-dimensional approach offers a holistic view of an athlete's training status, particularly in aerobic sports (Plews et al., 2013a; Buchheit, 2014). Recent advancements in web and AI technologies enable the seamless integration of multiple data sources, cloud storage, and computational power. These complex systems, hidden behind user-friendly interfaces, allow for training platforms that implement Sports Science 3.0 principles. By utilizing actionable AI, these platforms make response-informed training more accessible to coaches and athletes, representing a significant leap forward in sports science (Buchheit & Laursen, 2024).

In this paper, we present a framework for an HRV-driven training platform designed to optimize training load through contextual data. By improving the practical utility of HRV and RHR, we aim to make response-informed training more relevant to everyday practice for both athletes and coaches. Additionally, we explore the evolving role of AI-driven tools, such as Retrieval-Augmented Generation (RAG-AI) models, and their place alongside human expertise in exercise physiology and coaching. While AI can handle vast amounts of data and provide textbook-like answers to structured questions, it may lack the deeper, experience-based insights that human experts bring. This is especially relevant in contexts where emotional intelligence, broad thinking, and experience are vital. As AI systems become increasingly capable, the skills needed by educators and coaches in the Sports Science 3.0 era will likely emphasize critical thinking, decision-making, and the personal aspects of coaching, where human expertise remains invaluable.

Fig. 1. Individual variability in responses to identical training load progression. *Images designed by Freepik.

Methods

HRV Profile

The Heart Rate Variability (HRV) profile, specifically using the Root Mean Square of Successive Differences (RMSSD), serves as a cornerstone metric in HRV-guided training (Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, 1996). RMSSD quantifies the variation in time between consecutive heartbeats, providing a numerical representation of HRV. This metric is particularly significant as it reflects the activity of the autonomic nervous system (ANS), particularly the parasympathetic branch. The parasympathetic system, responsible for "rest and digest" functions, plays a critical role in recovery and relaxation, making RMSSD a valuable indicator of an athlete's recovery status and overall physiological readiness.

To measure HRV, RMSSD values are captured using wearable technology that records heart rate data continuously or during specific resting periods. These devices offer non-invasive, user-friendly methods for daily monitoring. The recorded RMSSD values are analyzed over time to identify trends and deviations. Higher RMSSD values generally indicate robust parasympathetic activity, suggesting the athlete is relaxed and well-prepared for recovery from physical and mental stressors. Conversely, lower RMSSD values may suggest reduced parasympathetic activity, indicating heightened stress or fatigue. While these interpretations are general, various subtleties in HRV data interpretation (e.g., saturation phenomenon) must still be considered (Plews et al., 2017). Tracking changes in RMSSD over time provides a nuanced understanding of the athlete's recovery status and guides training load adjustments accordingly.

RHR Profile

Resting Heart Rate (RHR) is another critical metric used to assess an athlete's cardiovascular health and fitness. Reported in beats per minute (bpm), RHR provides a baseline indicator of how efficiently the heart functions at rest. The RHR profile is particularly useful when used alongside HRV, as it helps contextualize the body's response to training and stress (Plews et al., 2017). RHR and HRV can also be assessed together to detect the saturation phenomenon, where lower HRV alongside lower RHR may indicate a state of stability in the body's response to stress. In contrast, a lower HRV combined with an increased RHR is often a sign of insufficient recovery or heightened physiological stress. This method is enhanced when using the HRV with the rMSSD:RR ratio, providing more practical insights for monitoring training responses (Plews et al., 2013a).

RHR is measured under standardized conditions, typically first thing in the morning before any physical activity. For elite athletes, or those with very low RHR, measuring while sitting up rather than supine can reduce the risk of HRV saturation, ensuring that HRV data remains responsive and interpretable (Michael et al., 2017). The data is then plotted over time to establish a reference value and detect deviations from this baseline. Increases in RHR can signal potential issues such as overtraining or insufficient recovery, while decreases following rest periods indicate improved cardiovascular efficiency and readiness for further training. As with HRV, these interpretations are general, and a more nuanced assessment, considering context, is essential (Buchheit, 2014).

Interpreting Data: Reference Value, Current Value, and Normal Range

Establishing a reference value and normal range is essential for the meaningful interpretation of HRV and RHR data. The reference value serves as an anchor point, offering a baseline for comparison with current values, while the normal range helps assess whether current values deviate significantly from what is typical for the individual. The reference value is determined by calculating the 60-day rolling average (albeit our experience suggests that 3 weeks of data are sufficient for a solid start) of RHR or HRV data, providing a robust estimate of the athlete's baseline physiological state. The normal range is derived from the coefficient of variation (CV) of the 60-day period, typically using a fraction of the CV (e.g., 0.5 x 60-day rolling CV) to define the acceptable range of variability. This approach accounts for natural day-to-day fluctuations and reduces the influence of outliers or measurement errors.

To ensure accuracy, the current value is computed as the rolling 7-day average, rather than relying on a single daily measurement. This method smooths out short-term variability and provides a more reliable indication of the athlete's physiological state (Plews et al., 2013b).

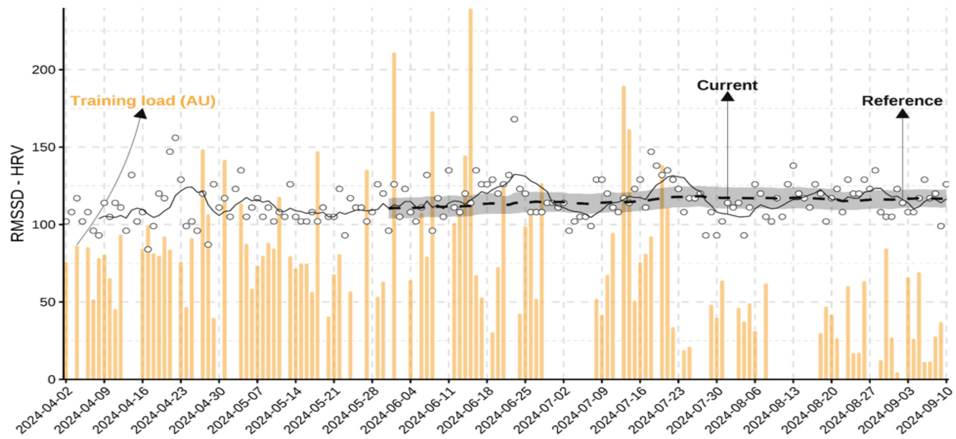

Fig. 2. Training load progression and Root Mean Square of Successive Differences (RMSSD) heart rate variability (HRV) responses. Daily measurements (white circles), 7-day current values (thin black line), 60-day baseline (dashed thick black line), and normal range (shaded gray area) are shown in a representative athlete.

Implementation: Teaching an AI About HRV

The question of whether an AI can truly "know" something about exercise physiology invites deep discussions about the nature of knowledge, expertise, and the current limitations of AI technology. While we cannot explore these intricate debates in this manuscript, we can introduce methodologies for building an AI capable of providing useful and insightful answers to highly structured questions within a specific domain of knowledge.

Large language models (LLMs) are used to generate structured knowledge spaces where concepts are interconnected. Broadly speaking, an LLM identifies relationships between concepts based on statistical patterns in the data, enabling it to construct representations of the world from text descriptions. Numerous LLMs are readily available and have been widely employed in chatbots and web/mobile applications, transforming human-machine interaction. However, as LLMs become more broadly adopted, they tend to lack deep domain-specific knowledge. This limitation has led to the emergence of RAG as a promising tool for creating AI solutions tailored to specific domains and contexts.

In this manuscript, we introduce a RAG workflow for generating and exploring knowledge graphs based on scientific articles related to HRV. This workflow follows the methodology presented in Buehler (2024), with queries adapted for this specific use case. For the purpose of building this RAG-AI and for display, we used only one scientific paper: Plews, D. J., Laursen, P. B., Stanley, J., Kilding, A. E., & Buchheit, M. (2013). Training adaptation and heart rate variability in elite endurance athletes: Opening the door to effective monitoring. Sports Medicine, 43, 773-781. By intentionally focusing on a single paper, we ensured the resulting knowledge graph would remain concise and easily queryable.

Process Overview

1. Text Processing:

a. We start by selecting PDF files arbitrarily and converting them into plain text.
b. The text is split into smaller chunks to make it digestible by a large language model (LLM).

2. Querying the LLM:

Using the LangChain Python package, we link a query template to the selected LLM. The following queries are executed:

a. **First Query**: We use the LLM (mistral-large-latest model) to generate a summary of each text chunk.
b. **Second Query**: From the summary, the same LLM generates a list of bullet points.
c. **Third Query**: The LLM then creates a title based on the summary.
d. **Fourth Query**: Using a different model (llama3-70b-8192), the LLM generates a list of triplets—two concepts (nodes) connected by an edge that represents a relationship.

3. Building the Knowledge Graph:

a. The triplets are used to construct a knowledge graph, which allows for visual navigation of the connections between concepts.
b. We use the BAAI/bge-large-en-v1.5 model to generate embeddings from the titles and summaries. This allows for quick navigation through the graph when specific information needs to be retrieved.
c. These embeddings are saved in a Redis vector database.

4. Query Pipeline:

a. All components are connected into a LangChain pipeline, allowing for queries to be received from either software or a user.
b. The LLM (tested with the llama3-70b-8192 model) interprets the query and retrieves the relevant context from the knowledge graph.
c. The context and query are then sent to another LLM, which is restricted to answering based solely on the information within the provided context.

The following table lists the triplets generated, which should be read as: Node 1 -> Edge -> Node 2.

Table 1. **Sample or the list of triplets generated from the scientific article: Plews, D. J., Laursen, P. B., Stanley, J., Kilding, A. E., & Buchheit, M. (2013). Training adaptation and heart rate variability in elite endurance athletes: opening the door to effective monitoring. Sports medicine, 43, 773-781.**

Node 1	Edge	Node 2
Heart rate variability (HRV)	is used to monitor	Training adaptation
Increases in HRV	signify	Positive adaptations
Decreases in HRV	indicate	Negative adaptations
Elite athletes	show	Inconsistent HRV responses
Methodological issues	exist in	Challenges in using HRV
Appropriate averaging	techniques	are Solutions to methodological issues
...	...	...

The concepts can be represented in a chord diagram, allowing them to be visualized, explored, and verified. This translation into natural language is crucial for human experts to assess the validity of the knowledge graph. By applying their expertise, they can either endorse or revise these knowledge graphs as necessary.

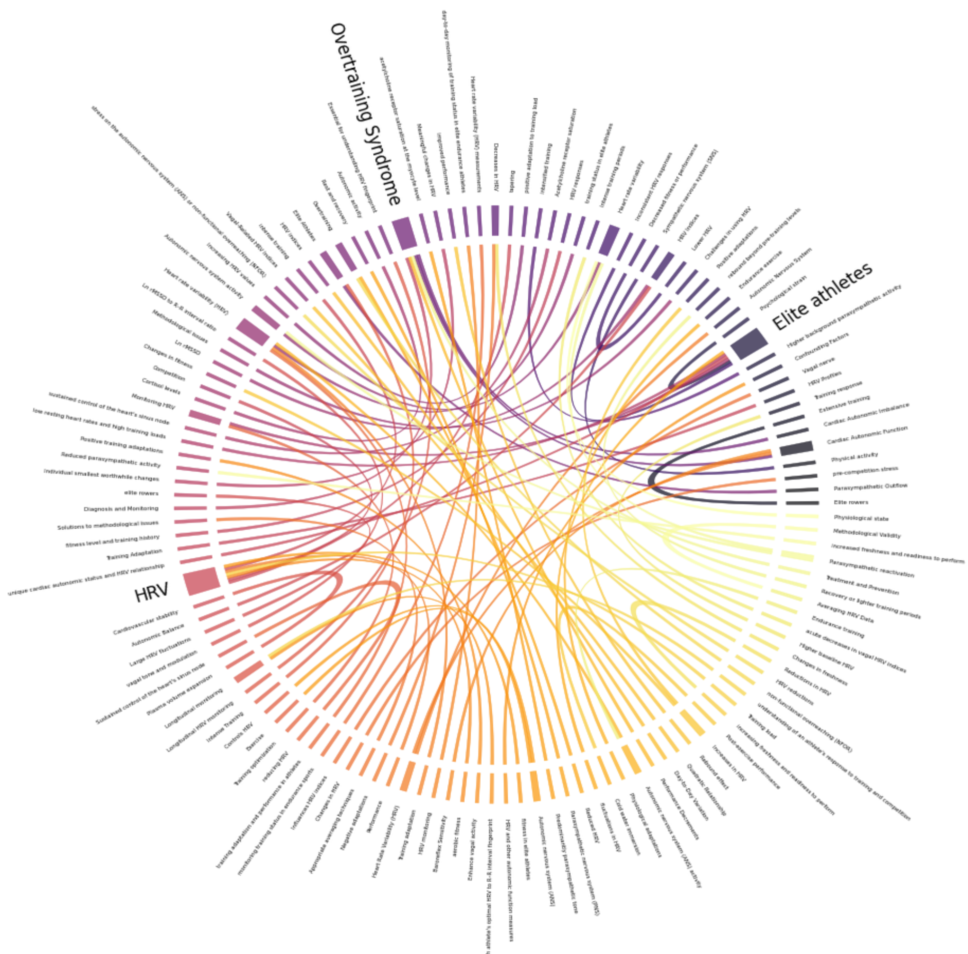

Fig. 3. **Chord diagram highlighting the connections between concepts, taken from the triplets generated from the scientific paper: Plews, D. J., Laursen, P. B., Stanley, J., Kilding, A. E., & Buchheit, M. (2013). Training adaptation and heart rate variability in elite endurance athletes: opening the door to effective monitoring. Sports medicine, 43, 773-781.**

Implementation: Automatically Adjusting Future Training Loads

The system detailed in Figure 4 assists coaches, athletes, and the RAG-AI in making informed decisions about training intensity, rest, and recovery, thereby promoting health and reducing the risk of injury. The framework operates similarly to an automatic control feedback loop. According to feedback control principles, a target performance improvement or maintenance is driven by the input—namely, the training load. The athlete's response to this prescribed load is evaluated using both internal variables (such as heart rate, RPE, or self-reported feelings) and external load variables (such as power output or speed) during and after the training session.

A first, internal feedback loop can be implemented to make adjustments for future sessions if the athlete's response deviates from expectations. A second, external feedback loop evaluates recovery metrics such as HRV and RHR. Based on these assessments and the principles discussed earlier, future training loads can be adjusted as needed.

One of the greatest challenges to the proper functioning of a feedback loop is the presence of "noise" in the process. Monitoring tools may have limitations and may not capture all the stress factors affecting an athlete. For instance, if training load is not the primary stressor in an athlete's life, HRV and RHR values might be misleading. Additionally, self-reported metrics like RPE and feelings can be difficult for an AI to interpret correctly, as it may struggle to understand the nuances or hidden messages within the feedback.

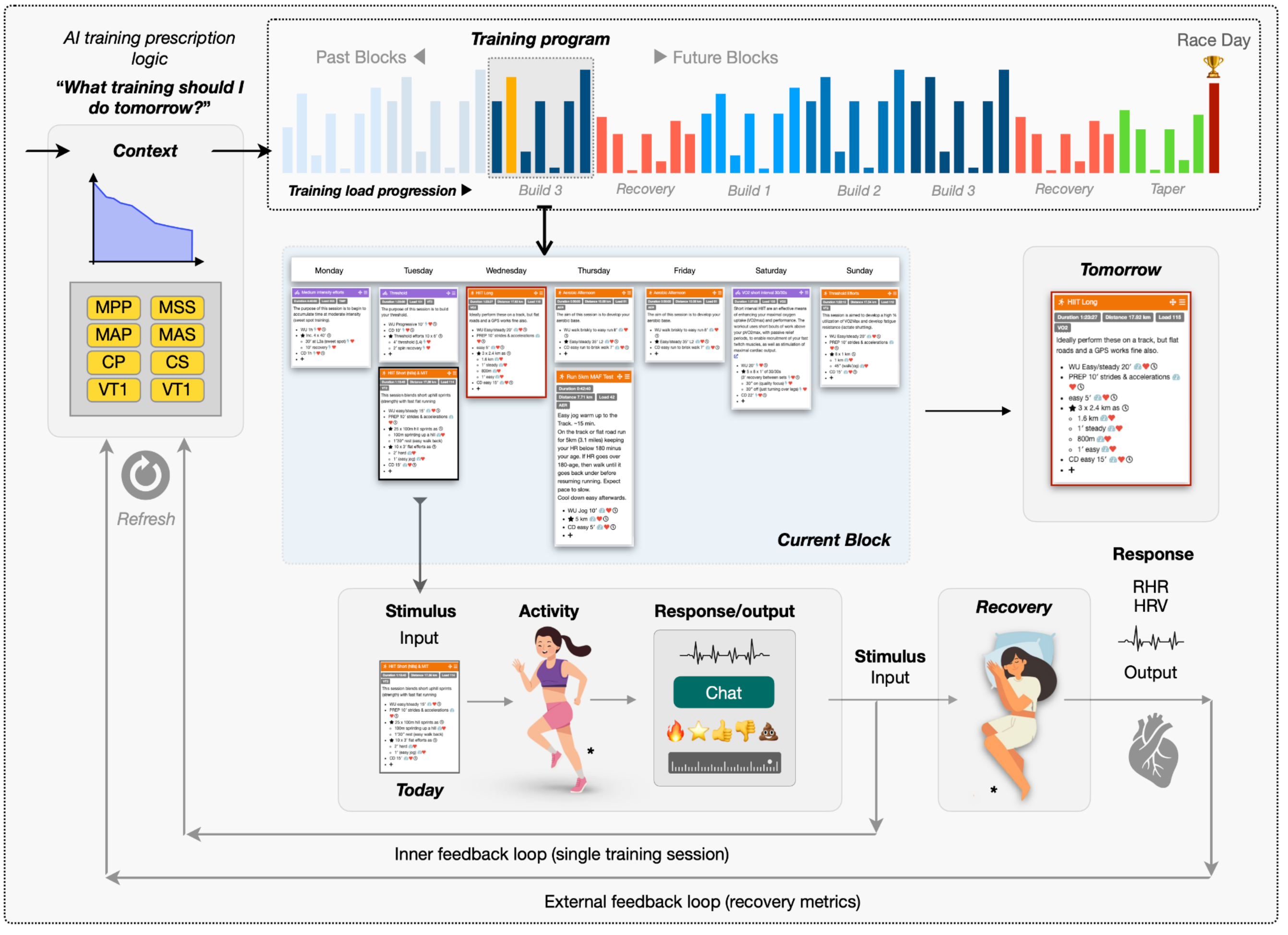

Fig. 4. **Schematic Representation of an HRV-Guided Training Plan Generator**
This flowchart illustrates the process of generating a training plan, where lines and arrows represent the flow of information. The core question the system addresses is: "What training should I do tomorrow?" To answer this, the generator builds the training program based on supercompensation principles while factoring in constraints such as time availability and total training volume. The plan is highly context-dependent (e.g., athlete's locomotor profile). Each day's session acts as a stimulus, to which the athlete responds individually. The effect of the stimulus continues throughout the day, culminating in recovery. After recovery, resting heart rate and heart rate variability oscillations, along with the outcomes from the training session, are used to update the context and refine the training plan. The next session is then generated, potentially including a rest day. *Images designed by Freepik.

Interpreting Traffic Lights

To facilitate the practical application of HRV and RHR data, a traffic light system can also be employed by comparing the current value (rolling 7-day average) with the reference value and normal range. The color-coded system suggested here provides immediate, actionable insights into the athlete's readiness and recovery status:

- **Optimal readiness**: No signs of fatigue or non-functional overtraining. The athlete is well-prepared for upcoming training loads.
- **Minimal concerns**: The athlete is generally ready but should monitor their condition closely to ensure continued readiness.
- **Minor concerns**: Signals the need for caution, with possible early signs of fatigue. The athlete should be mindful of their physical and mental state.
- **Moderate concerns**: Noticeable signs of stress or fatigue. Prioritize recovery to prevent performance decline or injury.
- **Significant concerns**: Compromised readiness. High-intensity training may not be advisable; rest or lighter training should be considered.
- **High concerns**: Readiness is seriously compromised. Intense training could be counterproductive. Rest is strongly recommended.
- **Very-high concerns**: Critical need for rest. Continuing intense training poses significant risks. Prioritize recovery to prevent injury or illness.

Discussion

Considerations on the Choice of the Baseline and the Narrow Range

From a computational standpoint, accurate interpretation of HRV and RHR data requires meticulous statistical analysis. When using a rolling 60-day window to compute the reference value, this same window is typically used to calculate the normal range. However, verifying the normality of the data distribution within this period is seldom discussed in the literature. The most common practice is to use the average to represent the central value. Additionally, since consecutive points in the RHR and HRV time series are often correlated, autocorrelation must be considered. Performing an autocorrelation analysis ensures that this correlation does not skew the outcome statistics, though this practice is not often emphasized. A robust alternative to the average is the use of the 60-day rolling median, paired with the interquartile range (Q1–Q3). This approach can reduce the influence of non-normality and outliers, offering a more reliable measure of central tendency and variability.

The definition of the normal range requires further clarification. We propose using 0.5 times the 60-day rolling coefficient of variation to calculate this range, as it provides a useful reference for comparing current values with historical data. An alternative approach is to use 0.2 times the 60-day rolling standard deviation, which is based on Cohen's effect size d, where a value of 0.2 indicates a "small" effect size (Sawilowsky, 2009). It is widely recognized that descriptors like Cohen's d are "rules of thumb," introducing a degree of subjectivity in determining what constitutes a "meaningful" deviation. In the context of magnitude-based inference (Hopkins et al., 2009), the smallest worthwhile change (SWC) is often defined as the smallest difference that would result in a Cohen's d of 0.2. However, defining a meaningful difference is inherently subjective, as both intra- and inter-individual variability can influence this decision. For this paper, we chose to define the normal range as 0.5 times the 60-day rolling CV.

AI and Human Domain-Specific Knowledge

AI has the ability to process vast amounts of information in a structured manner, quickly retrieving and synthesizing responses by combining pre-trained knowledge (from its model) with retrieved documents (in the case of RAG). In exercise physiology, it can be adapted to answer a wide range of queries, such as explaining how HRV relates to training load or recovery metrics. While AI may not "know" in the human sense, it can aggregate what it has learned from previous data and augment this with specific, relevant information. Human experts, on the other hand, are often needed to evaluate whether the outputs—such as Table 1 and Figure 2—are accurate and useful. It is important to remember that this information is derived from peer-reviewed sources, with concepts linked based on statistical patterns and semantic proximity.

Unlike AI, human experts bring intuition, experience, and a broader contextual understanding, allowing them to address ambiguous, cross-disciplinary, or unstructured questions. They can also draw on subjective experience, interpret real-world results, and assess exceptions.

AI-RAG and human experts may provide similar or different answers depending on the question. For example, when asked, "What is heart rate variability (HRV), and how does it relate to exercise recovery?" AI-RAG can provide a textbook-style response based on available data.

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HRV is the variation in time intervals between heart-
beats, which is influenced by the autonomic nervous
system.  A high HRV is generally considered a sign of
good recovery and readiness for physical exertion,
while a lower HRV might indicate that the body is
under stress or hasn't fully recovered from exercise.
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Given such a well-structured question, a human expert would likely provide a similar explanation. In this instance, both the AI-RAG and the human expert would offer technically accurate and useful responses, and for someone with basic knowledge, the difference might not be easily noticeable.

However, let's consider a more complex example that an AI-RAG might struggle to follow up on. We already know how to compute meaningful oscillations in HRV, so we might ask: "Given that my HRV dropped significantly from 56 to 48 outside of the normal range this week, but I feel fine, what should I do about my training schedule?"

The AI-RAG answer might sound like:

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A low HRV might indicate negative adaptations to
training or stress, so it's advisable to take a rest
day or reduce intensity.
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In the framework depicted in Figure 3, this might automatically prompt a change in tomorrow's session, perhaps leaving the choice between rest or a low-intensity session to the athlete or coach. However, it is difficult for the AI-RAG to truly assess the specific individual, especially when faced with subjective statements like "I feel fine." This is where human experts excel: they can recognize that low HRV may be due to factors unrelated to training stress (e.g., sleep patterns or life stress), or reasons that may not be apparent in the data. Human experts can ask and interpret the right follow-up questions, such as "How are you sleeping?" or "Are you feeling mentally or emotionally stressed due to X factor?" They can contextualize the data within the athlete's unique circumstances and provide a more tailored response. Most importantly, humans can quickly adapt their advice to unforeseen circumstances. Here, human experts can integrate subjective feedback, real-time data, and complex contextual knowledge to offer a nuanced, personalized response—something that even the most advanced AI-RAG cannot fully achieve.

AI-RAG excels at factual retrieval and can generate impressive responses from its knowledge base. Humans, on the other hand, excel at interpretation, particularly when the context is complex, ambiguous, or requires deeper, lived insight. The optimal approach involves blending the strengths of AI-RAG with human expertise to connect objective data with subjective, real-world considerations.

Prompting a Change in the Way We Teach?

AI systems like RAG-LLM, which are capable of delivering textbook-level answers, encourage us to rethink how we approach education, particularly in fields where factual knowledge has traditionally been the focus. For professionals, memorizing facts may become increasingly less relevant. Instead, students will need to emphasize critical thinking, problem-solving, and contextual understanding—skills that cannot be easily automated or retrieved. This shift in education should prioritize teaching "how to think" and "how to apply what you know" over "what to know." Encouraging students to develop decision-making skills, especially in situations where there are no easy answers, will be key.

A crucial skill for students will also be learning how to use AI effectively, especially in fields like medicine, engineering, or exercise physiology. Being able to critically assess and interpret AI-generated outputs will become an essential capability. While AI can offer vast amounts of knowledge, it lacks moral reasoning, ethical considerations, and emotional intelligence. These are areas where human experts will always be necessary, particularly in disciplines like medicine, law, and education. In this evolving landscape, education should focus on the ethical use of AI, understanding its limitations, and recognizing the importance of human oversight.

For example, instead of solely teaching students the facts about how HRV relates to recovery, instructors could present real-world case studies. Students would analyze HRV data for a specific athlete, make training recommendations, and then adjust those recommendations based on further data or feedback. While AI might assist in finding relevant research or identifying patterns, students would be responsible for interpreting and applying that knowledge within a particular context. Ultimately, AI-RAG and similar technologies should be viewed as co-pilots, not replacements. Students and professionals who understand how to collaborate with AI—knowing when and how to leverage it, and when human expertise is indispensable—will thrive in the emerging landscape of Sports Science 3.0.

Key Points

- **HRV and RHR as Core Metrics**: Heart rate variability (HRV) and resting heart rate (RHR) offer valuable, non-invasive tools for monitoring an athlete's physiological response to training and recovery.
- **AI Integration in Sports Science 3.0**: By integrating artificial intelligence (AI) with foundational sports science principles, response-guided training can be enhanced, providing personalized, actionable insights for athletes and coaches.
- **Rolling Averages for Reliable Insights**: The use of a 60-day reference value and a 7-day rolling average helps smooth out short-term variability, providing a more reliable assessment of an athlete's readiness and recovery status.
- **Traffic Light System for Practical Application**: A color-coded traffic light system offers immediate feedback on training readiness, enabling informed decisions about training intensity and recovery, optimizing performance while reducing injury risk.
- **RAG-AI Integration**: RAG models are used to synthesize domain-specific knowledge from HRV literature, allowing AI to assist coaches and athletes in interpreting data and making adjustments to training plans.
- **Human-AI Collaboration**: While AI can efficiently process and retrieve vast amounts of information, human expertise remains essential for contextualizing data, interpreting subjective inputs, and making nuanced training decisions.

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