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# Connecting heart and mind: Integrating heart rate variability, resting heart rate and self-reported subjective variables for athlete monitoring and training

**Carla Alfonso Martin**

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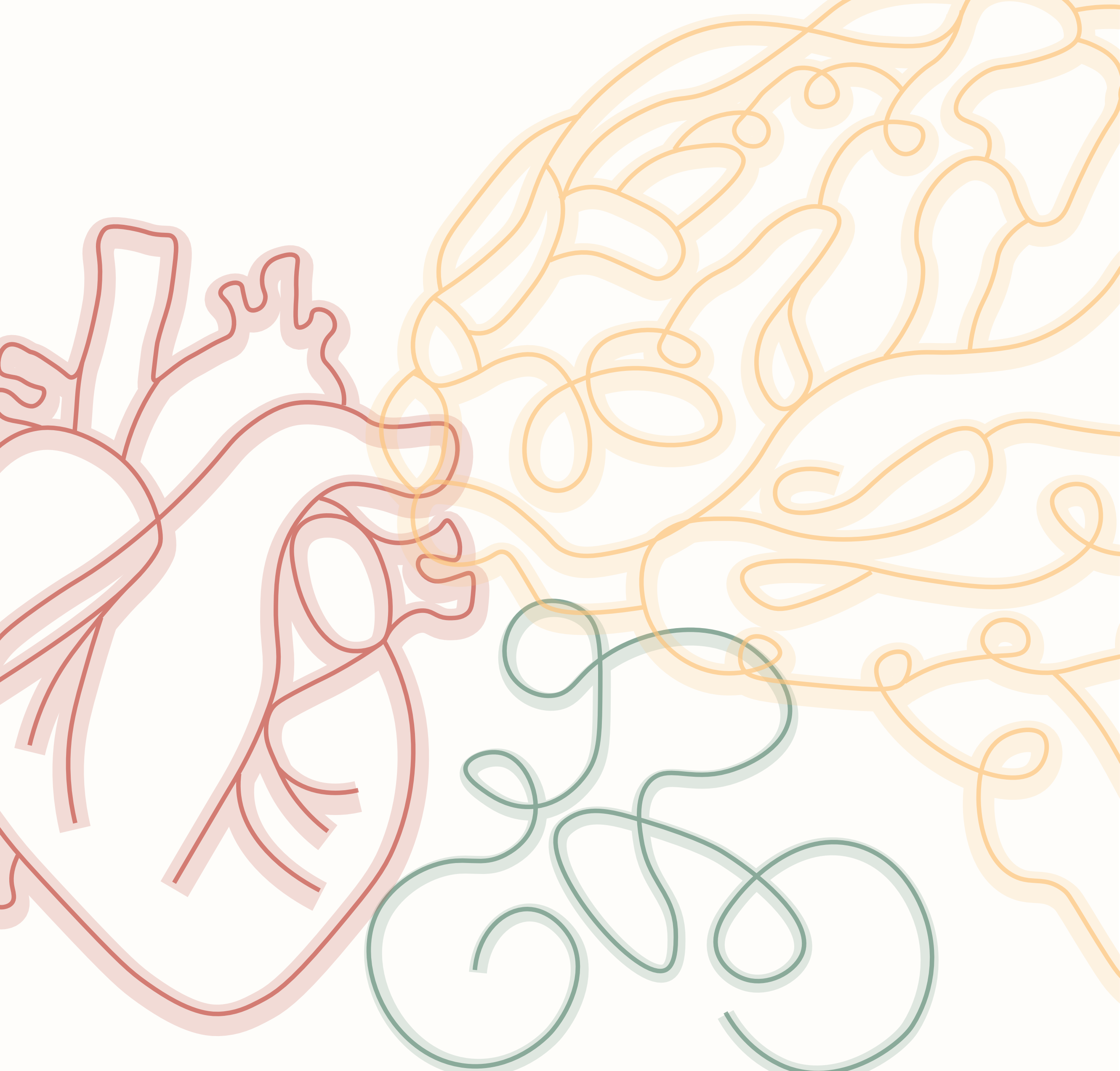
Doctoral Thesis
Directed by Prof. Lluís Capdevila



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# Connecting heart and mind: Integrating heart rate variability, resting heart rate and self-reported subjective variables for athlete monitoring and training

Ph.D. Dissertation presented by

**Carla Alfonso Martín**

to obtain the degree of Doctor in Psychology

This work has been performed under the supervision of

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Ph.D. Program in Sport and Health Psychology

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*«En el camino aprendí,*
*que llegar alto no es crecer,*
*que mirar no siempre es ver*
*ni que escuchar es oír*
*ni lamentarse sentir*
*ni acostumbrarse, querer...*

*En el camino aprendí*
*que estar solo no es soledad,*
*que cobardía no es paz*
*ni ser feliz, sonreír*
*y que peor que mentir*
*es silenciar la verdad.*

*En el camino aprendí,*
*que ignorancia no es no saber,*
*ignorante es ese ser*
*cuya arrogancia más vil,*
*es de bruto presumir*
*y no querer aprender.*

*En el camino aprendí*
*que puede un sueño de amor,*
*abrirse como una flor*
*y como esa flor morir,*
*pero en su breve existir,*
*fue todo aroma y color.*

*En el camino aprendí*
*que la humildad no es sumisión,*
*la humildad es ese don*
*que se suele confundir.*
*No es lo mismo ser servil*
*que ser un buen servidor.*

*En el camino aprendí,*
*que la ternura no es doblez,*
*ni vulgar la sencillez*
*ni lo solemne verdad,*
*vi al poderoso mortal*
*y a idiotas con altivez.*

*En el camino aprendí*
*que es mala la caridad*
*del ser humano que da*
*esperando recibir,*
*pues no hay defecto más ruin*
*que presumir de bondad.*

***En el camino aprendí,***
***que en cuestión de conocer,***
***de razonar y saber,***
***es importante, entendí,***
***mucho más que lo que vi***
***lo que me queda por ver...»***

Rafael Amor (1948 – 2019)

# AGRADECIMIENTOS

Este doctorado empezó como una formación profesional, pero rápidamente pasó a ser algo más. La presente tesis es el resultado del cruce entre crecimiento académico y personal. Sin una parte o la otra, este trabajo no sería el mismo, e incluso, seguramente, ni existiría. Además, es fruto de experiencias, conocimientos, y crecimiento compartido con otras personas. Mi profundo y sincero agradecimiento a todas ellas. En especial…

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…A mis padres, por brindarme una educación desde pequeña y por darme las herramientas que me han permitido dedicarme a estudiar durante tanto tiempo. También gracias por el apoyo en los largos días y años de escritura, y por la estima incondicional.

…A Max, por ser mi apoyo y sostén en este último año y medio de tesis, por cuidarme con paciencia infinita y por ser el mejor compañero de vida. Gracias por tu mirada artística y el desarrollo de las ilustraciones.

…A Carlos Fernández por las largas conversaciones sobre fisiología, rendimiento, números y técnicas. Y también por el apoyo, confianza y gran sentido del humor.

…A mis amigos, y en especial a Dani, Cris y Joan por acompañarme en el camino y recordarme que también es importante desconectar. A Carla Playa, por enseñarme el valor de la amistad, y por inspirarme con su espíritu aventurero. Gracias por las experiencias compartidas. A Rob y su familia, por ser una fuente de inspiración constante y un ejemplo a seguir. A Tomás, que en paz descanse, por enseñarme a luchar por los sueños, por lejos que se vean, y a saber pasar a la acción. También gracias a Pep, que me brindó una filosofía de vida que me acompaña, y por recordarme la importancia de las pequeñas cosas.

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Mientras escribo estas líneas, no puedo evitar mirar atrás y recapitular la historia de este recorrido. No ha sido un camino fácil. Durante los últimos 4 años, gran parte de mi tiempo y energía han estado dedicados a esta tesis, y lo he sufrido y disfrutado a partes iguales. Me siento orgullosa de ver cómo el trabajo llega a su fin, y, sobre todo, de lo aprendido durante el trayecto y de haber seguido, con constancia, a pesar de los obstáculos. Además, este trabajo es en gran parte resultado de todas las personas con las que me he ido cruzando y que me han acompañado; ha sido un privilegio estar rodeada de gente que cree en mí y me ha empujado a seguir y mejorar. Acabo esta tesis sintiéndome muy afortunada de haber tenido la oportunidad de estudiar sobre un tema que me apasiona, y, especialmente, por la gente que lo ha hecho posible.

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# ABSTRACT

Athletes and coaches increasingly use daily data to monitor and prescribe training, yet no single marker reliably reflects readiness of the athlete to train or need for recovery. This thesis examined whether and how integrating resting vagally-mediated heart rate variability (vmHRV), resting heart rate (RHR), and self-reported subjective variables (SVs) yields a more informative picture of the athlete's state and improves training outcomes. Notably, it evaluates these markers as captured by wearables used for ecological momentary assessment (EMA), which are now widespread in sport but still need evidence for their accuracy and practical utility.

Four studies were conducted to meet the objectives. A scoping review (31 studies, 514 athletes) mapped how vmHRV related to SVs. Asides from reporting correlations, the review highlighted substantial methodological heterogeneity and proposed a reporting checklist to harmonize protocols, as well as a classification for SVs into fatigue–recovery, psychological, and sleep variables. Then, two empirical studies were conducted with cyclists: a pilot and an intervention study. In the pilot, higher morning vmHRV co-occurred with better mood, and high-intensity sessions were followed by next-morning reductions in vmHRV and mood. In the intervention study, three prescription strategies were compared: HRV-only, HRV+well-being (WB), and HRV+WB+RHR, using rolling averages of daily RMSSD, WB (perceived fatigue, muscle soreness, stress, sleep quality), and RHR to guide intensity. All groups improved, but integrating WB and RHR produced greater gains in short- and mid-duration cycling performance than HRV-only prescription. Relationships between RMSSD and SVs also varied between individuals. Finally, a validation study compared two commercial devices (Apple Watch Series 6 and Polar Vantage M2) against an electrocardiogram (ECG) while lying, sitting, standing and walking. The Apple Watch showed higher agreement with ECG than the

Polar device, especially at rest. Accuracy declined with movement and improved with longer averaging windows. A new methodology was also developed to synchronize heart rate data from devices with different sampling rates and across multiple averaging windows –without interpolating time series– enabling precise multi-timescale agreement analyses.

Across studies, the associations between vmHRV and SVs were inconsistent in statistical significance and direction of relationship, potentially reflecting differences in protocols and theoretical bases, but also pointing to individual and context-dependent effects. Overall, the thesis concludes that combining vmHRV, RHR, and SVs provides a practical, personalized monitoring approach that outperforms single-marker strategies. It confirms that multi-marker monitoring is feasible and useful and underscores the importance of tracking SVs. At the same time, the thesis calls for standardized protocols for recording vmHRV and SVs in both research and field settings. It also urges caution when using wearables: favouring resting measures, synchronizing data streams, and treating outputs as estimates.

Looking ahead, advances in wearables and real-time, multi-marker adaptive training –where objective measures inform, subjective data contextualize, and their integration guides athlete-specific decisions– are promising.

# ABBREVIATIONS

| | |
|---|---|
| **ABQ** | Athlete Burnout Questionnaire |
| **ACF** | Autocorrelation Function |
| **ANOVA** | Analysis Of Variance |
| **ANS** | Autonomic Nervous System |
| **AV** | Atrioventricular Node |
| **B-A** | Bland-Altman plots |
| **bpm** | Beats Per Minute |
| **CAS** | Complex Adaptive Systems |
| **CV** | Coefficient of Variation |
| **DOMS** | Delayed Onset of Muscle Soreness |
| **ECG** | Electrocardiogram |
| **EMA** | Ecological Momentary Assessment |
| **FTP™** | Functional Threshold Power™ |
| **HF** | High Frequency |
| **HR** | Heart Rate |
| **HRV** | Heart Rate Variability |
| **IF™** | Intensity Factor™ |
| **IZOF** | Individual Zones of Optimal Functioning |
| **JBI** | Joanna Briggs Institute |
| **LF** | Low Frequency |
| **mHealth** | Mobile Health |
| **NIM** | Neurovisceral Integration Model |
| **NP™** | Normalized Power™ |

| | |
|---|---|
| **NTS** | Nucleus Tractus Solitarius |
| **OSF** | Open Science Framework |
| **Pmax** | Maximal Power |
| **PNS** | Parasympathetic Nervous System |
| **POMS** | Profile of Mood States |
| **PPG** | Photoplethysmography |
| **PRISMA-ScR** | PRISMA Extension for Scoping Reviews |
| **RESTQ-Sport** | Recovery-Stress Questionnaire for Athletes |
| **RHR** | Resting Heart Rate |
| **RMSSD** | Root Mean Square of Successive Differences |
| **RPE** | Rate of Perceived Exertion |
| **RR** | Cardiac intervals |
| **RSA** | Respiratory Sinus Arrhythmia |
| **SA** | Sinoatrial Node |
| **SDNN** | Standard Deviation of time between consecutive heartbeats |
| **SNS** | Sympathetic Nervous System |
| **SV** | Self-reported Subjective Variables |
| **SWC** | Smallest Worthwhile Change |
| **TQR** | Total Quality Recovery |
| **TSS™** | Training Stress Score™ |
| **VFC** | Variabilidad de la Frecuencia Cardíaca |
| **vmHRV** | Vagally-Mediated Heart Rate Variability |

# PRESENTATION

Regarding the present doctoral thesis:

- This thesis was developed within the research group of the Sport Psychology Lab at Universitat Autònoma de Barcelona, recognized as a consolidated group by the Government of Catalonia (2021SGR-00806). The doctoral candidate joined the group in 2020 as a collaborator on the R&D project "*EMA-based strategies to improve effort recovery and wellbeing in athletes and general population using mHealth technology*" (PID2019-107473RB-C21). Being part of this research group made this thesis possible.
- Specifically, the thesis focuses on the relationship between vagally-mediated heart rate variability (vmHRV) and self-reported subjective states (SVs) in athletes.
- The interest in this topic lay in the candidate's background as a cyclist with a Bachelor in Neuroscience (King's College London, United Kingdom) and a Master in Sports Psychology (Universitat Autònoma de Barcelona, Spain). Athletes in her circle often asked how to interpret data from their wearable devices (e.g., Oura Ring), because they noted that vmHRV readings often didn't match how they felt, leaving them unsure about which metric to prioritize when guiding their training. Thereby, the thesis emerged from an applied context to address a genuine concern among practitioners.
- The study of vmHRV and SVs aligns with the candidate's training in neuroscience and sport psychology, integrating physiological aspects of the nervous system with psychological factors. In fact, the starting point for this thesis was the Master's thesis in Sport and Health Psychology, in which the candidate also examined vmHRV in athletes.

- Another key motivation was being able to contribute to the development of wearables in the context of sports, providing scientific evidence for new devices and applications. Accordingly, the study places strong emphasis on practical contributions.
- The topic is complex, as performance and recovery are phenomena affected by multiple factors across time.

Regarding format and contributions:

- The thesis is presented as an article-based (*compendium*) dissertation.
- The included publications are:

  **Article 1:** Alfonso, C., Haydt, V., Allen, M. S., Capdevila, L., & Laborde, S. (2025). Monitoring training adaptation: a scoping review of the relationship between self-reported subjective variables and resting vagally-mediated heart rate variability (vmHRV) in adult athletes. *International Review of Sport and Exercise Psychology*, 1–38. https://doi.org/10.1080/1750984X.2025.2541350

  **Article 2:** Alfonso, C., & Capdevila, L. (2022). Heart rate variability, mood and performance: a pilot study on the interrelation of these variables in amateur road cyclists. *PeerJ*, *10*, e13094. https://doi.org/10.7717/peerj.13094

  **Article 3:** Alfonso, C., Clarke, D. C., Capdevila, L. (Accepted). Individual training prescribed by heart rate variability, heart rate and well-being scores in experienced cyclists. *Scientific Reports.*

  **Article 4:** Alfonso, C., Garcia-Gonzalez, M. A., Parrado, E., Gil-Rojas, J., Ramos-Castro, J., & Capdevila, L. (2022). Agreement between two photoplethysmography-based wearable devices for monitoring heart rate during different physical activity situations: a new analysis methodology. *Scientific reports*, *12*(1), 15448. https://doi.org/10.1038/s41598-022-18356-9

- The articles include: (1) a review of vmHRV and SVs in athletes; (2) a pilot study on vmHRV, mood, and performance; (3) an intervention prescribing individualized training using vmHRV, RHR, and SVs; and (4) validation of wearable devices for heart-rate measurement.
- The four studies follow a logical progression: from theoretical review → empirical evidence → practical application → technological validation. The order in which the articles are presented follows this logic, rather than publication chronology.
- The journals in which the included articles are published are ranked according to the Scientific Journal Ranking (SJR), as follows:
  Article 1: *Int. Rev. Sport Exerc. Psychol.* – SJR: Q1; IF: 6.7
  Article 2: *PeerJ* – SJR: Q1; IF: 2.4
  Article 3: *Scientific Reports* – SJR: Q1; IF: 3.9
  Article 4 (accepted): *Scientific Reports* – SJR: Q1; IF: 3.9
- Article 1 started during an international research stay at the *Deutsche Sporthochschule Köln* (German Sport University Cologne, Germany) between September 2023 and March 2024. The stay provided first-hand insight into various projects of the Performance Psychology Department related to vmHRV in athletes. It also provided an opportunity to learn how the team designs, implements, and analyses studies, bringing new research perspectives.
  The stay also led to the publication of an article for the general public, on vmHRV in Olympic athletes, coinciding with the Paris 2024 Olympic Games. The link to the article is provided in **Annex 1**.
- Article 3 was carried out in collaboration with Dr. Dave C. Clarke following a second, shorter international stay at the Department of Biomedical Physiology and Kinesiology, at Simon Fraser University (Vancouver, Canada), between July and August 2024. The aim of the stay was to train using RStudio (RStudio Team, Boston, MA) and analyse data for Article 3.
- This thesis is submitted for the International Doctorate Mention ("*Mención Internacional*"). Accordingly, the text is in English.

- Key contributions of this thesis are: mapping current research practices and findings on vmHRV and SVs in sport, proposing an integrated approach to guide training, providing methodological recommendations for researchers, practitioners, and device developers, and the validation of devices.
- The results have been presented at national and international conferences (see **Annex 2).**

# 1. INTRODUCTION

## 1.1 Introductory note

Aristotle stated: "*The totality is not, as it were, a mere heap, but the whole is something besides the parts*" (Metaphysics, Book VIII, 1045a.8–10). Centuries later, Gestalt theory further expanded this concept, emphasizing that individual components gain meaning only through their relationship with the whole (Ferkiss et al., 1976). This idea, commonly paraphrased as "*the whole is greater than the sum of its parts*," has influenced diverse fields, from philosophy to psychology and complexity science.

In sports science, this principle is fundamental. Athletic performance emerges from the interaction of multiple systems, and training adaptation depends on the interplay between external load and internal responses, each shaping the other over time. This thesis builds on this complexity-driven perspective, examining how physiological and psychological markers can be integrated to optimize athlete training, performance, and recovery. Without a systematic approach, training decisions risk being suboptimal, leading to overtraining or missed opportunities for peak performance and well-being. The following sections explore this issue in depth. I hope it is an enjoyable and profitable read.

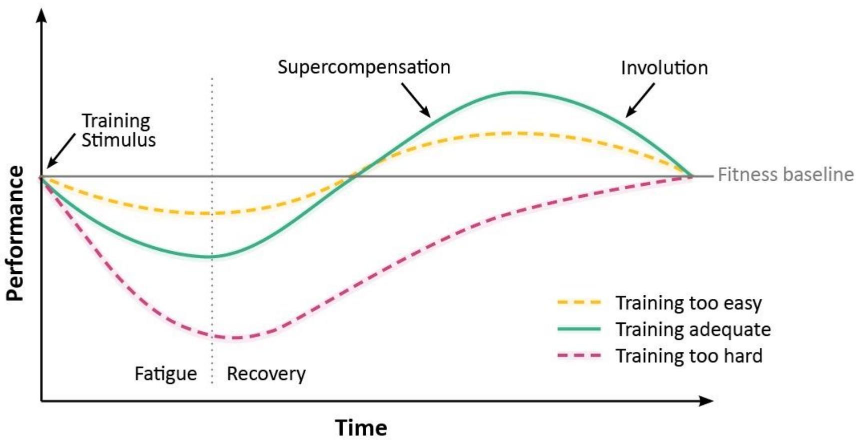
## 1.2 Performance

Performance in the context of sports psychology refers to an athlete's ability to execute a task or skill effectively under specific conditions. It encompasses physical, technical, tactical, and psychological dimensions, with a focus on optimizing outcomes. Performance can be quantified through continuous metrics (e.g., times, distances) and ordinal metrics (e.g., rankings, achievement of personal or national records), analysed by comparing an athlete's results to their own historical performance or to competitors' (Raysmith et al., 2019).

Improving performance has been the focus of extensive research, leading to multiple theories and models explaining how athletes can optimize their abilities. Three key frameworks –supercompensation theory, periodization model, and Individual Zones of Optimal Functioning (IZOF) model– offer insights into the mechanisms of performance.

At the physiological level, **supercompensation theory** explains how athletes improve performance through cycles of training and recovery (Bompa & Haff, 2009; Kellmann, 2010; Yakovlev, 1967). This theory is based on the concept that training depletes physiological reserves, triggering a recovery phase during which the body adapts and overcompensates, replenishing resources beyond the initial baseline. As illustrated in Figure 1, if sufficient recovery is allowed, this process results in improved performance capabilities. However, imbalances in training or recovery can lead to overtraining, preventing athletic progress and increasing the risk of injury, illness, and burnout (Kellmann & Kallus, 2001).

**Figure 1.** Supercompensation curve under varying training loads




The figure shows how different training loads influence performance over time. The green curve represents an optimal load that leads to supercompensation and improved performance. The yellow curve shows insufficient load, leading to minimal adaptation. The red curve depicts excessive load resulting in negative adaptation and potential overtraining. Adapted from Moffatt (2019)

To provide a training plan for sustained growth, **periodization** is a key concept. Periodization builds upon the principles of supercompensation by organizing training into distinct phases that balance load and recovery. This approach, commonly used in sports, includes cycles of training load (which will be also referred to as training stress) and adaptation, culminating in peak performance at key competitions. During periodization, short-term training goals are strategically aligned with long-term performance objectives. Also, while functional overreaching (a temporary performance decline due to intensified training) is often strategically incorporated into periodized plans, chronic overtraining is avoided (Legall et al., 2024).

Supercompensation and periodization focus on physiological adaptations, but psychological models such as the **IZOF** highlight the role of emotional states in performance. IZOF suggests that each athlete has a unique emotional range in which performance is optimal, and deviations from this zone (whether too high or too low) can impair outcomes (Hanin, 1995). Initially, the model was developed as the "Zones of Optimal Functioning" (Hanin, 1978) and indicated the existence of an optimal level of anxiety for performance. Then, an “I” was incorporated to IZOF to account for individual differences and describe within-individual emotional variability (Hanin, 1995). Since then, empirical support has grown and research has expanded the IZOF model beyond anxiety to include a spectrum of emotion and psychobiosocial states (see Ruiz et al., 2017).

Overall, both IZOF and supercompensation highlight the importance of personalization and timing for training and competition. Supercompensation requires tailored and balanced training strategies to maximize physiological adaptation, and predicts peak performance based on recovery cycles. IZOF complements this by demonstrating that peak performance is achieved when emotional states align with physiological preparedness. Since physiological adaptation and emotional zones vary between individuals, it becomes essential to determine what factors to monitor and how to assess training stress and recovery in athletes.

## 1.3 Training: adaptation balance and monitoring metrics

Monitoring training adaptation and recovery is complex, due to the significant variability in individual responses. A given training load for one athlete may lead to positive adaptation, while the same load could risk overtraining in another (Main & Grove, 2009). In that sense, the same training could lead to different supercompensation responses depending on the athlete. This challenge has traditionally been addressed by measuring external and internal loads, two distinct yet complementary approaches to evaluating an individual's adaptation to training (Gabbett, 2020). External load refers to the measurable physical stimuli applied to the athlete, such as time, speed, distance, or resistance. Internal load, in contrast, reflects the athlete's unique physiological and psychological responses to these external stimuli. Physiological responses are measured by metrics such as heart rate, lactate or hormonal responses, while psychological responses encompass cognitive-affective dimensions (Fuster et al., 2021). Cognitive load refers to the amount of mental resources an athlete invests in a task and depends on task complexity and athlete state, while affective responses describe how the athlete feels (e.g. perceived fatigue) and are influenced by an array of signals, including physiological-cognitive demands. Key metrics used to assess internal load, therefore, include physiological markers such as resting heart rate (RHR) and heart rate variability (HRV), as well as an array of self-reported metrics such as perceived fatigue or stress. These variables are the focus of the thesis and will be presented in the following sections.

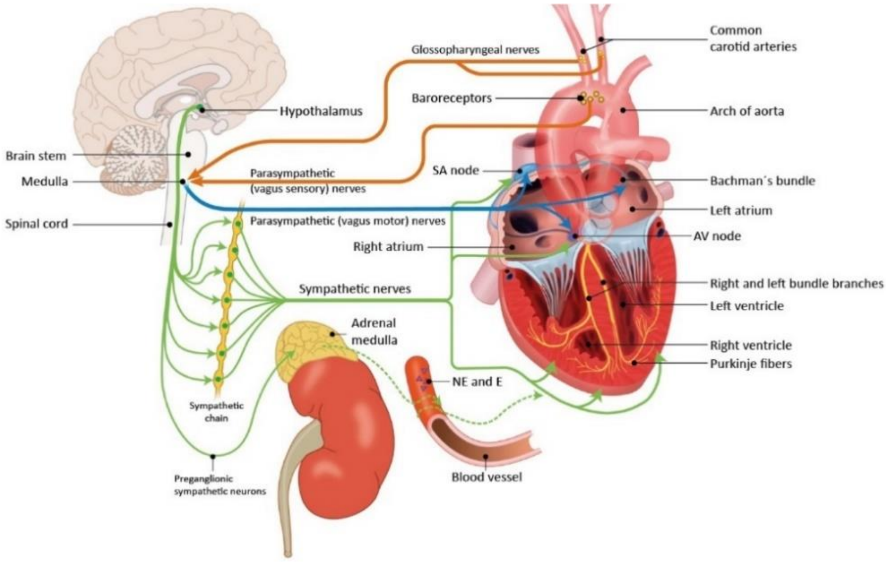
Importantly, because a given external load can elicit different internal responses across individuals, it is essential to adopt reliable methods for monitoring. Evaluating internal states provides insights into the athletes and allows to promote performance and well-being (Coutts et al., 2018; Main & Grove, 2009). However, despite numerous proposed tools, no singular marker exists to consistently monitor internal responses (Halson, 2014; Lac & Maso, 2004).

### *1.3.1 Heart Rate and Resting Heart Rate*

The heart is a key organ of the cardiovascular system. It is roughly the size of a closed fist, weighs 250 to 350 grams and beats around 100,000 times a day. Structurally, it consists of two atria, which receive venous blood, and two ventricles, which pump blood from the heart into the lungs and arteries. Functionally, the heart acts as a specialized pump, maintaining circulation through rhythmic and continuous contractions. These contractions are driven by electrical impulses that cycle repeatedly, producing what is known as heart rate (HR) or pulse. HR reflects the speed of the heartbeat, and it is typically quantified as the number of beats per minute (bpm). The gold standard method for measuring HR is the electrocardiogram (ECG), which provides information about the heart's electrical activity (Quigley et al., 2024). The ECG was first standardized by the Dutch physiologist, physician and Nobel Prize winner W. Einthoven in 1924.

Regarding the rhythm of the heart, it first originates from autorhythmic cells, which spontaneously generate pacemaker potentials to initiate cardiac contractions. The sinoatrial (SA) node and atrioventricular (AV) node are the two primary pacemakers (Shaffer et al., 2014), and for reference, the SA node has an intrinsic rate of about 107 bpm at age 20 (Opthof, 2000). Then, regulation of the heart pace and circulatory system is managed by higher brain centres and the autonomic nervous system (ANS), which operates through the brainstem. A critical component of this control lies in the medulla oblongata of the brainstem, specifically within the nucleus tractus solitarius (NTS). This area integrates and processes sensory signals from proprioceptors, chemoreceptors, and baroreceptors from the heart, along with inputs from the brain and limbic system (Shaffer et al., 2014). The ANS is divided into the sympathetic (SNS) and parasympathetic (PNS) branches, both of which play distinct roles in cardiac regulation. The SNS, through the activation of α- and β-adrenoreceptors, increases HR, contractility, and conduction velocity, while the PNS, primarily mediated by the vagus nerve and muscarinic acetylcholine receptors, has opposing effects, reducing HR by slowing the pacemaker potential at the SA node (Campbell et al., 1989). In a healthy individual, the HR reflects the combined influence of neural signals from the SNS and PNS. At rest, both SNS and PNS are active, but PNS activity predominates, decreasing HR (Campbell et al., 1989). Figure 2 illustrates the process.

**Figure 2.** Simplified autonomic control of the cardiovascular system



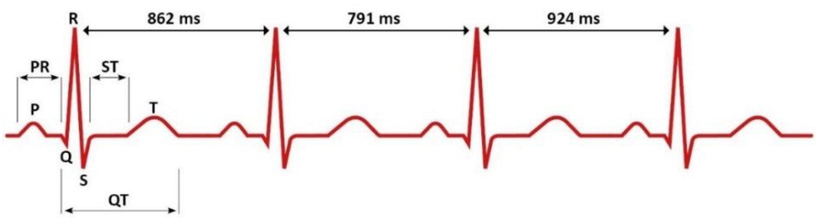

The diagram illustrates the autonomic regulation of the cardiovascular system, including sympathetic and parasympathetic pathways, and the anatomy of the heart. The figure highlights neural circuits from the brainstem and spinal cord to the heart and adrenal medulla, depicting their influence on cardiac structures such as the sinoatrial (SA) node, atrioventricular (AV) node, and myocardial pathways. Sensory input from baroreceptors via glossopharyngeal and vagus nerves is shown. Adapted from Nederend et al. (2016).

**In sports context**, HR has been extensively used, for example during exercise to estimate training intensity zones (Zhu et al., 2022). It is also one of the most common means of assessing internal load in athletes during exercise (Halson, 2014) based on its linear relationship with oxygen consumption during steady-state exercise. Additionally, measuring HR during rest (Resting Heart Rate, RHR) has been considered an indicator of an athlete's physical status (Bosquet et al., 2008), with elevated RHR as a sign of accumulated fatigue and the need for recovery (Buchheit, 2014; Jeukendrup et al., 1992). This is because sustained aerobic training strengthens the heart muscle over time, enhancing its efficiency and increasing the volume of blood that can be ejected with each beat. As a result, RHR typically decreases, making it a useful indicator of an individual's physiological adaptation to aerobic exercise (Grässler et al., 2021a).

### *1.3.2 Heart Rate Variability*

**HRV refers to the fluctuation in time intervals between consecutive heartbeats** (R-R intervals, Figure 3), and is predominantly influenced by HR and the ANS (Rajendra Acharya et al., 2006; Rodas et al., 2008). In healthy individuals at rest, the ECG reveals periodic variations known as respiratory sinus arrhythmia (RSA). The RSA is a natural and rhythmic variation in HR that synchronizes with the breathing cycle, with HR increasing during inspiration and decreasing during expiration (Eckberg, 1983). RSA reflects the parasympathetic component of HRV, primarily mediated by the vagus nerve, which is the 10$^{th}$ cranial nerve and a key component of the PNS. During expiration, vagal activity predominates, while during inspiration, it is temporarily reduced or absent, making RSA a crucial mediator of HRV (Lalanza et al., 2023; Lehrer & Gevirtz, 2014).

**Figure 3.** Illustration of heart rate variability




The figure presents an electrocardiogram (ECG) waveform showing the components of the cardiac cycle: P wave, QRS complex, and T wave, along with the intervals PR, ST, and QT. The RR intervals between consecutive R peaks (862-ms, 791-ms, and 924-ms) are depicted to illustrate the beat-to-beat heart rate variability.

Recognizing the need for consistency in HRV research, an International Task Force was established in 1979 to standardize analysis, terminology, and definitions. This foundational work culminated in the widely referenced Task Force report of 1996 (Malik et al., 1996), which outlined two primary methods for HRV assessment: **frequency-domain and time-domain analysis**. Frequency-domain analysis classifies HRV power into four frequency bands: ultra-low frequency (ULF), very-low frequency (VLF), low frequency (LF), and high frequency (HF). LF (0.04–0.15 Hz) is primarily associated with sympathetic activity, while HF (0.15–0.4 Hz) mostly reflects parasympathetic (vagal) modulation of HR. In contrast, time-domain analysis involves statistical measures of the variability between successive heartbeats (R-R intervals). Two examples are the root mean square of successive differences (RMSSD) and the standard deviation of the time between normal heartbeats (SDNN)**. Of particular relevance is vagally-mediated HRV (vmHRV)**, which encompasses HRV parameters specifically associated with parasympathetic regulation of cardiac function, including RMSSD and HF. RMSSD is often preferred because it is less influenced by breathing rate variations (Laborde et al., 2017; Penttilä et al., 2001; Saboul et al., 2013), making it a more robust and reliable measure.

**The clinical relevance** of HRV was recognized early in the 1960s, with Hon & Lee (1963) identifying changes in HRV as a marker of foetal distress, preceding alterations in heart rate itself. By the 1970s, HRV was recognized as an early marker of autonomic dysfunction in diabetic patients, even before clinical symptoms manifested (Ewing et al., 1976). Since then, research has consistently linked low HRV to various health complications, including cardiovascular disease, all-cause mortality (Jarczok et al., 2022), and even disorders such as depression (Jandackova et al., 2016).

HRV also serves as a **dynamic indicator** of physiological and psychological loads, reflecting the body's adaptability to both internal (e.g., homeostatic challenges) or external (e.g., physical training) stressors (Rajendra Acharya et al., 2006). Experimental studies have shown that cognitive and emotional challenges, such as making complex decisions, significantly reduce HRV (Forte et al., 2022). Beyond acute responses, HRV is a marker of cumulative physiological strain, with a natural decline associated with aging and reduced vagal tone. Nonetheless, regular physical activity has been shown to counteract age-related reductions in HRV by enhancing vagal tone (Grässler et al., 2021b).

**Within sports science**, vmHRV is increasingly recognized as a key tool for monitoring training adaptation. In particular, by tracking vmHRV trends, coaches and athletes can determine optimal training loads to enhance performance while avoiding overtraining or excessive fatigue (Bellenger et al., 2016; Buchheit, 2014; Mosley & Laborde, 2022). Higher levels of vmHRV are linked to better adaptation to training demands and quicker recovery, whereas reductions in vmHRV are commonly observed in conditions of overtraining and fatigue (Buchheit, 2014; Plews, Laursen, Stanley, et al., 2013).

### *1.3.3 Resting Heart Rate & Heart Rate Variability*

The use of HR and HRV measurements in sports has spread widely in the last decades, largely due to their ease of use, non-invasive nature, cost-effectiveness, time efficiency (Buchheit, 2014) and reliable reproducibility when measured under standardized conditions (Kleiger et al., 1991). However, while HR and HRV are often analysed independently, increasing evidence highlights the importance of interpreting them in combination, as HRV is inherently influenced by average HR through both physiological and mathematical mechanisms.

**At the physiological level**, HRV decreases as HR increases because faster heart rates reduce the time available for autonomic modulation between beats, limiting variability (Sacha, 2013). **Mathematically**, the relationship arises because HRV indices, such as RMSSD, are calculated based on consecutive R-R intervals. When HR increases, R-R intervals shorten, restricting the range of possible variability, which may lead to HRV reductions that do not necessarily reflect changes in autonomic function (Sacha, 2014). This mathematical dependency can mislead interpretations unless HRV is normalized for HR. Consequently, researchers have proposed **normalizing HRV by average HR** to minimize mathematical bias and enhance the accuracy of interpretation, especially in populations with varying heart rates (Sacha, 2013, 2014). Building on this framework, studies combining HR and HRV have demonstrated their utility in distinguishing between states of overtraining and recovery, particularly in athletes with high training loads (Buchheit, 2014; Plews et al., 2012). This HR-HRV ratio may help capture subtle changes in fitness and fatigue, making it useful for athlete monitoring. Despite these insights, further research is needed to refine and confirm the practical applications of its integration (Perrotta & Warburton, 2020; Schneider et al., 2019).

### *1.3.4 Subjective self-reported variables*

Historically, advancements in exercise physiology during the mid-20th century led to an interest towards quantifiable measures of performance and recovery, such as HR or HRV, or others, such as blood lactate or hormonal profiles. Nonetheless, another type of variables was also being used to monitor athletes: subjective variables. Subjective variables in this context are defined as personal experiences based on beliefs or feelings, and encompass self-reported measures, reflecting data provided by individuals based on their perceptions and experiences (Cambridge University Press, 2024).

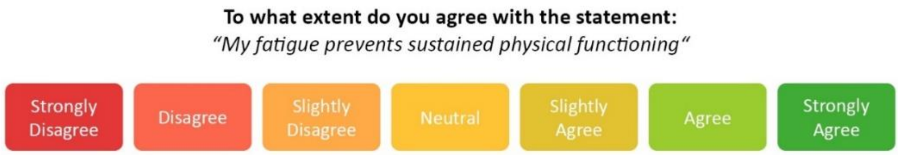
Research has demonstrated that self-reported subjective measures (SV) such as perceived stress, mood, or fatigue are correlated with both training adaptations and performance outcomes. Particularly, SVs have proven as highly sensitive and often precede physiological markers in detecting overtraining and maladaptation (Kellmann, 2010; Purvis et al., 2010; Urhausen & Kindermann, 2002). For instance, fatigue and perceived stress have been shown to predict overtraining before significant changes in physiological markers (Hooper et al., 1995). Furthermore, various forms of overtraining have been attributed to cumulative stress not only from physiological factors, but also psychological and social ones. Research indicates that even low levels of physiological load can lead to overtraining if accompanied by high psychological stress (Morgan et al., 1987). In fact, non-training stressors, including occupational or social conflicts, can impact recovery and negatively impact performance (Budgett, 1990), highlighting the multifactorial nature of training responses.

Beyond overtraining detection, SVs have shown value for optimizing training adaptations and predicting performance. Morgan et al. (1987) introduced a Mental Health Model linking positive mental health with superior performance, supported by studies achieving an accuracy of approximately 80% in predicting performance changes. Positive mood states (e.g., vigour) are associated with improved performance and readiness, while negative states (e.g., fatigue, anger) correlate with increased distress, burnout risk, and performance declines (Main & Grove, 2009; Saw et al., 2016).

Over the years, various tools and methods have been developed to measure SVs, ranging from single-item Likert scales to validated questionnaires. They often involve athlete responses regarding mental, emotional, and physical well-being. Single-item scales and brief composites, often based on Likert scales (Figure 4), are simplest and practical tools for capturing subjective perceptions. For instance, Hooper et al. (1995) employed daily ratings of sleep quality, fatigue, stress, muscle soreness to evaluate well-being and identified overtrained swimmers. Besides single-item, advancements in sports science have led to the development of validated scales such as the Profile of Mood States (POMS) or the Recovery-Stress Questionnaire for Athletes (RESTQ-Sport), for capturing subjective experiences. For example, the POMS (McNair et al., 1981) is a well-documented tool used to monitor mood disturbances and has consistently shown that heightened mood disturbances accompany increased training loads, across multiple sports (Morgan et al., 1987). The RESTQ-Sport assesses both perceived stress and recovery activities across life domains, offering a comprehensive view of an athlete's stress-recovery balance (Kellmann & Kallus, 2001). Another example is the Total Quality Recovery

(TQR), which also focuses on athletes' perceived recovery states, linking higher scores with reduced risks of overtraining and injury (Selmi et al., 2022).

**Figure 4.** Example of a 7-point Likert scale




Example of question answered based on a 7-point Likert scale. The question is extracted from the Fatigue Severity Scale Questionnaire (Fatigue Severity Scale (FSS), 2011).

SVs span multiple domains, reflecting the diversity of self-reported measures used in athlete monitoring. Researchers have also explored simultaneous assessments using multiple scales and/or questionnaires, across various domains and sports (e.g., Hooper et al. [1995]). Taken together, the evidence indicates that tracking SVs provides valuable insights in athlete monitoring, training adjustment and performance.

### *1.3.5 Combination of subjective variables and HR-related metrics*

The previous sections highlight the value of both psychological and physiological markers in monitoring athletes' internal states. However, despite their widespread use and utility, **neither approach seems to be entirely sufficient on its own** (Lac & Maso, 2004; Meeusen et al., 2013). This section highlights their limitations.

On the one hand, Saw et al. (2016) showed through a systematic review that **SVs** often demonstrate greater sensitivity and consistency in detecting training loads than physiological markers like HR, and even argued that training decisions could prioritize perceptual well-being. However, another review showed that the reliability of single-item SV measures can be inconsistent (Duignan et al., 2020), with their sensitivity influenced by factors such as exercise intensity distribution (Schliep et al., 2020). Additionally, perceived stressors can impair performance even in low-exertion sports, such as golf (Kenttä et al., 2001), and mood fluctuations may occur without corresponding changes in physical performance (Beedie et al., 2000). The efficacy of SV also depends heavily on their implementation (Saw et al., 2015), interpretation, external influences and subjective biases (Heidari et al., 2019), making careful selection and systematic application crucial (Nässi et al., 2017).

On the other hand, **HR or HRV**, despite their objectivity and quantifiability, also have weaknesses. HR metrics alone often fail to fully capture training responses, fatigue, or performance adaptations, as its relationship with these factors is not always linear (Bellenger et al., 2016; Buchheit, 2014). Additionally, methodological inconsistencies (Buchheit, 2014) and contradictory findings (Bellenger et al., 2016) further complicate interpretation. Misinterpretations can arise when HR is assumed to be a direct indicator of fatigue (Achten & Jeukendrup, 2003). For example, research on rugby players found that perceptual muscle soreness provided insights into training demands that objective measures failed to capture (Tavares et al., 2018).

Given the limitations of relying on a single metric to quantify training effects and predict performance, both researchers and practitioners increasingly **advocate for an integrative approach** that combines both subjective and objective measures (Barrero et al., 2020; Bourdon et al., 2017; Leti & Bricout, 2013). It is thought that given the complexities of athlete's responses, combining markers might improve the precision of training monitoring (Plews et al., 2012; Rothschild et al., 2024). In fact, some research has already shown that integrating HR-based and SV metrics enhanced the detection of overtraining and improve training recommendations (Barrero et al., 2020; Buchheit, 2014; Leti & Bricout, 2013; Plews, Laursen, Kilding, et al., 2013; Rothschild et al., 2024). For example, combining subjective measures like training tolerance with vmHRV was effective in interpreting changes in post-exercise RMSSD, which isolated vmHRV measures alone struggled to predict

(Bellenger et al., 2021). Despite its promising application, **many key questions arise regarding integrative approaches**, including the optimal combination of variables, their relationships, methods for integration, and their application in athletic contexts. Addressing these gaps requires understanding the interactions between physiological and psychological data. Before deepening the main question of this thesis, the next section explores the theoretical basis for such an integrative approach.

## 1.4 Psychophysiological perspective: integration of physiological & psychological factors

If research points to the integration of physiological and psychological markers in athlete monitoring, an interesting question is whether these markers are fundamentally interrelated, and if so, how. This section provides **historical and scientific context** on the link between heart physiology and psychological variables, tracing evidence from early observations to recent research.

### *1.4.1 Historical perspective: heart as centre of emotion and intellect*

The understanding of the cardiovascular system has evolved over millennia, with early civilizations attributing profound physical, emotional, intellectual and spiritual significance to the heart. In ancient Egypt, the heart (*ib*) was considered the most important organ in the body and the source of conscience, intelligence, and moral judgment. During embalming, it was the only organ returned to the body to ensure guidance in the afterlife. Similarly, in ancient Greece, the heart (*thymos*) was thought to govern emotions and desires, while the brain (*psyche*) was associated with eternal life and rational thought. Aristotle viewed the heart as the seat of the soul and observed that it is the first organ to form in chick embryos (Figueredo, 2021). Modern science confirms this, showing that the heart is the first organ to develop during embryogenesis, beginning to beat and pump blood by week three and reaching morphological maturity by week seven (Zaffran & Frasch, 2002). In contrast, brain development spans a much longer timeline, from the formation of the neural plate in week three to postnatal refinement of neural connections (Kostovic & Vasung, 2009).

Religious and philosophical traditions further reinforced the symbolic and functional importance of the heart and its link to emotion. Early Hebrews and Christians linked the heart to emotional, intellectual and moral actions, considering it the dwelling place of divine knowledge. Islamic teachings similarly described the heart as the vessel of emotions, intention and spirituality. Meanwhile, ancient Chinese texts translate heart (*Xin)* as "heart-mind", seen as the source of intelligence, ruling the body (Figueredo, 2021). Interestingly, Traditional Chinese Medicine describes the heart as the "emperor" of the body, standing as the most important of the 5 yin organs (heart, liver, lung, spleen and kidneys), and playing a central role in emotional balance. When disrupted, it may lead to conditions such as anxiety or insomnia (Maciocia, 1989).

These historical perspectives emphasize the longstanding cultural and symbolic importance of the heart, and its associations with emotions and cognition, foreshadowing modern scientific observations.

### *1.4.2 Physiology: early research and neurocardiology*

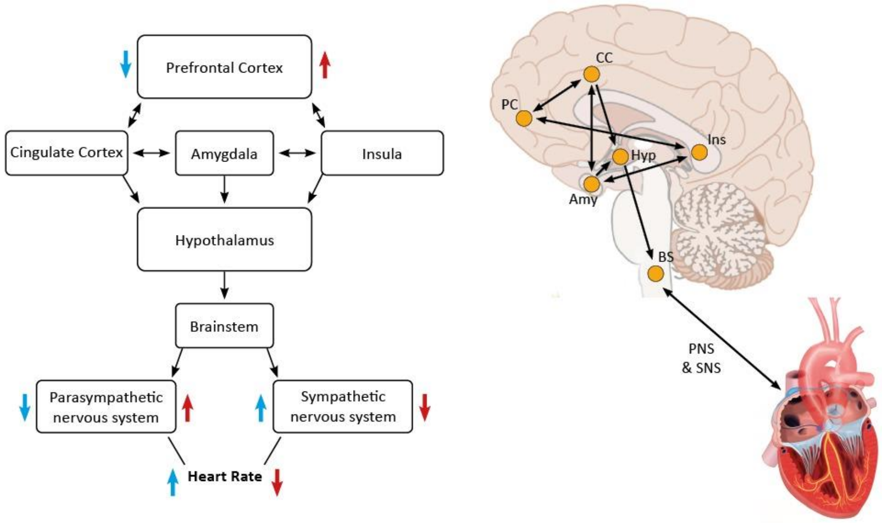
The link between cardiac activity and the brain began gaining empirical support in the mid-20th century. John and Beatrice Lacey pioneered research on heart-brain interactions, suggesting that the heart plays a causal role in modulating cognitive functions (Lacey & Lacey, 1974; Lacey, 1967; Lacey & Lacey, 1970). They proposed that afferent input from pressure-sensitive neurons in the heart, carotid arteries, and aortic arch influence cortical functions (Lacey, 1967). Building on this, Velden and Wölk (1987, 1989) found that cognitive performance fluctuates rhythmically, aligning with cardiac cycles and neural activity in the thalamus, a key structure for cortical synchronization. Their research stated that the rhythm of cardiac afferent signals, rather than the quantity of neural bursts within the cardiac cycle, plays a critical role in modulating thalamic activity.

These findings were one of several key contributors to the emergence of the field of neurocardiology, a field that examines the complex anatomical and functional connections between the heart and brain. Neurocardiology has since revealed that the connections between the heart and brain are far more intricate than previously thought. For instance, while descending (efferent) pathways, primarily mediated by the ANS, regulate heart function, newer research has shown that intrinsic cardiac neurons play an equally significant role (Kukanova & Mravec, 2006). The intracardiac nervous system, sometimes referred to as the "little brain of the heart" (Armour, 2008), consists of sensory, interconnecting, afferent, and motor neurons (Verkerk et al., 2012). These neurons can operate autonomously, processing mechanical and hormonal signals locally before transmitting information to the brain via afferent (ascending) pathways, primarily through the vagus nerve and spinal cord (Kukanova & Mravec, 2006; Verkerk et al., 2012). A striking finding is that around 85–90% of vagus nerve fibers are afferent, meaning they sent more signals from the heart to the brain than the other way around (Cameron, 2002). These afferent signals influence higher-order brain regions, including frontocortical areas (Lane et al., 2001) and motor cortex (Svensson & Thorén, 1979), affecting attention, motivation (Schandry & Montoya, 1996), perceptual sensitivity (Montoya et al., 1993), and emotional processing (Zhang et al., 1986).

### *1.4.3 Physiology: NIM and VTT*

Building on these discoveries, Thayer & Lane (2000) introduced the Neurovisceral Integration Model (NIM), which describes how the heart's neural feedback integrates into higher-level cognitive and emotional regulation, and in particular the central autonomic network (CAN, Figure 5). The NIM framework proposes that the CAN links the brainstem's NTS to forebrain regions including the anterior cingulate, insula, ventromedial prefrontal cortex, amygdala, and hypothalamus. These structures form complex feedback (and feed-forward) loops that regulates visceromotor, neuroendocrine, and behavioural responses that are critical for goal-directed behaviour, adaptability, and health.

**Figure 5.** The Neurovisceral Integration Model




The diagram illustrated the neural pathways linking brain structures to the regulation of heart rate via the brainstem and the sympathetic and parasympathetic nervous systems. The left panel shows how the prefrontal cortex modulates subcortical structures (e.g., amygdala, insula, hypothalamus), which in turn influence brainstem output to the ANS. Blue arrows indicate decreased parasympathetic activity, associated with higher heart rate, while red arrows indicate the opposite. Adapted from Nikolin et al. (2017) and Park & Thayer (2014), using brain and heart illustrations from Nederend et al. (2016).

Thayer et al. (2012) argue that HRV, and particularly vmHRV, serves as a physiological marker of neuro-visceral integration through dynamic connections between the amygdala and prefrontal cortex, which evaluate threat and safety signals and which regulate vmHRV via connections to the NST in the brainstem. They propose that vmHRV is linked to higher-level executive functions and emotional regulation and thereby reflects the functional capacity of these structures for working memory, self-regulation and stress (e.g., from training) resilience. Self-regulation is referring to the psychological and physiological processes that allow both goal-directed behaviour and keeping an organism healthy (Thayer et al., 2009). In this model, when the CAN decreases prefrontal cortical activation, HR increases and vmHRV decreases, impairing autonomic flexibility and cognitive control. Supporting this, research has shown that patients diagnosed with anxiety disorders exhibit lower vmHRV, suggesting impaired self-regulation and heightened threat sensitivity (Friedman, 2007).  Conversely, higher vmHRV is associated with greater prefrontal cortical activation, enhancing psychological resilience and cognitive stability (Appelhans & Luecken, 2006; Balzarotti et al., 2017).

Building onto the NIM, the Vagal Tank Theory (VTT; Laborde et al., 2018) describes cardiac vagal activity (e.g., vmHRV) as a physiological marker of how capable a system is at mobilising and applying self-regulatory resources. The VTT introduces the metaphor of a “vagal tank” that can fluctuate between depletion and replenishment and proposes three systematic levels of analysis for vmHRV: at rest, during a task, and in recovery. While the NIM emphasizes resting vagal tone as a marker of regulatory capacity, the VTT highlights the importance of phasic changes, meaning how cardiac vagal activity dynamically responds to and recovers from stressors (e.g., exercise). In this view, not only the level of vmHRV but also its direction and magnitude of change provides information into self-regulation. In line with the NIM, higher vmHRV at rest indicates a fuller tank and greater self-regulatory, associated with improved stress response and emotional regulation.

Together, the NIM and VTT form the conceptual foundation of much current HRV research: the NIM providing a neurobiological basis for the role of vagal control in cognitive and emotional processes, and the VTT emphasising context. Accordingly, vmHRV is treated as an indicator of emotional state and may be expected to vary positively with SVs (e.g., higher vmHRV with positive ratings). At the same time, SVs reflect conscious appraisal and are generated by higher-order cortical networks within the CAN (e.g., Craig, 2009). Thus, while these frameworks provide a biological basis for the interplay between vmHRV and SVs, in the current context of athlete monitoring questions arise about what can each type of variable (vmHRV, SVs) capture and whether their integration provides a more comprehensive monitoring approach or not.

## 1.5 Current technology for the monitoring of athletes

The previous sections emphasize the importance of tracking the balance between training load and recovery in athletes and presented some candidate metrics. This section explains how these metrics can be measured.

Advances in wearables, smartphones, and cloud platforms over the past decades have transformed real-time data collection. A key approach is Ecological Momentary Assessment (EMA), defined as “strategies for tracking or sampling to evaluate phenomena in real time within natural environments” (Dunton, 2017). EMA maximizes ecological validity, minimizes recall bias by collecting brief, in-situ reports. EMA, however, must be paired with tools capable of real-time data collection, such as mobile health (mHealth). mHealth broadly refers to the use of mobile technology to monitor, manage, and improve health. These systems facilitate the collection of physiological, cognitive and behavioural information via integrated sensors (e.g., accelerometers, GPS) or external Bluetooth-connected devices (e.g., HR monitors, temperature sensors). Wearable devices, such as fitness trackers, smartwatches, or specialized medical-grade devices, can be considered a subset of mHealth. These devices expanded dramatically in recent years, from simple stopwatch timing in the 1950s to wireless, real-time monitoring of biomechanical, physiological, and performance data (Foster et al., 2017; Montull et al., 2022). Nowadays, most devices sync with mobile applications and cloud services, enabling users and practitioners to visualise, analyse, and interpret the data. In this way, wearable technology extends mHealth by enabling continuous monitoring and timely feedback, for example on training adaptations.

In the fields of sports and fitness, wearables can now quantify both internal and external load indicators (Cardinale & Varley, 2017). For instance, these devices measure HR-related variables, including HR and HRV, primarily using photoplethysmography (PPG). In the case of HRV, a key driver of its growth in popularity is precisely its accessibility, facilitated by mHealth. Unlike other physiological markers such as lactate or muscle oxygen saturation, HRV can be measured non-invasively with commercially available devices. Moreover, ultra-short-term protocols (<1-min) and smartphone-compatible apps have increased user compliance (Nakamura et al., 2015).

Beyond physiological tracking, mHealth platforms also allow the assessments of SVs, encouraging athletes to self-report experiences such as perceived exertion or perceived stress levels via smartphone-based questionnaires. When paired with wearable-derived physiological metrics, these self-reports aim to create a profile of an athlete's condition. So, the capacities of mHealth technology is growing in parallel with the interest in integrating physiological and psychological variables into athlete monitoring (Thorpe et al., 2016).

However, despite the growing adoption of advanced monitoring technologies, a significant challenge arises: the commercial development of new tools often outpaces scientific validation. There is an array of organizations that are currently heavily investing in new technologies to monitor daily training and general health. The rise of big data and AI-driven sports analytics has further intensified the demand for continuous monitoring and predictive modelling. However, many of these innovations use metrics without a clear vision of how the data will be interpreted or applied (Montull et al., 2022). This approach diverges from scientific best practices, which emphasize developing models and hypotheses before conducting empirical tests. Overall, while technological advancements hold promise for improving athlete monitoring, a scientifically grounded approach is necessary to ensure meaningful, evidence-based contributions to sports science. In this case, a grounded approach combining HR-related and SVs metrics could be explored.

# 2. RATIONAL AND PURPOSE OF THE THESIS

Athletes and coaches need tools and systems to monitor a balance between training and recovery to ensure performance, health and well-being, and to reduce the risk of overtraining. Although several metrics have been proposed, no single marker seems to provide information that is both reliable and sufficient for these purposes. Instead, there is a growing idea that an effective monitoring system for athletes should incorporate both physiological and psychological markers, combining them into a comprehensive approach that can accounts for the complexity of training adaptation (Heidari et al., 2019). In this context, three key studied metrics are vmHRV, RHR and SVs, which together offer information about autonomic regulation, self-regulatory capacity, and psychological states. Moreover, there is a long-recognized historical connection between the heart and brain, which has evolved into more scientific models, such as the NIM and the VTT, offering a physiological rationale for linking cardiac measures and self-reports.

Nevertheless, the use and integration of vmHRV, RHR and SVs in athlete monitoring still poses several practical and methodological challenges, such as which parameters should be used, or how should they be collected and interpreted. Additionally, while wearable technology now allows real-time monitoring of multiple metrics, its scientific validation and practical application remain questionable. Addressing these challenges is necessary to advance athlete monitoring systems that are both evidence-based and practically useful, and which responds to demands of researchers and practitioners.

In summary, the above literature identifies 3 main gaps:

1. The need (still largely unmet) for athlete internal load monitoring systems that combine multiple variables.
2. A lack of standardized protocol for the selection, integration and interpretation of variables.
3. Inconsistent validation and feasibility of wearable technology.

**Based on this foundation, the main purpose of the present thesis is to explore the role and integration of vmHRV, RHR, and SVs in athlete monitoring.**

The specific subgoals are the following:

1. **Synthesize current evidence** of the use of vmHRV and SVs in athlete monitoring. This includes identifying what variables are studied, what correlations have been found, and what methodological practices are being used.
2. **Assess the application** of vmHRV and SVs in training responses and performance optimization.
3. **Validate the accuracy and feasibility** of wearable devices for HR monitoring, determining their practical reliability.
4. **Connect and interpret the findings in light of existing HRV-related frameworks** (NIM and VTT).

Beyond these subgoals –and because the thesis is grounded in real needs within the field– it also seeks to provide practical findings and tools to:

- **Inform practitioners (coaches, athletes, staff) and sports scientists** about monitoring systems that incorporate reliable markers.
- **Bridge research-practice gaps** by providing a practical implementation of vmHRV, RHR, and SVs in endurance sports.
- **Provide evidence-based guidance** on the use of wearable technology for athlete monitoring.
- **Lay the groundwork for future research**.

In simpler terms, it seeks to explore whether and how vmHRV, RHR, and SVs can be integrated to monitor athletes. It also aims to identify current challenges, inconsistencies, and considerations, in order to contribute to the foundation for a structured, evidence-based integration.

## Publications & structure of the thesis

To pursue the goal, the thesis comprises four studies. The sequence of studies is organized based on a logical progression, from theoretical understanding to real-world application, with each study building on the previous one. In summary, the trajectory is:

Conceptual review → Experimental findings → Real-world applications → Technological feasibility

Below, the four studies are presented with their title, citation, and a brief description of the purpose and contribution to the thesis.

**Article 1:**

- **Reference**: Alfonso, C., Haydt, V., Allen, M. S., Capdevila, L., & Laborde, S. (2025). Monitoring training adaptation: a scoping review of the relationship between self-reported subjective variables and resting vagally-mediated heart rate variability (vmHRV) in adult athletes. *International Review of Sport and Exercise Psychology*, 1–38. https://doi.org/10.1080/1750984X.2025.2541350
- **Purpose**: To synthesize existing research correlating vmHRV and SVs in athletes. Describe the types of variables examined and the directions of correlations. Also, identify prevailing methodological practices.
- **Contribution**: Offers a theoretical foundation and highlights what is currently known, research gaps and methodological inconsistencies in the literature investigating the integration of vmHRV and SVs in athletes. It also sets the stage for the empirical studies.

**Article 2:**

- **Reference**: Alfonso, C., & Capdevila, L. (2022). Heart rate variability, mood and performance: a pilot study on the interrelation of these variables in amateur road cyclists. *PeerJ*, *10*, e13094. https://doi.org/10.7717/peerj.13094

- **Purpose**: To investigate how HRV changes in response to training loads and how it correlates with mood in athletes.
- **Contribution**: It is a pilot study that explored the interplay between mood and HRV indices. It allowed the PhD candidate to become familiar with research planning and implementation, as well as with the metrics studied.

**Article 3** (Accepted for publication at *Scientific Reports*)**:**

- **Authors and title:** Alfonso, C., Clarke, D. C., Capdevila, L. Individual training prescribed by heart rate variability, heart rate and well-being scores in experienced cyclists.
- **Purpose**: To test the effect on performance of three protocols that prescribe training intensity based on a combination of vmHRV, RHR and SVs. Also, explore the correlation amongst these markers during the intervention.
- **Contribution**: This study suggests that a combination of vmHRV, RHR, and SVs can help personalize training and improve performance, contributing to the development of monitoring systems. It also explores the interplay between vmHRV and SVs, extending evidence summarized in Article 1.

**Article 4:**

- **Reference**: Alfonso, C., Garcia-Gonzalez, M. A., Parrado, E., Gil-Rojas, J., Ramos-Castro, J., & Capdevila, L. (2022). Agreement between two photoplethysmography-based wearable devices for monitoring heart rate during different physical activity situations: a new analysis methodology. *Scientific reports*, *12*(1), 15448. https://doi.org/10.1038/s41598-022-18356-9
- **Purpose**: To assess the accuracy of two commercially available wearable devices in tracking HR under different conditions.
- **Contribution**: Tests whether wearables can accurately measure HR, a prerequisite for using HRV in monitoring systems. By assessing device feasibility, it bridges the gap between research and practice, determining whether current technology is suitable for in-field use in sports.

# 3. PUBLICATIONS

This chapter presents the four publications that form the core of this doctoral thesis, including one literature review and 3 experimental articles.

Each publication is preceded by a summary of its goal and the main findings, along with supplementary analyses that, although not included in the original manuscripts, contribute to the overall discussion of the thesis. Together, the 4 studies aim to answer the research questions formulated in the introduction.

## 3.1 Article 1

Alfonso, C., Haydt, V., Allen, M. S., Capdevila, L., & Laborde, S. (2025). Monitoring training adaptation: a scoping review of the relationship between self-reported subjective variables and resting vagally-mediated heart rate variability (vmHRV) in adult athletes. *International Review of Sport and Exercise Psychology*, 1–38. https://doi.org/10.1080/1750984X.2025.2541350

Note: Attached below is the Accepted Manuscript (posprint) version of the article published by Taylor & Francis in *International Review of Sport and Exercise Psychology* on 4th August 2025, available online: www.tandfonline.com/doi/full/10.1080/1750984X.2025.2541350.
The journal's copyright does not permit posting the publisher's original manuscript.

### *Aim and results*

This scoping review aimed to explore the relationship between resting RMSSD-based vmHRV and SVs in athletes, as well as examining methodological protocols and tools used to assess these markers. The study selection process followed a systematic approach aligning with the guidance provided by the Joanna Briggs Institute (JBI) for scoping reviews (Peters et al., 2020).

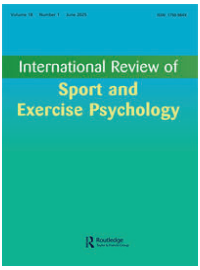
The results were the following:

**Studies:** A total of 31 studies met the inclusion criteria and were analysed. The studies covered a range of sports, including team and individual disciplines. The majority of studies were published from 2020 to 2025. The studies varied in sample size (5 to 117 participants), with a total of 514 athletes analysed. Most studies included elite athletes (65%), while a minority focused on recreational.

**HRV recording:** Across studies, vmHRV was primarily assessed using RMSSD or derivatives such as LnRMSSD (25%), followed by HF power (8%). Differences were observed in recording conditions, including morning (63%), nearing training or competition (20%), or nighttime (6%). Body positions varied, with nearly 50% of studies using supine measurements, 39% seated, and 10% orthostatic recordings. Regarding duration, short-term (1–5 min) recordings were most common (n = 18), while the rest used longer recordings (≥10 min). The frequency of HRV recordings ranged from single assessments to daily monitoring over multiple weeks. Also, ECGs were used in 5 of the 31 studies, chest-strap monitors in 20, and PPG-based in 6. Overall, variability was found in HRV measurement tools, data processing techniques, and SVs assessment methods.

**SV recordings:** Subjective variables were assessed using questionnaires and single-item Likert scales. The most recorded SV was perceived stress (16%), followed by fatigue (15%), perceived recovery (14%) and sleep quality (11%). A total of 21 different types of SVs were identified. Studies differed in how they categorized and interpreted SVs, with some studies aggregating multiple SVs into composite scores, while others analysed them individually. Overall, there were differences in questionnaire design, response scales, and data synchronization.

**RMSSD and SVs:** Studies were categorized based on the subjective variables assessed: fatigue and recovery-related, psychological, and sleep-related variables. Twenty-five results indicated a significant relationship (positive or negative) between vmHRV and recovery-related variables, with higher vmHRV being mostly associated with lower fatigue. Muscle soreness was assessed in 10 studies, with 6 reporting inconsistent relationships. A total of 52 results investigated vmHRV in relation to psychological variables, with 8 studies reporting that higher vmHRV was associated with lower perceived stress, while 9 studies found no significant association. The directions of these relationships varied greatly across studies. Finally, sleep-related variables were reported in 16 cases, with 4 studies reporting a positive association between higher vmHRV and better sleep quality. Nonetheless, the relationship was mostly non-significant.

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# Monitoring training adaptation: a scoping review of the relationship between self-reported subjective variables and resting vagally-mediated heart rate variability (vmHRV) in adult athletes

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## Abstract

**Purpose**: Explore the relationship between vagally-mediated heart rate variability (vmHRV) and self-reported subjective variables (SVs) in adult athletes, and evaluate the methods used to measure these markers. It aims to provide evidence-based recommendations for athletic monitoring and future research.

**Method**: Following the PRISMA-ScR framework, a systematic search of Web of Science, PubMed, PsychINFO and Sport Discus identified 9359 records. Additional backward and forward citation searches were conducted. Studies were included if they were peer-reviewed, in English, involved athletes, and examined vmHRV in correlation with SVs. Studies in clinical populations, animals, and reviews were excluded. Thirty-one studies met inclusion criteria. Methodological quality was assessed using the Joanna Briggs Institute (JBI) appraisal, and inter-rater consistency was evaluated with Cohen's Kappa.

**Results**: SVs were grouped into fatigue-recovery indicators, psychological states, and sleep-related variables. Higher vmHRV often correlated with improved recovery, better sleep, and lower perceived stress, though results were inconsistent. Substantial methodological heterogeneity was also observed. Cohen's Kappa indicated high agreement, and JBI no discrepancies.

**Conclusion**: The relationship between vmHRV and SVs is complex, influenced by individual (e.g., training status) and methodological (e.g., timing, tools) factors. This review highlights the need for personalised, integrated athlete monitoring, and presents new guidelines for future research.

**Keywords**: *psychophysiology, sports, fatigue, recovery, perceived stress, overtraining*

## Introduction

Athletic performance relies on a carefully managed balance between training and recovery. This balance promotes physiological adaptations through a process called supercompensation (Bompa & Haff, 2009; Kellmann, 2010; Yakovlev, 1967), and mitigates the risks of overtraining and burnout. Overtraining refers to a maladaptive response to excessive training load, resulting in decreased performance, while burnout is a syndrome characterized by emotional and physical exhaustion, reduced sense of accomplishment, and sport devaluation. Both conditions stem from prolonged exposure to chronic stress and share overlapping psychological and physiological manifestations, including vulnerability to injury, illness, and hindered athletic progress and well-being (Kellmann & Kallus, 2001; Moore et al., 2025). However, given that athletes respond to training loads differently, reliable methods to monitor and optimize adaptation are essential for coaches and athletes to support sustained athletic performance (Coutts et al., 2018; Main & Grove, 2009). Despite a variety of tools proposed, there is no single reliable marker to predict and prevent overtraining and burnout (Halson, 2014; Lac & Maso, 2004; Schmitt et al., 2013a). This review aims to explore how psychological and physiological markers of recovery, specifically self-reported subjective variables (SVs) and heart rate variability (HRV), may be associated to better understand how these markers may complement each other in monitoring athlete training status.

SVs have a long-standing role in athletic training as indicators of both recovery and overtraining. SVs capture subjective experiences, based on personal beliefs or feelings (Cambridge University Press, 2024), and often reflect mental stress and fatigue before physiological metrics show changes (Kellmann, 2010; Saw et al., 2016). Among SVs, certain variables (e.g., muscle soreness, perceived tiredness, recovery-stress state) offer insight into the balance needed between training load and recovery (Cheung et al., 2003; Kellmann, 2010; Maso et al., 2005). Other SVs (e.g., mood, anxiety) focus on reporting psychological states, known to impact the health and well-being of athletes, as well as performance (Rice et al., 2016). For instance, anxiety is a psychosocial emotion that influences rehabilitation outcomes (Forsdyke et al., 2016). Sleep-related SVs, such as sleep quality and duration, highlight rest as a critical component of recovery (Vitale et al., 2019), with poor sleep linked to higher injury rates (Gao et al., 2019). Overall, SVs provide insight into athlete adaptation to training. However, several concerns limit their practical use. Research shows that some validated questionnaires have only moderate psychometric properties, and customized tools often used in applied settings may lack reliability and validity (Jeffries et al., 2020; Saw et al., 2017). Athletes can also show poor compliance with daily monitoring, often due to lack of feedback or perceived unfair use of the data, leading to dishonest or inconsistent reporting (Neupert et al., 2019). Furthermore, issues associated with subjective interpretation and external influences can also distort athletes' self-reported status (Heidari et al., 2019). As a result, the use and interpretation of SVs is often approached with caution.

In addition to SVs, physiological measures like HRV, particularly vagally-mediated HRV (vmHRV), have gained prominence as indicators of training adaptation and recovery (Bellenger et al., 2016; Buchheit, 2014; Mosley & Laborde, 2022). HRV refers to the variation in time intervals between successive heartbeats and is considered a non-invasive marker of the autonomic nervous system's regulation of cardiac function (Laborde et al., 2017; Quigley et al., 2024). Specifically, vmHRV reflects parasympathetic nervous system (PNS) activity, which is primarily regulated by the vagus nerve, the tenth cranial nerve and the main afferent pathway of the PNS (Brodal, 2016; Shaffer et al., 2014). As such, vmHRV provides insight into the body's ability to adapt to both internal and external self-regulatory demands, including those induced by training (Mosley & Laborde, 2022). Among vmHRV parameters, the Root Mean Square of the Successive Differences (RMSSD) and its derivatives (e.g., logarithm of RMSSD) are frequently studied (Laborde et al., 2017; Quigley et al., 2024). Higher resting RMSSD levels have been associated with adaptation to training loads and faster recovery, whereas lower levels are often observed in states of overtraining and fatigue (Bellenger et al., 2016; Buchheit, 2014). Emerging evidence also links lower resting RMSSD to higher levels of burnout, particularly based on several longitudinal studies within the Dresden Burnout Study cohort (Moore et al., 2025; Penz et al., 2018). A recent review further emphasised the value of HRV in determining and monitoring exercise intensity (Tanner et al., 2024). However, individual variability, stemming from age for instance, and contextual factors, such as prior exercise, can affect the magnitude of these associations (Buchheit, 2014; Plews, Laursen, Kilding, et al., 2013). Much like psychological factors, the role of vmHRV as a monitor of training is more nuanced than would be expected (Bellenger et al., 2016; DeBlauw et al., 2023).

To capture a more comprehensive view of athletes' adaptations to training, some studies suggest the potential advantages of monitoring both physiological and psychological dimensions of recovery. Integrating these metrics has shown to reinforce overtraining markers and improve training recommendations (Barrero et al., 2020; Bourdon et al., 2017; Buchheit, 2014; Leti & Bricout, 2013; Plews, Laursen, Kilding, et al., 2013; Rothschild et al., 2024). For example, combining subjective measures like training tolerance with vmHRV data was effective in interpreting changes in post-exercise RMSSD, which isolated RMSSD measures alone struggled to predict (Bellenger et al., 2021). At a theoretical level, this integration also draws from the Neurovisceral Integration Model (NIM), which highlights vmHRV as a measure not only of physical stress responses but also the body's capacity for psychological self-regulation (Thayer et al., 2009). According to the NIM, vmHRV is framed as an indicator of self-regulation capacities that integrate emotional and physiological responses through brain structures based on the central autonomic network (Thayer et al., 2009), with higher vmHRV indicating greater adaptability and emotional regulation (Appelhans & Luecken, 2006; Balzarotti et al., 2017). This integration implies that combining vmHRV and SVs might offer a more holistic perspective on an athlete's adaptability to training (Balzarotti et al., 2017). Nevertheless, a consensus on the integration of these markers is lacking, with ongoing debates about measurement standardization and the best evidence-based and efficient applications for athletic monitoring (Catai et al., 2020; Laborde et al., 2017; Quintana et al., 2016).

The aim of this review is to explore the relationship between RMSSD-based measures of vmHRV and SVs (fatigue-recovery indicators, psychological states, sleep-related measured) in athletic populations. Specifically, it focuses on observational, non-intervention contexts to examine how these variables interact without the influence of experimental manipulation. In addition, it aims to critically evaluate the methods used to measure vmHRV and SVs, with respect to their strengths and weaknesses. By exploring how psychological and physiological markers are interrelated, the review seeks to develop evidence-based recommendations for optimizing athletic monitoring and guiding future research in the field.

## Method

This scoping review was developed based on the PRISMA Extension for Scoping Reviews (PRISMA-ScR) recommendations (Tricco et al., 2018). A completed PRISMA-ScR checklist is provided as supplementary material (Supplementary Material A). The protocol was registered on the Open Science Framework (OSF, doi: https://doi.org/10.17605/OSF.IO/VCJHN) prior to study screening. Study selection and methodology quality assessments are also provided on the OSF. A scoping approach was selected due to the substantial heterogeneity in study designs and measurement protocols, which precluded a meta-analysis.

### *Literature search*

Bibliographic searches were conducted on May 15th 2025, in the electronic databases PubMed, PsycINFO, Web of Science Core Collection and SportDiscuss. The terms used for the searches are found in Table 1. Boolean operators (including "AND", "OR" and "NOT") were used. No restriction was applied for publication period, age or sex of participants. The studies found were incorporated into Zotero, and a total of 3,034 duplicate records were manually removed before screening. In addition to database searching, backward citation searching (screening the reference lists of included articles) and forward citation searching (identifying articles that cited the included studies using Google Scholar) were also performed. A total of ten full-text articles could not be accessed, and the ten corresponding authors were contacted to request the texts. Seven authors responded and provided the requested documents, while three did not reply, and those studies were excluded.

**Table 1.** Terms of search used in Pubmed, PsycINFO, Web of Science and SportDiscuss

| Boolean operator | Search terms |
|---|---|
| | "Heart rate variability" OR “hrv” OR “RMSSD” OR “parasympathetic” OR “vagal” or “vagus” |
| **AND** | “Athlet*” OR “sport*” OR “exercise” OR “physical activity” OR “perform*” OR “overload*” OR “taper*” OR “train*” OR “match*” OR “compet*” OR “game*” OR “fitness*” |
| **AND** | “Psycholog*” OR “subjectiv*” OR “psychometr*” OR “mood*” OR “questionnair*” OR “wellbeing” OR “well-being” OR “wellness” OR “sleep*” |
| **NOT** | “Review” OR "meta-analysis" OR “editorial” OR “protocol” OR “animal” OR “diabetes” OR “cancer” OR “phobia” OR “panic” OR “fibromyalgia” OR “disease” OR “hypertension” OR “overweight” OR “epileps*” or “autis*” |

### *Eligibility criteria*

The types of study included were selected based on the following criteria: (a) observational studies (i.e., cross-sectional and cohorts), (b) assess athletes at any competitive level, (c) examined the vmHRV metric RMSSD or its derivatives (e.g., LnRMSSD) in conjunction with SVs, (d) and had undergone peer review to be published within an English language journal or book.
Exclusion criteria included: (e) case reports, psychometric studies focused on developing or validating an instrument, reviews, guidelines, protocols, opinion reports, letters to the editor and non-peer-reviewed works such as doctoral dissertations, (f) animal studies, (g) studies involving populations with clinical illnesses, and (h) a mean sample age below age 18 years.

As additional information, the decision to focus on RMSSD-based vmHRV was based on their methodological robustness and lower susceptibility to respiratory influences compared to other vmHRV indices, such as high-frequency power (Hill & Siebenbrock, 2009; Laborde et al., 2017; Penttilä et al., 2001), along with their widespread use in sports settings (Buchheit, 2014). Also, the definition of *athlete* was based on the work of McKinney et al. (2019), which defines athletes based on the intent of physical activity, the level of competition, and the volume of exercise. The review included individuals engaging in physical activity with the goal of athletic achievement, involving “elite” athletes (>10 h/week of training, highest level of competition), “competitive” athletes (>6 h/week of training, aiming to improve performance), and “recreational” athletes (>4 h/week of training, competing in unregulated events). The remaining population, exercising towards health and fitness, was excluded. Also, *subjective* referred to “influenced by or based on personal beliefs or feelings, rather than based on facts”, and *self-reported* refers to “data is information about something provided directly by the person perceiving it” (Cambridge University Press, 2024). No exclusion criteria were applied to subjective self-reported variables.

### *Study selection*

Studies were reviewed by two authors (CA, VH), in a two-step process based on the eligibility criteria: first by screening the title and abstract, and subsequently by reviewing the full text. Agreement with a second reviewer (VH) was analysed using Cohen's Kappa (κ), who reviewed 50 articles for each agreement. Cohen's Kappa was 1.00 for the first screening and 0.85 for full-text selection. A third reviewer (SL) supervised the final inclusion list.

### *Risk Of Bias (RoB)*

The Risk of bias (RoB) of the included studies was evaluated using the critical appraisal checklists developed by the Joanna Briggs Institute (JBI; Moola et al., 2024). Cohort and cross-sectional studies were appraised using the JBI checklists of 11 and 10 questions, respectively. Each item was assessed with responses categorized as *yes, no, unclear* and *not applicable*. Two reviewers (CA, VH), independently conducted the RoB assessments, reporting no discrepancies.

### *Data extraction*

Data extraction was conducted independently by CA and VH, using a standard extraction form developed in Microsoft Excel. Disagreements were discussed and resolved by consensus and, in case of discrepancy, with the participation of a third reviewer (SL). Two discrepancies were identified, both related to the direction of the correlation between vmHRV and SVs, which had to be inferred from figures. One corresponding author was contacted to request missing data. The information extracted included:

a. General: authors, publication year, aim(s) of the study, sample characteristics (size, biological sex, age, sports, geographic origin).
b. vmHRV-related: length of recording, time of the day, periodicity, conditions, position, HRV parameters (all reported parameters were extracted, with specific focus on RMSSD and its derivatives: lnRMSSD, logRMSSD, RMSSDcv [coefficient of variation of lnRMSSD], and 7-day Rolling lnRMSSD), breathing, device used, software and analyses.
c. SV-related: type of variable(s) under study, measurement of the variables, time of the day, periodicity, conditions, device or app, calculations.
d. Reported effects (positive, negative, none): between vmHRV and SVs.

### *Strategy for data synthesis*

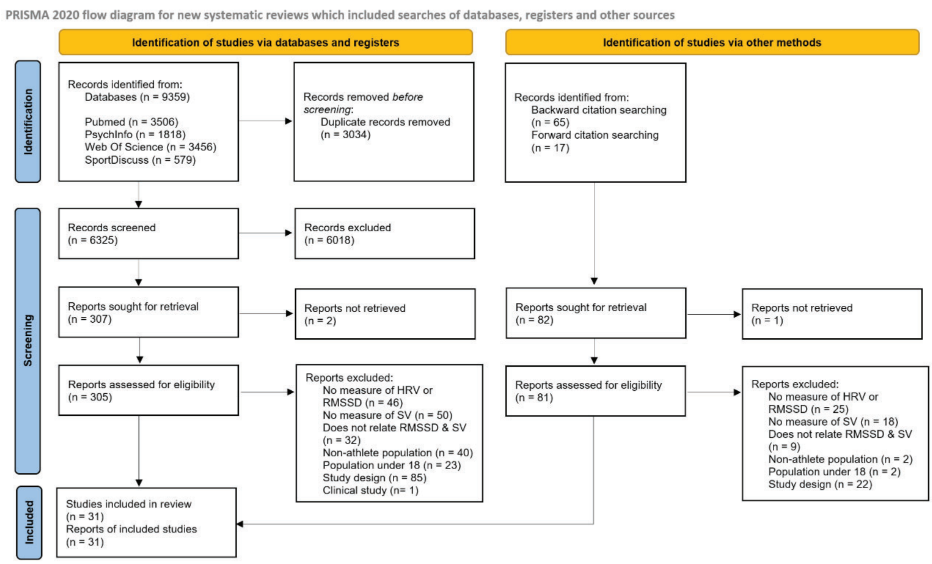
The findings of this review are presented through a narrative synthesis, offering an overview of the existing literature. A narrative synthesis was chosen because the characteristics of the included studies, such as SVs constructs and measurement protocols, were too heterogeneous to support a quantitative summary of effect sizes (McKenzie & Brennan, 2019). Descriptive analyses focus on the correlations between vmHRV and various SVs (fatigue-recovery indicators, psychological states, sleep-related), as well as examine the methodologies employed to evaluate both vmHRV and SVs. Moreover, to assess the consistency of associations between RMSSD-based vmHRV and SVs, including positive, negative, and null findings, the review applied a sum code classification system proposed by Sallis et al. (2000) and used in recent systematic reviews (e.g., Hase et al.2019). This approach focuses on the proportion of studies reporting statistically significant associations. Finally, the synthesis concludes with a discussion addressing the implications of the findings, acknowledges the limitations of current research, and provides evidence-based recommendations to guide future studies in this domain.

## Results

### *Study search and methodological quality*

A total of 9359 articles resulted from the initial database search, with an addition 82 coming from forward and backward citation searches. After removing duplicates, and screening based on title and abstract, 386 articles were selected and reviewed at full text. From these, 31 articles finally meet the inclusion criteria and were incorporated into the review. The selection process is summarised in **Fig. 1**.

**Fig. 1** PRISMA flow diagram for scientific search and selection of literature (Page et al., 2021)




*HRV*: Heart Rate Variability; *RMSSD*: Root Mean Square of Successive Differences; *SVs*: Self-reported subjective variables. *Backward citation searching* refers to reference list screening of included articles; *forward citation searching* refers to identifying studies that cited included articles.

All 31 included studies were appraised using the JBI checklists appropriate to their design (cohort or cross-sectional). The methodological quality of the 31 studies was acceptable and all rated as “Include”, although 21 studies did not clearly report strategies to address confounding factors. The results of the assessment are provided in Supplementary Material B.

Details on included studies are presented in Supplementary Material C, with an overview of results summarized in Table 2. To address the review’s aim of examining the relationship between vmHRV and SVs in athletes and the methodologies used, the results are organized into three sections: 1) vmHRV assessment, 2) SVs assessment, and 3) interrelationships between SVs and vmHRV.

### *Study characteristics*

The included studies were published between 2007 and 2025, with publication rates increasing over time: more articles were published in the last 5 years (2020-2024) than in the previous 13 (2007-2019). Across the 31 studies, sample size ranged from 5 to 117 participants, totalling 514 individuals with a grand-mean age of 23.45 ± 4.17 years. Most studies included females-only (*n* = 12), followed by male-only (n = 8) and mixed-sex cohorts (n = 8). Geographical origins were diverse and are summarized in Table 2. Most participants were classified as elite (n = 20) or competitive (n = 7) athletes, with one study involving recreational athletes. Based on the criteria from McKinney et al. (2019), these classifications indicate participants trained at least 4 hours per week with the intent of athletic achievement. The sports were diverse and categorised as either team-based (e.g., soccer, basketball) or individual-based (e.g., swimming, running).

**Table 2.** An overview of the scoping review results

| | | | |
|---|---|---|---|
| **Study characteristics** | Year of publication | | 2007 (*n* = 2), 2010 (*n* = 1), 2012 (*n* = 1), 2013 (*n* = 1), 2017 (*n* = 3), 2018 (*n* = 3), 2019 (*n* = 3), 2020 (*n* = 7), 2021 (*n* = 4), 2022 (*n* = 3), 2023 (*n* = 2), 2025 (n = 1) |
| | Design | | Cohort (*n* = 26), Cross-sectional (*n* = 5) |
| **Sample characteristics** | Sample size | | *n* = 514<br>Range: 5 – 117. |
| | Biological sex | | Female (*n* = 12), Male (*n* = 8), Mix (*n* = 8), Not reported (*n* = 3) |
| | Age (mean ± SD) | | 23.45 ± 4.17 |
| | Geographic origins | | USA (*n* = 6), Spain (*n* = 5), France (*n* = 3), Iran (*n* = 2), Japan (*n* = 2), Austria (*n* = 1), Turkey (n = 1), Brazil (*n* = 1), Britain (*n* = 1), Mexico (*n* = 1), Various (*n* = 3), Not reported (*n* = 5) |
| | Sport studied | | **Team-based:** Football (*n* = 8), Volleyball (*n* = 3), Badminton (*n* = 1), Hockey (*n* = 1), Lacrosse (*n* = 2), Rugby (*n* = 1), Waterpolo (*n* = 1)<br>**Individual-based:** Swimming (*n* = 4), Cycling (*n* = 3), Running (*n* = 2), CrossFit (*n* = 1), Dance (*n* = 1), Judo (*n* = 1), Power athletes (*n* = 1), Speed skaters (*n* = 1)<br>**Mix** (*n* = 1) |
| | Level | | Elite (*n* = 20), Competitive (*n* = 7), Recreational (*n* = 1), Not reported (*n* = 3) |
| **vmHRV assessment** | Recording protocols | Recording duration | **Orthostatic:** 7-min supine +7-min standing (*n* = 1), 10-min supine + 5-min standing (*n* = 1), 10-min supine + 7-min standing (*n* = 1)<br>**Rest periods:** 1-min rest + 1-min (*n* = 6), 1-min rest + 3-min (*n* = 1), 1-min rest + 5-min (*n* = 2), 5-min rest + 5-min (*n* = 3), 5-min rest + 10-min (*n* = 2), 15-min rest + 8-min (*n* = 1)<br>**Fixed duration:** 1-min (*n* = 4), 5-min (*n* = 1), 10-min (*n* = 5), 15-min (*n* = 1)<br>**During sleep:** 4-hour (*n* = 1), 5-min (*n* = 2) |
| | | Measurement position | Supine (*n* = 15), Seated (*n* = 12), Orthostatic (*n* = 3), Supine & seated (randomized) (*n* = 1) |
| | | Time of the day | Morning, upon waking (*n* = 22), Before competition or training (*n* = 5), During competition (*n* = 1), After competition (*n* = 1), During sleep (*n* = 2), In the lab (*n* = 1), Not specified (*n* = 3) |
| | | Frequency and periodicity | **Once or twice** (*n* = 7), from within 3 days to 6 weeks<br>**Three or four times**: Within 1 week (*n* = 2), Within 2 weeks (*n* = 1), Within 7 weeks (*n* = 1), Within 25 weeks (*n* = 1)<br>**Once per week:** for 13 weeks (*n* = 1), for 14 weeks (*n* = 1)<br>**4-5 times/week**: for 3 weeks (*n* = 3)<br>**Daily:** for 4-14 days (*n* = 5), for 15-30 days (*n* = 7), for 3+ months (*n* = 2) |

| | | | |
|---|---|---|---|
| | | Measurement device | **Chest Belt** ($n$ = 20): Polar RS800 ($n$ = 4), Polar RS800CX ($n$ = 2), Polar S810 ($n$ = 3), Polar S810i ($n$ = 1), Polar V800 ($n$ = 2), Polar Team 2 ($n$ = 2), Suunto Memory Belt ($n$ = 1), Polar Holter system ($n$ = 1), EliteHRV with chest strap ($n$ = 4)<br>**PPG (Finger-App)** ($n$ = 5): HRV4Training with PPG ($n$ = 1), ithlete™ with PPG ($n$ = 4)<br>**ECG** ($n$ = 5): BioHarness ($n$ = 1), Finapres Finometer Pro ($n$ = 1), FirstBeat Bodyguard 2 ($n$ = 1), FirstBeat Sports ($n$ = 1), Omega Wave Sport System ($n$ = 1)<br>**PPG (Device)** ($n$ = 1): Whoop ($n$ = 1) |
| | Standardization & control measures | Inclusion criteria | **Health assessment:** No medical condition or injury ($n$ = 7), Medical evaluation ($n$ = 4), Anthropometric measures ($n$ = 8), Health history questionnaire ($n$ = 4), Menstrual cycle ($n$ = 4)<br>**Athletic profile:** Experience in the sport (training, competing) ($n$ = 5), Current training status ($n$ = 5), Consistent team and/or coaching structure ($n$ = 7), Vo2Max ($n$ = 3), Certain period of the season ($n$ = 1)<br>**No specific criteria reported** ($n$ = 4) |
| | | Conditions pre/during measurement | **Instructions for breathing frequency**: "Spontaneously" ($n$ = 4), Paced 15breaths/min ($n$ = 3), "Normally" ($n$ = 2), "Naturally" ($n$ = 2), Paced 7.5breaths/min ($n$ = 1), Paced 10-12breaths/min ($n$ = 1), "Stabilize a lowest possible frequency" ($n$ = 1), Unclear from article text ($n$ = 4), No guidance ($n$ = 13)<br>**Experimental room environment** ($n$ = 26): Noise ($n$ = 13), Light ($n$ = 4), Temperature ($n$ = 7), People ($n$ = 2)<br>**Assessment conditions** ($n$ = 23): Speaking ($n$ = 11), Moving ($n$ = 7), Eyes open ($n$ = 1), Elimination ($n$ = 4)<br>**Pre-assessment food intake** ($n$ = 10): Fasting ($n$ = 6), No food for +1h ($n$ = 1), No food for +2h ($n$ = 1), No food for +3h ($n$ = 2)<br>**Pre-assessment substance intake** ($n$ = 15): No stimulants for 2-4h ($n$ =4), No stimulants for 24h ($n$ = 4), No stimulants for 48h ($n$ = 1), No stimulants no time specified ($n$ = 1), No depressants for 12h ($n$ = 1), No depressants or oral contraceptive during the study ($n$ = 1), No smoking for +24h ($n$ = 1), No smoking for +48h ($n$ = 1), No drugs for 1 week ($n$ = 1)<br>**Pre-assessment exercise** ($n$ = 4): No strenuous exercise for +1h ($n$ = 1), no strenuous exercise for 24h ($n$ = 3)<br>**Pre-assessment sleep** ($n$ = 4): After 6–8h of sleep ($n$ = 1), "Normal night of sleep" ($n$ = 2), No late sleeping the day before testing ($n$ = 1)<br>**Familiarization** with devices and protocol ($n$ = 3)<br>**Nothing reported** ($n$ = 8) |

| | | | |
|---|---|---|---|
| | HRV parameters and analyses | HRV parameters | **Time domain** ($n$ = 76): RMSSD ($n$ = 22), LnRMSSD ($n$ = 14), logRMSSD ($n$ = 2), LnRMSSDcv ($n$ = 2), MeanRR ($n$ = 3), SDNN ($n$ = 10), pNN50 ($n$ = 8), RRi ($n$ = 6), NN50 ($n$ = 2), NN50+ ($n$ = 1), NN50– ($n$ = 1), pNN50+ ($n$ = 1), pNN50– ($n$ = 1), SDANN ($n$ = 1), SDNNIDX ($n$ = 1), STDRR ($n$ = 1)<br>**Frequency domain** ($n$ = 63): HF ($n$ = 13), LF ($n$ = 13), HFnu ($n$ = 6), LFnu ($n$ = 4), FFT ($n$ = 3), LogLF ($n$ = 1), logHF ($n$ = 1), LF/HF ($n$ = 14), VLF ($n$ = 4), TP ($n$ = 3), Ptot ($n$ = 1)<br>**Non-linear domain** ($n$ = 17): SD1 ($n$ = 4), SD2 ($n$ = 3), SD1/SD2 ($n$ = 1), DFA (detrended fluctuation analysis) ($n$ = 2), SampEn ($n$ = 2), α1 ($n$ = 2), α2 ($n$ = 1), DFAa1 ($n$ = 1), DFAa2 ($n$ = 1)<br>**Other:** Stress Score ($n$ = 1), HRV Score (n = 1) |
| | | Software used | Kubios HRV Software ($n$ = 14), EliteHRV built-in processing algorithm ($n$ = 4), ithleteTM built-in processing algorithm ($n$ = 4), Firstbeat Sports proprietary software (n = 1), Custom software (aHRV v11.0.4, Nevrokard Kiauta®, Slovenia) (n = 1), Omega Wave Sport System (Eugene, OR) ($n$ = 1), Not reported ($n$ = 6) |
| | | Record RHR? | Yes ($n$ = 18) |
| | | Correlation analyses between RHR and vmHRV? | No ($n$ = 18) |
| | | Rolling averages? | Yes ($n$ = 2), No ($n$ = 29) |
| | | Coefficient Variation (CV)? | Yes ($n$ = 3), No ($n$ = 28) |
| | | Smallest worthwhile change (SWC)? | Yes ($n$ = 6), No ($n$ = 25) |
| **SV assessment** | Measurement tool(s) | | 10-point Likert scale ($n$ = 5), 5-Likert scale ($n$ = 2), 7-Likert scale ($n$ = 3), 8-item questionnaire ($n$ = 1), 9-Likert scale ($n$ = 3), Athlete Burnout Questionnaire (ABQ) ($n$ = 1), Basic sleep questionnaire ($n$ = 1), Competitive State Anxiety Inventory-2 (CSAI–2) ($n$ = 2), CSAI-2R ($n$ = 2), Daily Analysis of Life Demands for Athletes (DALDA) ($n$ = 1), Karolinska Sleepiness Scale (KKS) ($n$ = 1), Perceived Recovery Status (PRS) ($n$ = 2), Profile of Mood States (POMS) ($n$ = 2), Perceived Stress Scale (PSS-10) ($n$ = 1), Oslo Sports Trauma Research Center (OSTRC) Overuse Injury Questionnaire ($n$ = 1), Recovery Stress Questionnaire (RESTQ) ($n$ = 1), RESTQ-52 ($n$ = 1), RESTQ-Sport ($n$ = 3), French Society for Sports Medicine (SFMS) Overtraining questionnaire ($n$ = 1), Short Recovery and Stress Scale for Sports (SRS) ($n$ = 1), Total Quality of Recovery (TQR) ($n$ = 3), Pittsburgh Sleep Quality Index (PSQI) N = 1), Body Awareness Questionnaire (BAQ) (n =1) |
| | Variable(s) under study* | | Anxiety (pre-competitive state, somatic, cognitive, self-confidence) ($n$ = 4), Body awareness (n = 1), Burnout (sport devaluation, reduced accomplishment, emotional exhaustion, self-efficacy) ($n$ = 1), |

| | | |
|---|---|---|
| | | Energy levels (*n* = 1), Fatigue (including “Perceived tiredness”) (*n* = 13), Hours slept (*n* = 1), Mood (*n* = 6), Muscle soreness (DOMS, muscle soreness, general muscle soreness) (*n* = 9), Sleepiness (*n* = 1), Perceived recovery (also includes "Recovery condition" and “Perceived physical fitness”, as well as General recovery, Sport-specific recovery and Total recovery from RESTQ questionnaires) (*n* = 12), Perceived risk of injury (*n* = 1), POMS (Tension, Depression, Anger, Confusion, Vigor, Total Mood Disturbances) (*n* = 2), Total recovery–stress balance (from RESTQ questionnaires) (*n* = 1), Risk of overuse (*n* = 1), Sleep quality (*n* = 10), Stress (also includes General stress, Sport-specific stress, and Total stress from RESTQ questionnaires) (*n* = 14), Stress Tolerance (*n* = 1), Wellbeing (*n* = 7) |
| | Time of the day | Morning, upon waking (*n* = 18), Before competition/training (*n* = 9), During competition (*n* = 1), After competition (n = 1), Not specified (*n* = 5) |
| **Synchronization of measurement between vmHRV and SV** | | Yes (*n* = 18), No (*n* = 4), Closely (HRV during sleep and SV upon waking) (*n* = 1), On some occasions (*n* = 6), Unclear (*n* = 2) |

*ECG:* Electrocardiogram; *PPG*: Photoplethysmography; *RMSSD*: Root Mean Square of the Successive Differences; *LnRMSSD*: Natural Logarithm of Root Mean Square of the Successive Differences; *logRMSSD*: Logarithm of Root Mean Square of the Successive Differences; *LnRMSSDcv*: Coefficient of Variation of the Natural Logarithm of RMSSD; *MeanRR*: Mean of RR Intervals; *SDNN*: Standard Deviation of NN Intervals*; RRi*: RR Interval; *pNN50*: Percentage of NN Intervals Greater Than 50 ms; *NN50*: Number of NN Intervals Greater Than 50 ms; *NN50*+: Number of Positive NN Intervals Greater Than 50 ms; *NN50*–: Number of Negative NN Intervals Greater Than 50 ms; *pNN50+*: Percentage of Positive NN Intervals Greater Than 50 ms; *pNN50*–: Percentage of Negative NN Intervals Greater Than 50 ms; *SDANN*: Standard Deviation of the Averages of NN Intervals; *SDNNIDX*: Mean of Standard Deviations of NN Intervals in Short Periods; *STDRR*: Standard Deviation of RR Intervals; *HF*: High Frequency Power; *LF*: Low Frequency Power; *HFnu*: High Frequency Power in Normalized Units; *LFnu*: Low Frequency Power in Normalized Units; *FFT*: Fast Fourier Transform; *LogLF*: Logarithm of Low Frequency Power; *logHF*: Logarithm of High Frequency Power; *LF/HF*: Ratio of Low Frequency to High Frequency Power; *VLF*: Very Low Frequency Power; *TP:* Total Power; *Ptot*: Total Power of the Spectrum; *SD1*: Standard Deviation 1; *SD2*: Standard Deviation 2; *SD1*/SD2: Ratio of Short-term to Long-term Variability; *DFA*: Detrended Fluctuation Analysis; *SampEn*: Sample Entropy; *α1*: Short-term Scaling Exponent in DFA; *α2*: Long-term Scaling Exponent in DFA; *DFAα1*: Short-term Scaling Exponent in Detrended Fluctuation Analysis; *DFAα2*: Long-term Scaling Exponent in Detrended Fluctuation Analysis

*Muscle soreness*: includes articles mentioning DOMS (Delayed Onset Muscle Soreness), Muscle soreness and General muscle soreness; *Fatigue* includes articles mentioning Fatigue, General fatigue, and Muscle fatigue (if ‘Muscle soreness’ was also recorded in the same article); *10-Likert scale* includes 10cm visual analogue scale; *9-Likert scale* includes 9-point Visual analogue scale and 9-point Sliding scale; *Mentions the variables analysed and highlighted in the results of the study.

## *Methodological insights: vmHRV assessment*

*Recording Protocols for vmHRV Assessment*

As presented in Table 2, the most common positions for recording vmHRV were supine (*n* = 15) or seated (*n* = 12), recorded mostly with 1-min of rest followed by 1-min recording (*n* = 6) or for 10-min (n = 5). Regarding hardware, a variety of ECG and photoplethysmography (PPG)-based devices were used across studies. ECG devices were most common, particularly from the Polar brand paired with a chest strap (e.g., Polar V800, RS800, S810; total n = 14), as well as other devices such as the Suunto Memory Belt (n = 1), OmegaWave Sport System (n = 1), and BioHarness (n = 1). PPG-based systems included the applications ithlete™ (n = 4) and HRV4Training (n = 1), as well as the wrist-worn device Whoop (n = 1). While all these devices measure HRV, they vary in sampling rate, sensor type, and data processing algorithms. A complete list is available in Supplementary Material C.

Most recordings were done in the morning upon waking (*n* = 22), followed by recordings conducted in proximity to training or competition (n = 7), including sessions completed shortly before or after exercise or competitive events. Finally, the duration of the study varied widely, from one recording to daily measured over 3 months.

*Standardization and Control Measures in vmHRV Assessment*

Standardization procedures and controls for factors influencing vmHRV measurements included factors such as breathing (*n* = 14), experimental room environment (*n* = 26), or intake of food (*n* = 10) or substances (*n* = 15). A total of 8 studies did not report any factor under control. Notably, breathing instructions were diverse, from "Spontaneously" (*n* = 4) to paced 15breaths/min (*n* = 3), paced 7.5breaths/min (*n* = 1), or "Stabilize a lowest possible frequency" (*n* = 1). Table 2 also lists potential confounding factors and participant inclusion criteria, divided into health and athletic factors.

*vmHRV analysis and methodological consistency*

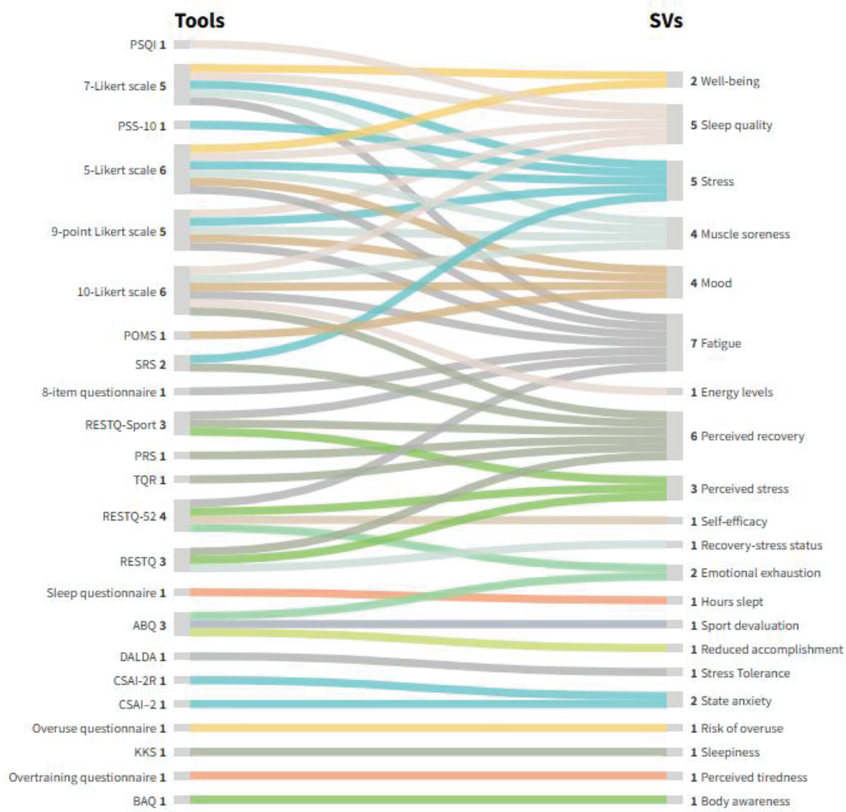
Regarding the processing of HRV data, key areas include the HRV parameters chosen, the software used, and filters applied. In the included studies, 40 different HRV parameters were analyzed, with some articles investigating multiple parameters. Time domain analyses were the most common type (n = 76), followed by frequency-domain (n = 63) and non-linear domain analyses (n = 17). Kubios in different versions (n = 14) was the most used software, and for details of filters reported see Supplementary Material C. Table 2 also reports methods used to identify trends of HRV.

## *Methodological insights: SV assessment*

*Assessment and measuring tools*

This section presents the SVs reported and measuring tools used in the included studies. In total, over 20 different types of SVs were investigated, which were collected using 19 different types of questionnaires and 4 types of scales. The most popular SVs were fatigue (*n* = 13) and perceived stress (*n* = 14), and the most used questionnaires were the Recovery-Stress Questionnaire for Athletes (RESTQ-Sport) and the Total Quality Recovery Scale (TQR) (*n* = 4 and 3, respectively). Since a same SV was reported from different measuring tools, **Fig. 2** outlines the interrelationship between the SV and the questionnaires and scales utilized to record them.

**Fig. 2** Overview of tools (questionnaires and scales) used and the corresponding SV recorded




Like vmHRV, SVs were mostly measured in the morning upon waking (*n* = 18), or in training or competition settings (*n* = 11). Table 2 highlights when vmHRV and SVs were measured in relation to one another. Most measurements were taken simultaneously (*n* = 18), with a study having recorded vmHRV during sleep and SVs upon waking. A total of 6 articles recorded vmHRV and SVs together at least once but not in all instances. “Unclear” means the article did not provide sufficient information to determine timing of vmHRV and SVs measurements (*n* = 2).

*SV classification*

While all SVs recorded in this review monitored aspects of athletes’ states, a suggestion of categorization, based on their primary focus, is provided as follows: first, fatigue and recovery variables encompass perceptions of the capacity to balance training demands with recovery; second, psychological states reflect conditions that may impact athlete health and well-being; and last, sleep-related variables focus on rest as a component of recovery. The categorization of each SVs is presented in Table 3, and definitions are provided in Supplementary Material D.

**Table 3.** Categorization of SV reported in the reviewed studies

| *Category* | *SV* |
|---|---|
| **Fatigue and Recovery Indicators** | Burnout |
| | Energy levels |
| | Fatigue |
| | Muscle soreness or Delayed Onset Muscles Soreness (DOMS) |
| | Perceived Recovery |
| | Recovery-stress status |
| | Risk of overuse |
| | Stress tolerance |
| **Psychological States** | Anxiety |
| | Body awareness |
| | Mood |
| | Perceived stress |
| | Well-being |
| **Sleep-related Variables** | Sleepiness |
| | Sleep quality |

### *Correlation between SVs and vmHRV*

**Table 4** presents a summary of the relationships found between vmHRV metrics and SVs in the reviewed studies. The correlations are categorized into positive, negative or none, with significance defined as $p < 0.05$. For instance, perceived recovery was positively associated with vmHRV in nine instances, potentially indicating a relationship between higher vmHRV and improved recovery states in athletes. In contrast, stress and fatigue showed predominantly negative associations, in eight and nine instances, respectively, suggesting that higher values may be associated with lower vmHRV. Other SVs, such as state anxiety and well-being, showed mostly no correlation with vmHRV. Variables like sleep quality, mood or stress have mixed findings, with some studies showing positive or negative correlations and others none. Overall, 93% of SVs present a sum code of zeros or “?”, indicating that the correlations are inconsistent or weak. The table also highlights the limited data for certain SVs, like sleepiness, energy levels, or stress tolerance. For complete results, including numerical values, refer to Supplementary Material C.

**Table 4.** Correlations between vmHRV and SVs, including sum code classifications

| SVs | | Reference | Correlation between vmHRV and SVs: Positive | Negative | No association | Sum code: % Positive | % Negative | Sum Code |
|---|---|---|---|---|---|---|---|---|
| Fatigue and Recovery Indicators | **Burnout** | Dobson et al. (2020) | | | 2 $^{\text{lnRMSSD-sup}}$ | 0 | 0 | **0** |
| | **Energy levels** | Flatt et al. (2022) | | | 1 $^{\text{lnRMSSD-seat}}$ | 0 | 0 | **0** |
| | **Fatigue** | Atlaoui et al. (2006), Barrero et al. (2020), DiPasquale et al. (2021), Edmonds et al. (2021), Flatt et al. (2017a), Flatt et al. (2017b), Flatt et al. (2018), Iizuka et al. (2020a), Iizuka et al. (2020b), Parrado et al. (2010), Fields et al. (2020) | 1 $^{\text{lnRMSSD-seat}}$<br>1 $^{\text{RMSSD-stand}}$ | 2 $^{\text{RMSSD-sup}}$<br>2 $^{\text{RMSSD-seat}}$<br>1 $^{\text{lnRMSSDcv-sup}}$<br>3 $^{\text{lnRMSSD-seat}}$<br>1 $^{\text{lnRMSSD-ortho}}$ | 1 $^{\text{RMSSD-sup}}$<br>1 $^{\text{RMSSD-seat}}$<br>1 $^{\text{RMSSD-ortho}}$<br>2 $^{\text{lnRMSSD-seat}}$ | 12 | 56 | **??** |
| | **Delayed Onset Muscles Soreness (DOMS)** | Barrero et al. (2020), Edmonds et al. (2021), Flatt et al. (2017a), Flatt et al. (2017b), Flatt et al. (2018), Flatt et al. (2022) | | 1 $^{\text{RMSSD-sup}}$<br>2 $^{\text{lnRMSSD-seat}}$<br>1 $^{\text{lnRMSSD-ortho}}$ | 1 $^{\text{RMSSD-stand}}$<br>1 $^{\text{RMSSD-ortho}}$<br>1 $^{\text{lnRMSSDcv-sup}}$<br>3 $^{\text{lnRMSSD-seat}}$ | 0 | 40 | **??** |
| | **Perceived recovery** | Botonis et al. (2022), Flatt et al. (2022), Hauer et al. (2020), Lundstrom et al. (2023), Morales et al. (2019), Miranda-Mendoza et al. (2023), Rundfeldt et al. (2018), Fields et al. (2020), Ravé et al. (2020) | 4 $^{\text{RMSSD-sup}}$<br>1 $^{\text{RMSSD-stand}}$<br>3 $^{\text{lnRMSSD-sup}}$<br>1 $^{\text{7-day lnRMSSD-seat}}$ | | 5 $^{\text{RMSSD-sup}}$<br>3 $^{\text{lnRMSSD-seat}}$ | 53 | 0 | **??** |
| | **Recovery-stress balance** | Lundstrom et al. (2023) | | | 1 $^{\text{RMSSD-sup}}$ | 0 | 0 | **0** |
| | **Risk of overuse** | Williams et al. (2017) | | 1 $^{\text{7-day lnRMSSD- sup}}$ | | 0 | 100 | **–** |
| | **Stress tolerance** | Figueiredo et al. (2019) | | | 1 $^{\text{lnRMSSD-sup}}$ | 0 | 0 | **0** |
| Psychological States | **Anxiety** | Mateo et al. (2012), Morales et al. (2013), Oliveira-Silva et al. (2018), Parrado et al. (2010) | 1 $^{\text{RMSSD-sup}}$ | 5 $^{\text{RMSSD-sup}}$ | 6 $^{\text{RMSSD-seat}}$ | 8 | 42 | **??** |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Body awareness** | Tekin et al. (2025) | | | 1 RMSSD-sup<br>1 lnRMSSD-sup | 0 | 0 | **0** |
| | **Mood** | Edmonds et al. (2021), Flatt et al. (2017a), Flatt et al. (2017b), Flatt et al. (2018), Flatt et al. (2022), Nuissier et al. (2007) | 2 lnRMSSD-seat | 2 lnRMSSD-seat | 1 RMSSD-ortho<br>2 lnRMSSD-seat<br>1 lnRMSSDcv-sup | 25 | 25 | **00** |
| | **Perceived stress** | Barrero et al. (2020), Chihaoui Mamlouk et al. (2021), Dobson et al. (2020), Edmonds et al. (2021), Flatt et al. (2017a), Flatt et al. (2017b), Flatt et al. (2018), Hauer et al. (2020), Lundstrom et al. (2023), Miranda-Mendoza et al. (2023), Morales et al. (2019) | 1 RMSSD-sup<br>2 lnRMSSD-sup<br>1 lnRMSSD-seat | 5 RMSSD-sup<br>1 RMSSD-stand<br>2 lnRMSSD-seat | 2 RMSSD-sup<br>1 RMSSD-ortho<br>1 lnRMSSD-sup<br>3 lnRMSSD-seat<br>1 lnRMSSD-ortho<br>1 lnRMSSDcv-sup | 19 | 38 | **??** |
| | **Well-being** | Flatt et al. (2017b), Juarez Santos-Garcia et al. (2022), Rabbani et al. (2019), Rabbani et al. (2021) | 1 lnRMSSD-seat | 1 RMSSD-sup<br>1 lnRMSSDcv-seat | 1 RMSSD-sup<br>3 lnRMSSDcv-sup<br>2 lnRMSSDcv-seat | 11 | 22 | **00** |
| **Sleep-related Variables** | **Sleepiness** | Rundfeldt et al. (2018) | | | 1 RMSSD-sup | 0 | 0 | **0** |
| | **Sleep quality** | Barrero et al. (2020), Edmonds et al. (2021), Flatt et al. (2017a), Flatt et al. (2017b), Flatt et al. (2018), Flatt et al. (2022), Tekin et al. (2025) | 3 lnRMSSD-seat<br>1 7-day lnRMSSD-seat | 1 RMSSD-sup<br>1 lnRMSSD-ortho | 1 RMSSD-sup<br>1 RMSSD-stand<br>1 RMSSD-ortho<br>1 lnRMSSD-sup<br>4 lnRMSSD-seat<br>1 lnRMSSDcv-sup | 27 | 13 | **00** |

Percentages round to the nearest whole number and may not total 100%. The "Sum Code" classification is adapted from Sallis et al. (2000) and reflects the proportion of studies reporting a statistically significant association. Sum codes indicate: "+" ≥60% of studies reported a positive association, "–" ≥60% of studies reported a negative association, "0" ≤33% of studies found no correlation in either direction, "?" reflects inconsistent findings, with 34–59% of studies showing a positive or negative association. Codes are doubled (e.g., "++", "--", "00", "??") when the number of studies contributing to the classification is four or more. The indexed abbreviations refer to the vmHRV metric and the body position during recording, including RMSSD (Root Mean Square of the Successive Differences), lnRMSSD (Natural Logarithm of RMSSD), lnRMSSDcv (Coefficient of Variation of lnRMSSD), and 7-day lnRMSSD (7-day rolling average lnRMSSD), *sup:* supine; *seat:* seated; *stand:* standing; *ortho:* orthostatic.

## Discussion

This scoping review aimed to investigate the relationship between vmHRV and SVs in athletic populations, as well as the methodologies used for the recording of these metrics. A systematic analysis of 31 observational studies revealed considerable variability in both the reported correlations and methodology, underscoring the complexity of integrating vmHRV and SVs in athletic monitoring. This section discusses the findings by situating them within the broader theoretical and empirical context, and finally addresses the challenges, proposing recommendations for future research.

The studies reviewed involved athletes with a mean age of 23.5 ± 4.2 years, reflecting a young adult population, and most (20 out of 31 studies) were classified as elite-level athletes based on the criteria proposed by McKinney et al. (2019). These individuals engage in more than 10 hours of training per week and participated in structured competition, representing high-performance environments where precise monitoring tools are critical. By encompassing both individual sports (e.g., speed skating) and team sports (e.g., football), the sample provided diverse contexts, providing an understanding of how vmHRV and SVs interact across different athletic settings. This diversity reinforces the relevance of exploring these markers in varied sports contexts.

### *Relationship between vmHRV and SVs: correlation results*

The correlation found between vmHRV and SVs are presented following the suggested categories of SVs from Table 3.

#### *Fatigue and recovery indicators*

The first group of SVs reflects an athlete's capacity to balance training demands with recovery. This category is grounded in the Scissor's Model (Kellmann & Kallus, 2001), which conceptualizes stress and recovery as interrelated processes. According to the model, stressors, whether physical or psychological, impact performance and adaptation, while recovery is a multilevel process involving psychological, physiological, and social factors that restore baseline conditions. Importantly, when perceived stress levels do not exceed physical and mental recovery capacities, athletic performance improves (Heidari et al., 2019; Kellmann, 2010). Thus, monitoring recovery is critical, as insufficient levels may lead to overtraining, burnout, and injury (Gerber et al., 2023; Smith, 2003).

In this review, the two most used tools to measure perceived stress and recovery were the TQR (Selenta & Hassmén, 1998), and the RESTQ- questionnaires (Kellmann & Kallus, 2024). The findings indicate that perceived recovery was positively correlated with vmHRV in 53% of cases, while fatigue and muscle soreness were negatively correlated in 56% and 40% of cases, respectively. These findings align with existing literature suggesting that higher vmHRV reflects greater parasympathetic activity and increased parasympathetic influence on the heart, which is associated with improved recovery states (Buchheit, 2014; Quigley et al., 2024), whereas increased physical strain correlates with reduced vmHRV, reflecting the body's reduced recovery capacity under physical stress (Mosley & Laborde, 2022; Plews, Laursen, Stanley, et al., 2013). For example, Flatt & Howells (2022) found that fitness level and perceived fatigue significantly predicted variations in LnRMSSDcv. Overall, these findings reinforce current knowledge about the recovery-stress balance and its relationship with vmHRV, and also support the NIM, which posits that vmHRV reflects the central autonomic network's ability to regulate both emotional and physical stress responses (Thayer & Lane, 2000). Thus, the positive correlations between vmHRV and recovery-related variables, and the negative correlations with fatigue indicators, highlight vmHRV's role as a potential biomarker of both physiological and psychological readiness.

The sum code classifications in Table 4, however, suggest that these relationships are not consistent across studies and instead point to a more nuanced relationship than initially thought. Despite promising directional trends, fatigue, perceived recovery and DOMS were overall classified as "??", indicating inconclusive findings even if studied in multiple articles. Similarly, burnout which has previously been associated with reduced vmHRV, specifically lower RMSSD (Wekenborg et al., 2019), was assigned a "0", reflecting an lack of significant associations. Interestingly, diverging results were sometimes observed within the same study. For instance, Edmonds et al. (2021) found positive correlations between fatigue and vmHRV in certain athlete subgroups (e.g., sophomores), but not in others (e.g., freshmen, seniors). Similarly, Rundfeldt et al. (2018) observed that RMSSD and perception of recovery positively correlated in the "non-finisher" group of an ultra-endurance race, but not in "finisher". Thereby, inconsistencies might stem from study-specific conditions and context-specific factors that influence outcomes, indicating that subjective perceptions of recovery do not always align with physiological measures. This idea is supported by the finding that vmHRV is often reduced before competition indicating readiness to perform, rather than fatigue that could impair performance (Buchheit, 2014). Findings in neuroscience also show that subjective perceptions of fatigue often diverge from physiological markers of fatigue (Casamento-Moran et al., 2023). In addition, external factors such as consecutive matches can influence recovery perceptions (Botonis et al., 2022).

In short, while vmHRV is generally considered to correlate negatively with fatigue, tiredness, and burnout, and positively with recovery, the inconsistent or weak findings across studies highlight a potential complex interplay. This suggests a need for context-sensitive interpretations in assessing athlete fatigue and recovery states (Saw et al., 2016). Integrating objective indices of autonomic regulation, such as vmHRV, with subjective experiences of fatigue and recovery, though SV, may offer researchers and practitioners a more holistic and individualised understanding of an athlete's readiness to train and compete.

*Psychological states*

This second group of variables explores athletes' psychological states, particularly those related to affect regulation, perceived stress, and anxiety, with the NIM providing a theoretical foundation for grouping these SVs together. The NIM posits that the prefrontal cortex regulates the body's response to physical or perceived stress through cardiac vagal activity, reflected in vmHRV (Thayer & Lane, 2000). Athletes with high psychophysiological flexibility (i.e., higher neurovisceral integration, and higher vmHRV) tend to exhibit superior self-regulatory capacity and emotional resilience (Gross & Thompson, 2007; Park & Thayer, 2014). Conversely, lower vmHRV is associated with higher anxiety and impaired emotion regulation (Gaebler et al., 2013; Pittig et al., 2013). Despite these theoretical expectations, the findings in this review were inconsistent. For instance, mood had less than one-third of studies with a significant association in either a positive or negative direction, while anxiety and perceived stress presented inconclusive results. For stress specifically, 38% of results reported negative correlations with vmHRV (Barrero et al., 2020; Chihaoui Mamlouk et al., 2021; Flatt et al., 2018; Lundstrom et al., 2023; Morales et al., 2019), while 42% showed no association at all. This near-even split highlights the complexity of stress as a construct and the challenge of drawing conclusions from the current evidence.

The inconsistencies may be, in part, explained by how psychological variables are subjectively experienced and contextually interpreted. For instance, in the case of stress, the Transactional Model of Stress and Coping (Lazarus & Folkman, 1984) posits that stress is not just a physiological response but a product of how individuals appraise and cope with situations. In this framework, stress perceived as a challenge may elevate vmHRV, while stress perceived as overwhelming can have the opposite effect (Meijen et al., 2020). This dual interpretation could explain the mixed findings across the reviewed studies. Furthermore, as noted by Mosley and Laborde (2022), stress is physiologically multifaceted, involving a complex interplay between the HPA-axis and the ANS, which vmHRV alone cannot fully capture. Taken together, perceived stress appears as a complex variable to assess, and this complexity may extend to other psychological variables, where variability in results is also evident. For example, well-being showed contradictory findings, even within the same research team. For instance, Rabbani et al. (2019) initially linked higher LnRMSSD to improved well-being (lower Hooper's index), but later reported a negative correlation (Rabbani et al., 2021). Overall, the findings also reinforce the importance of context when interpreting psychological variables in relation to vmHRV.Methodological differences further complicate the relationship between vmHRV and psychological states. For example, the calculation of well-being scores varied across studies, with some using summed or averaged scores of a mix of variables like fatigue or sleep quality, while others analysed variables individually or used different scales (Supplementary Material C). This lack of standardization complicates cross-study comparisons and underscores the need for consensus on protocols. As another example, Juarez Santos-Garcia et al. (2022) reported differing correlations between well-being and RMSSD depending on whether measurements were based on 5 minute or 4 hour recordings during sleep. Temporal factors are also important: subjective well-being (Grainger et al., 2022), fatigue and muscle soreness (Fazackerley et al., 2019) recover slower than ANS responses, potentially leading to lack of correlation in same-day assessments. Such disparities raise concern and highlight the importance of standardizing protocols for both vmHRV and SVs.

In summary, the heterogeneity in observed associations between vmHRV and psychological states reflects an interplay of individual variability, methodological inconsistencies, and the dynamic nature of these metrics. While the NIM provides a theoretical basis for linking vmHRV to affective regulation, the empirical evidence remains mixed, and the findings reinforce the need for standardized measurement protocols and context-aware interpretations.

*Sleep-related*

This category includes SVs related to sleep, which is critical for athlete recovery, performance, and long-term health (Vitale et al., 2019). In the present review, findings on the association between vmHRV and subjective sleep quality were mixed. Only 27% of results indicated a positive correlations between vmHRV and sleep quality, suggesting that better sleep might enhance vmHRV (Chouchou & Desseilles, 2014; Lins-Filho et al., 2023; Sajjadieh et al., 2020; Schlagintweit et al., 2023). These findings support the hypothesis that sleep facilitates physical restoration, particularly after physical effort (Chandrasekaran et al., 2020; Shapiro et al., 1981). This is supported by evidence linking improvements in vmHRV with improvements in subjective sleep qualityfollowing a 30-day slow-paced breathing intervention (Laborde et al., 2019). However, 60% of reviewed studies reported no significant correlation, suggesting that although there is evidence linking better perceived sleep with increased vmHRV, the overall body of research in athletes remains inconclusive. From a theoretical standpoint, this variability is not entirely surprising. The NIM (Thayer et al., 2009) posits that vmHRV reflects the adaptability of the central autonomic network in regulating recovery processes, including sleep. When sleep is perceived as restorative, it may coincide with higher cardiac vagal activity, reflected in increased vmHRV. In this sense, positive correlations could indicate enhanced parasympathetic modulation and recovery capacity. However, the high rate of non-significant findings also suggests that vmHRV and perceived sleep quality do not always align.

One explanation is the lies in the distinction between subjective and objective sleep quality. In subjective assessments, the influence of stress, emotional dysregulation, or perception biases, can simultaneously distort the evaluations of sleep (Harvey & Tang, 2012; Tworoger et al., 2005). In fact, there are known differences between perceived and actual sleep quality well documented in both healthy individuals and in clinical samples, such as insomnia patients (Harvey & Tang, 2012). For instance, Goelema et al. (2019) found that men tended to overlook nighttime awakenings compared to women, leading to a more positive self-assessment of sleep quality. Additionally, other factors such as mental or physical stress can further impair the perception of sleep quality (Tworoger et al., 2005), further complicating subjective assessments. Thus, while research confirms that acute sleep deprivation impairs athletic performance (Gong et al., 2024), and that vmHRV correlates with objective sleep parameters (Fonseca et al., 2020), its relationship to subjective sleep quality assessments is still unclear. This review's findings suggest that vmHRV might better reflect physiological processes than subjective perceptions of sleep.

Given the importance of sleep in athlete health and performance (Doherty et al., 2021), it is essential that future research addresses these measurement limitations. To effectively integrate sleep-related SVs with vmHRV, researchers should prioritize longitudinal data collection to capture variability across multiple nights, use validated assessment tools, and account for individual differences in sleep perception, stress reactivity, and recovery behaviour (Goelema et al., 2019). A combined approach that includes both objective (e.g., vmHRV) and subjective measures could improve the utility of sleep-related SVs in monitoring athlete recovery and performance.

### *Methodological Issues and Recommendations*

Discrepancies in the correlations between vmHRV and SVs might stem from methodological inconsistencies. For instance, Table 4 aimed to illustrate how many different RMSSD-based vmHRV parameters and recording positions (e.g., seated, supine, orthostatic) were used within the same SV category. This variability can introduce bias when interpreting results, as different parameters and postures may reflect distinct aspects of autonomic regulation. Thus, despite the widespread use of vmHRV and SVs in assessing training adaptation in athletes (Olmos et al., 2024), the review identified substantial differences in measurement protocols that complicated cross-study comparison (Laborde et al., 2017). Similar challenges have been reported in elite soccer research (Mirto et al., 2024) and aligns with calls for standardization in exercise-based HRV research, where promising HRV thresholds face validation challenges due to inconsistent methodologies hindering comparability (Kaufmann et al., 2023). This section outlines methodological practices, limitations, and recommendations for standardization.

*vmHRV Assessment: Standardization*

- **Inclusion criteria:** Control over participant health status varied, with only 7 of 31 studies excluding participants with medical conditions, despite their known impact on autonomic regulation (Malik et al., 1996). For participants with medical conditions, documentation of medications and conditions is essential (Laborde et al., 2017). Also menstrual cycle considerations were reported in only 4 studies, despite its influence on RMSSD (Kokts-Porietis et al., 2020; Sherman et al., 2022). Ideally, participants would be tested in a given phase (e.g., follicular phase in Morales et al., 2013). Athletic experience, coaching structure, and seasonality also relate to vmHRV, yet were inconsistently reported. For example, vmHRV and SVs can vary depending on the time of the season, but only 5 studies accounted for this by measuring vmHRV outside of competition periods (e.g., Chihaoui Mamlouk et al., 2021). Also, more experienced athletes usually exhibit higher vmHRV (Aubert et al., 2003; Kozjek et al., 2016), and similar team or coaching structures can improve comparability by reducing variability in study outcomes (Proietti et al., 2017). Therefore, future research is encouraged to provide detailed reporting on participants' health and training-related variables.

- **Conditions pre/during measurement:** Studies varied in controlling external, physiological, and behavioural factors that affect vmHRV. One-third failed to regulate environmental variables like temperature and lighting, which affect autonomic function (Achten & Jeukendrup, 2003; Laborde et al., 2017; Pitzalis, 1996). Similarly, pre-assessment consumption of caffeine, alcohol, or food was inconsistently managed, despite their known effects on vmHRV (Lu et al., 1999; Quintana et al., 2013; Zimmermann-Viehoff et al., 2016). The recommendation is to avoid caffeine for two hours and alcohol for 24 hours before testing (Laborde et al., 2017). Breathing control also varied, with 14 studies providing specific guidance ranging from spontaneous to paced, and 16 studies offering unclear or no guidance. Although RMSSD is less influenced by breathing rate than other parameters (Hill & Siebenbrock, 2009), spontaneous breathing is recommended to avoid artificially elevated vmHRV values (Laborde et al., 2017). Given the portential effects of these factors, controlling and reporting them is important to maintain a high level of standarization.

*vmHRV Assessment: Recording Protocols*

- **Recording duration:** Most studies followed Task Force guidelines (Malik et al., 1996), using recordings of 1 (n = 10) or 5 minutes (n = 7) recordings. Interestingly, while short-term (5 min) and ultra-short-term (1 min or less) recordings share mathematical formulas, they capture different physiological processes and are not fully interchangeable (Shaffer et al., 2020). However, under resting conditions, RMSSD for ultra-short term recordings has proven reliable in both athletes and non-athletes (Esco & Flatt, 2014; Munoz et al., 2015), supporting their practical use due to time efficiency. Regarding prestabilization, a 1 to 15 minute rest period prior to recording was employed in 15 studies, providing stabilization of vmHRV indices and enhancing reliability (Krejčí et al., 2018). Nonetheless, research on this aspect remains limited (Mirto et al., 2024).

- **Measurement position:** Supine (n = 15) and seated (n = 12) positions were almost equally represented, with supine yielding higher vmHRV values due to minimized sympathetic activation (Gronwald et al., 2024). However, orthostatic measurements, which capture dynamic physical stress responses, were underrepresented despite their potential for assessing recovery and exertion (Bourdillon et al., 2017; Gronwald et al., 2024; Schmitt et al., 2015). In fact, recent research has highlighted the advantages of orthostatic testing as a means to assess autonomic reactivity and fatigue levels, particularly in mitigating PNS saturation in well-trained endurance athletes (Gronwald et al., 2024). The Vagal Tank Theory aligns with this perspective, proposing that phasic vmHRV, reflecting responses to short-term stressors, provides more information when reactivity to a stimulus is measured, compared to assessments conducted solely in a resting position (Laborde et al., 2018). In Rabanni et al. (2021), seated LnRMSSD showed stronger associations with training status than supine.
- **Time of the day:** Morning assessments were most common, recorded in 22 studies, offering stable baselines unaffected by daily activities (Buchheit, 2014). Fewer studies (n = 7) measured vmHRV near training or competition, which can provide insights into acute stress responses (Buchheit et al., 2007; Stanley et al., 2013) but may introduce variability due to immediate physical exertion (Laborde et al., 2018). Finally, vmHRV during sleep was only measured in 2 studies, despite its potential for autonomic assessment without external interference (Brandenberger et al., 2005) and more tools available (Bianchi & Mendez, 2013). Thus, while there is still no clear consensus on the optimal time for HRV monitoring, particularly between morning and nocturnal assessments, morning measurements offer greater standardization, and provide a replicable approach (Plews, Laursen, Stanley, et al., 2013).
- **Measurement device:** ECGs remain the gold standard for vmHRV measurement (Berntson & Stowell, 1998; Laborde et al., 2017; Quigley et al., 2024), but chest belts, used in 20 studies (e.g., Polar RS800), dominated in capturing electrocardiac signals in the present studies. Although not classified as ECGs, chest belts provide accurate RR interval data (Gilgen-Ammann et al., 2019; Pasadyn et al., 2019). PPG devices were used in 6 studies, and while less precise (Singstad et al., 2021), offer accessible, field-based alternatives (Holmes et al., 2020; Plews et al., 2017). In this way, both chest belts and PPG-based devices help bridge the gap between laboratory science and field-based vmHRV monitoring, but while they can be valuable in practical settings, researchers should acknowledge their limitations in the articles.

*vmHRV Assessment: analysis and methodological consistency*

- **HRV parameters:** A total of 40 different parameters of HRV were reported, with the vagally-mediated RMSSD parameter as the most common (n = 22) due to its reliability and ease of calculation (Buchheit, 2014; Mirto et al., 2024). Some studies favoured its logarithmic transformation (LnRMSSD), as it stabilizes data and reduces sensitivity to outliers (Penttilä et al., 2001; Plews, Laursen, Stanley, et al., 2013).

- **Software and data processing:** Most analyses used Kubios software, known for its user-friendly interface and robust filtering options (Tarvainen et al., 2014). However, filters were inconsistently reported, compromising replicability (Berntson & Stowell, 1998; Shaffer & Combatalade, 2013). Proper reporting of data processing is critical (Laborde et al., 2017).
- **Additional analyses:** When monitoring long-term changes, analyses like rolling averages, coefficients of variation (CV), and smallest worthwhile change (SWC) can help reveal trends in vmHRV data. CV quantifies day-to-day variability, offering insights into physiological adaptation, while SWC identifies practically meaningful changes (Buchheit, 2014; Plews, Laursen, Stanley, et al., 2013). Also, despite 18 studies measuring resting heart rate alongside vmHRV, none correlated them, an omission worth exploring (Plews et al., 2012; Sacha, 2014). Although not all longitudinal studies implemented these calculations, the findings indicate a shift towards the common use of these methods.

*Self-reported subjective variables*

The analysis of SVs across studies revealed significant heterogeneity in both the variables measured and the tools used. As illustrated in Fig. 2, over 20 SVs were assessed using 19 questionnaires and 4 types of scales. Perceived stress and fatigue, for example, were evaluated using diverse tools, from the Perceived Stress Scale-10 (PSS-10) to Likert scales. Researchers also varied in their reporting terminology: for instance, seven studies measured multiple single-item variables such as perceived fatigue and sleep quality and aggregated them into composite scores, but two of these studies referred to the score as the Hooper Index (Rabbani et al., 2019; Rabbani et al., 2021), while five labelled it as well-being (e.g., Flatt et al., 2017). Moreover, another four studies reported the same single-item measures individually, without aggregation (e.g., Chihaoui Mamlouk et al., 2021). At the same time, many SVs were poorly defined; for example, *stress* was often ambiguous, lacking justification as a stressor, distress, or general stress (Wheaton & Montazer, 2009). Improving the clarity and definition of these variables is key to reduce bias. Regarding tools, the most common were the RESTQ-Sport and TQR, with recognized reliability and validity (Kellmann & Kallus, 2024; Germanr Kenttä & Hassmén, 1998). Likert scales were also widely used but varied in format (e.g., 5, 7, 10 points). Thus, despite the use of SVs in assessing training adaptation, the lack of standardization limits cross-study comparisons. In the future, validated, sport-specific tools should be prioritized while considering the pros and cons of each one (DeVellis, 2016; Jebb et al., 2021).

*Study duration*

The duration of the reviewed studies ranged from single measurements (n = 7) to daily recordings over three months (n = 2), raising questions about optimal monitoring frequency. Given the non-linear nature of HRV responses to life stressors (Plews et al., 2017), single-day (Bechke et al., 2020) and long-term (Nakamura et al., 2015) monitoring provides more accurate insights into HRV responses to stress and recovery, especially for establishing individual baselines in athletes and detect meaningful changes (Plews, Laursen, Stanley, et al., 2013). Nonetheless, daily long-term monitoring may not always be practical, as it may cause participant fatigue or inaccurate responses. A hybrid approach, combining brief daily assessments with periodic comprehensive tools, balances accuracy with practicality. For instance, daily self-reports could be complemented by weekly POMS or RESTQ-Sport questionnaires (Saw et al., 2015). Moreover, the frequency of HRV monitoring would depend on the analysis expected: weekly averages work well for microcycle trends (Nakamura et al., 2015), while daily measures are necessary to monitor CVs.

*Simultaneous measurement of vmHRV and SVs*

Simultaneous measurement of vmHRV and SVs is key for understanding their interaction. In this review, 58% of studies measured both variables concurrently (e.g., in the morning), capturing real-time links between vmHRV activity and subjective states. This approach aligns with the NIM (Thayer & Lane, 2000), which emphasizes the dynamics between physiological regulation and emotional responses. In contrast, measuring vmHRV and SVs at different times of the day (e.g., Miranda-Mendoza et al., 2023) or on different days (e.g., Williams et al., 2017), risks missing phasic fluctuations and stress-recovery correlations. For instance, Mohammadi et al. (2019) found that subjective stress and physiological markers like cortisol did not align when measured separately. Overall, while some recommend staggered measurement frequencies (Saw et al., 2015), this review argues that simultaneous assessment provides clearer insights into the stress-recovery balance.

### *Methodological guidelines*

The array of tools and protocols observed in the studies underscores the need for reliable and standardized methodologies in vmHRV and SVs research. While existing guidelines offer general directions for HRV measurement (Catai et al., 2020; Laborde et al., 2017; Quigley et al., 2024; Quintana et al., 2016) and reporting consistency (Bossuyt et al., 2003; Dobbs et al., 2019; Quigley et al., 2024), the field of sports science requires more specific, actionable protocols. Based on the findings discussed, a methodological checklist is proposed for conducting and reporting vmHRV and SVs research in athletes. Presented as a table for practical use as suggested previously (Han et al., 2017), it can be adapted to suit the specific requirements of each study. References and detailed recommendations are provided throughout the manuscript or referenced in Table 5.

**Table 4.** Methodological checklist for vmHRV and SV research in athletes

| | Methodological Information |
|---|---|
| ☐ | Aim(s) of the study |
| ☐ | Study design |
| | Sample |
| ☐ | Allocation (Lalanza et al., 2023) |
| ☐ | Sample size: with justification (e.g., based on power analysis) |
| ☐ | Inclusion/exclusion criteria. E.g.:<br>Athletic profile (e.g., experience in the sport, season/training status, team and/or coaching structure) |
| ☐ | Medication or health factors (e.g., antidepressants, antihypertensives, medical condition or injury, menstrual cycle) |
| | Demographic Characteristics |
| ☐ | Anthropometric measures (e.g., weight, height) (Yi et al., 2013) |
| ☐ | Biological sex assigned at birth (Umetani et al., 1998) |
| ☐ | Gender identity (male, female, non-binary, other) |
| ☐ | Age (e.g., mean and/or range) (Umetani et al., 1998) |
| ☐ | Geographical origin (e.g., region or country distribution) |
| ☐ | Sport: specific sports or activity type |
| ☐ | Level (e.g., recreational, competitive, elite) |
| | vmHRV Protocol and Analysis |
| ☐ | Recording duration: length of recording, including rest periods (if applicable) |
| ☐ | Measurement position: participant position during recording (e.g., supine, seated) |
| ☐ | Time of the day: timing of HRV measurement (e.g., morning upon waking, pre/post-exercise) |
| ☐ | Measurement device: provide details on the device used (e.g., ECG, PPG) and specifications |
| ☐ | HRV parameters: identify the HRV metrics analysed (e.g., RMSSD, LnRMSSD) |
| ☐ | Software and data processing: specify the software used and any applied filters |
| ☐ | Frequency and periodicity: describe the number and timing of repeated measurements (e.g., daily, weekly) |
| ☐ | Additional analyses: mention complementary analyses performed (e.g., LnRMSSD/R-R ratio, rolling averages, CV, SWC) |
| | Conditions Pre/During Measurement |
| ☐ | Breathing instructions: specify the type of breathing used, if applicable (e.g., spontaneous, paced at specific rates) |
| ☐ | Environmental room conditions: control and report room settings (e.g., temperature, lighting, noise levels) |
| ☐ | Substance intake: detail restrictions on pre-assessment intake (e.g., caffeine, alcohol, smoking, energy drinks) |
| ☐ | Food intake: detail protocols on fasting or meal timing before assessment (e.g., no intake for 2h) |
| ☐ | Exercise restrictions: detail protocols for pre-assessment exercise (e.g., avoiding for 24h) (Stanley et al., 2013) |
| ☐ | Sleep requirements: detail sleep guidelines (e.g., minimum hours) (Stein & Pu, 2012) |
| ☐ | Participant familiarization: detail whether participants are trained on devices and procedures (Robertson et al., 2014) |
| | Subjective Self-Reported Variables Protocol |

| | |
|---|---|
| ☐ | Measurement tools: specify the questionnaire or scale used, including validation status and reliability (if available). |
| ☐ | Variable under study: indicate the subjective variable. Ideally, categorize the variable under fatigue-recovery indicators, psychological states, sleep-related factors, or other domains. |
| ☐ | Frequency and periodicity: describe the number and timing of repeated measurements (e.g., daily, weekly) |
| ☐ | Synchronization with vmHRV: clearly specify whether vmHRV and SV are recorded simultaneously or at different times |

### *Implications for athletic monitoring*

This scoping review is a response to the increasing demand for effective tools and protocols to monitor athletes' training adaptation, by exploring the integration of vmHRV and SVs metrics. The findings support their complementary application for three reasons.

First, the review highlights that vmHRV and SVs metrics often do not align, as suggested by prior research (Saw et al., 2016; Vacher et al., 2019). This variability reflects the multifactorial nature of these measures, where factors like stress perception influence both vmHRV and SVs outcomes, making it difficult to expect linear relationships. While it might seem ideal for low vmHRV to consistently correlate with high fatigue, for example, findings indicate the relationship is not straightforward. By providing distinct yet complementary information, adopting an approach with both vmHRV and SVs provides a more comprehensive view of training adaptation.

Second, the results highlight the role of context and associated limitations of relying on a single marker to monitor adaptation. Different SVs categories (fatigue-recovery indicators, psychological states, and sleep-related) offer unique insights shaped by individual and situational factors (e.g., training phase, pre-competition anxiety or travel-induced sleep disruptions) (Ayuso-Moreno et al., 2020; Da et al., 2015). For example, increased training load typically decreases vmHRV and fatigue-recovery indicators, but the absence of negative SVs feedback despite physiological declines might indicate positive adaptation (Coutts et al., 2018). Incorporating and refining the interpretation of physiological data could further contextualize changes and refine our understanding of athlete health and performance. This would include, for example, orthostatic HRV assessment to inform about autonomic reactivity beyond resting HRV alove (Gronwald et al., 2024), or other biomarkers such as cortisol, a glucocorticoid hormone involved in metabolic processes such as protein breakdown, increased gluconeogenesis, and immune function. In sport contexts, acute increases of cortisol are observed following moderate to high-intensity exercise (Hill et al., 2008) and are often used to assess training strain and recovery, especially in combination with testosterone as part of a testosterone/cortisol ratio, a used indicator of anabolic-catabolic balance (Soler-López et al., 2024). Overall, multifaceted approach of markers would align with the NIM, emphasizing the dynamic interplay of physiological and psychological processes (Thayer & Lane, 2000).

Third, the individual variability in both vmHRV and SVs means the measurement of both is crucial for future athlete monitoring. Both vmHRV and SVs should be interpreted against individualized baselines rather than generic thresholds, as HRV reflects differences in autonomic responses (Botonis et al., 2021; Olmos et al., 2024) and certain SVs hold greater relevance for specific athletes (Hamlin et al., 2019). Individualized monitoring systems accounts for natural variations and ensures more accurate and actionable insights.

As a last note, wearable technology offers promising applications for real-time monitoring of vmHRV and SVs. By offering immediate feedback, wearables bridge the gap between research and practice, enabling practical applications (Plews et al., 2017). With half of the included studies published between 2020 and 2024, interest in integrating physiological and psychological variables into athlete monitoring is growing (Thorpe et al., 2016). In fact, apps such as HRV4Training, EliteHRV, or ithlete™ have already integrated both vmHRV and SVs, demonstrating how consumer-grade technologies can support such monitoring. This evolution is also evident in the expanding examination of HRV beyond resting measures, particularly in exercise-based monitoring (Tanner et al., 2024). Thereby, the present scoping review provides a scientific foundation, and practical guidelines and suggestions, for advancing these tools.

In summary, this review supports the integration of vmHRV and SVs measures as a more comprehensive approach to athlete monitoring, capturing both physiological and psychological dimensions. Given that athletes respond to training loads differently, and away from seeking a single conclusive marker (Halson, 2014; Lac & Maso, 2004; Schmitt et al., 2013a), future systems should prioritize combining these metrics in user-friendly ways that consider individual variability and contextual factors (Bourdon et al., 2017; Filaire et al., 2003; Halson, 2014; Saw et al., 2016; Schmitt et al., 2013b). Such systems should support personalized training monitoring, advancing athlete performance and well-being, and reducing the risk of overtraining.

***Deviation from the pre-registered protocol***

The protocol for this review was pre-registered on the OSF, with a few adjustments made during the process. First, articles involving interventions were excluded. While interventions can provide insights into the effects of manipulations on vmHRV and SVs, the review aimed to explore their natural relationship within the context of sports. Although this focus was clear to the authors, it was not explicitly stated in the original protocol. Excluding intervention studies allowed examining how vmHRV and SVs interact organically, without the influence of experimental manipulations. Additionally, data on the reliability and validity of SVs, other physiological markers, training and performance-related variables were extracted but ultimately excluded from the manuscript to maintain focus and adhere to the recommended word count.

### *Limitations and future directions*

This review comes with some limitations. First, studies without direct correlations between SVs and vmHRV were excluded, ensuring focus but narrowing the review's scope. Correlations were compared primarily using p-values, which can increase type-II errors, especially in small sample sizes (Batterham & Hopkins, 2006; Quintana, 2017). Including effect sizes and thereby performing a meta-analysis could address this limitation (Schäfer & Schwarz, 2019). However, this was not feasible in the present review due to methodological heterogeneity in SV constructs and measurement protocols across studies. Attempting a meta-analysis at this stage would risk comparing conceptually distinct variables. Instead, this scoping review aimed to map the literature, establish SV categories, and provide a structured overview to support future targeted meta-analyses as the field matures. Additionally, while correlation coefficients evaluate relationship strength, methods like Bland-Altman could better assess agreement between measures (Prince et al., 2008). Second, we acknowledge that the categorization of SVs into fatigue-recovery indicators, psychological states, and sleep-related variables involves a degree of subjectivity, and alternative frameworks may also be valid. Also, some SVs were over-represented. For example, Edmonds et al. (2021) reported multiple outcomes on fatigue, perceived stress, mood, sleep quality, and muscle soreness, potentially over-relying on a limited pool of data and reducing generalizability. Non-significant correlations were only reported when explicitly mentioned, suggesting potential reporting bias if some results were omitted from figures or text. Third, there was also an overrepresentation of female participants, potentially biasing findings due to known gender differences in RMSSD (Koenig & Thayer, 2016). Future studies should address these issues by recruiting larger, more balanced samples in terms of gender, as well as explore generalizability to other fit populations, such as military personnel, firefighters, or disciplines without competition, like yoga. Fourth, regarding guidelines, this review adhered to PRISMA-ScR and aligned with prior recommendations (Sabiston et al., 2022), except that no formal stakeholder consultation was conducted. Consulting other experts and practitioners in future research could enhance the relevance and applicability of findings within the field. Fifth, while the review deliberately focused on RMSSD-based vmHRV measures, the exclusion of other vmHRV parameters, such as $HFms^2$, due to their greater susceptibility to respiratory influences, may have narrowed the scope of the review. Future studies could consider including these additional measures to provide a more comprehensive perspective. Finally, theoretical issues were evident, with studies often lacking frameworks and using variable protocols. These inconsistencies limited the robustness of the research base. Future research should adopt relevant vmHRV theories (NIM and Vagal Tank Theory) and adhere to methodological guidelines.

## Conclusion

This scoping review explored the relationship between vmHRV and SVs in athletes, focusing on their complementary role in monitoring training adaptations. Although some consistent correlations were found between vmHRV and SVs, such that higher vmHRV was showed associations with improved recovery, better sleep, and lower fatigue or stress, most results were largely inconsistent. These discrepancies seemed to stem from both individual and contextual factors (e.g., training status, perception biases), highlighting the need for personalised baselines and context-sensitive interpretations that include both physiological and psychological markers to capture distinct yet complementary dimensions of athlete readiness and adaptation. Moreover, the review also identified critical gaps in methodological standardization, including inconsistencies in data collection, definitions, and interpretation. To address these issues, it proposes a guideline for conducting research on SVs and vmHRV in sports settings, aiming to improve comparability across studies. From a practical perspective, the findings support the development of real-time, multifactorial monitoring systems to provide a complete understanding of athlete's states within the broader context of their lives. Future research should harmonise methodologies, expand to diverse athletic populations, and explore additional physiological markers like cortisol. Overall, this review aims to advance precise, evidence-based training systems, reducing overtraining risks while improving performance and well-being.

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**Data availability:** The data supporting the findings of this study are available within the article and its supplementary materials. Additionally, the datasets generated during and/or analysed during the current study are available in the Open Science Framework repository, [https://osf.io/utxb3/?view_only=003f745f9b2f43119b99b751ea75e532]

**Authors contributions:** CA and SL conceptualized the objectives and scope of the review. CA conducted the literature search and screening. Data extraction was performed by CA and VH. Methodological quality and consistency were evaluated by CA, VH, and SL. CA and VH analysed and synthesized the results with feedback from SL. CA and SL drafted the initial manuscript, and VH, LC, and MA provided critical revisions to subsequent versions. All authors read and approved the final manuscript.

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## 3.2 Article 2

Alfonso, C., & Capdevila, L. (2022). Heart rate variability, mood and performance: a pilot study on the interrelation of these variables in amateur road cyclists. *PeerJ*, *10*, e13094. https://doi.org/10.7717/peerj.13094

### *Aim and results*

Article 2 aimed to investigate the relationship between HRV, mood state, and performance in cyclists over a six-week period. The focus was on exploring the relationships between these variables.

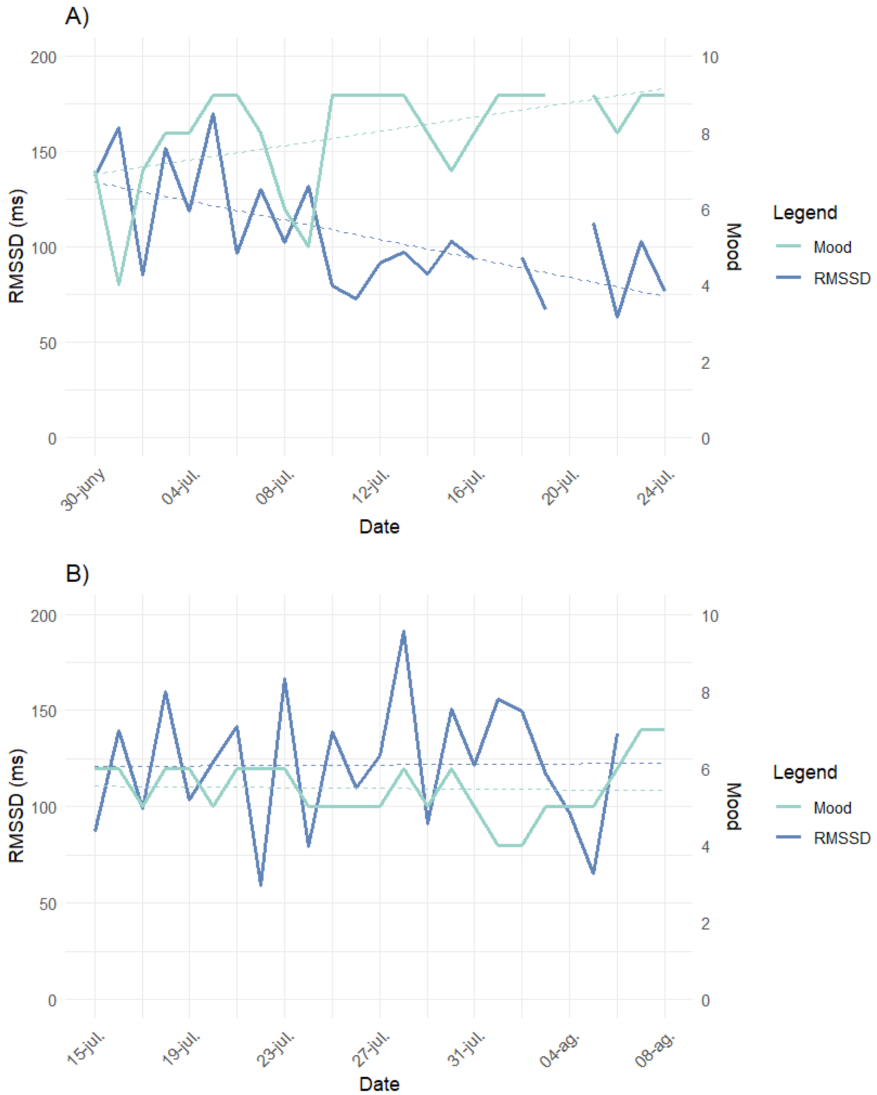
The results were the following:

**Recordings:** A total of 123 morning registers (including mood and HRV) and a total of 66 training registers were recorded. A total of 57 HRV recordings were not preceded by a road training the day before. During the 6-week study period, each participant completed an average of 25 morning registers (4 per week) and 12 training registers (2 per week).

**Parameters:** In the article, the HRV parameters reported were mean RR, HFnu, LFnu, LF/HF and SDNN, while the SV included was mood, and the training-related parameters were NP$^{TM}$, TSS$^{TM}$, IF$^{TM}$ and RPE.

**HRV and mood:** Results indicated that mood significantly correlated with all HRV parameters. Of particular relevance, higher HFnu values were associated with improved mood states ($p < 0.001$).
As an additional analysis, not included in the published article, Figure 6 shows RMSSD and mood scores across 25 days for two participants. These graphs illustrate the interindividual variability in how RMSSD and mood fluctuates. Participant #1 (A) displays an increasingly positive mood, more stable and elevated after day 10, together with a fluctuating and decreasing RMSSD. In contrast, Participant #5 (B) displays a more stable RMSSD and mood across the study period.

**Figure 6.** Daily RMSSD and mood scores from two participants




Daily RMSSD (ms) and mood scores for Participant 1 (A) and Participant 5 (B) over a 25-day period. Solid lines represent the raw daily values of each variable, while dashed lines indicate linear regression trends. The coefficient of determination ($R^2$) for each linear model is 0.387 for RMSSD and 0.244 for mood in Panel A, and 0.000 for RMSSD and 0.002 for mood in Panel B.

**HRV and training load**: Morning HRV parameters exhibited training load-dependent variations. Specifically, HFnu values were significantly lower on mornings following high-intensity training sessions compared to rest days ($p < 0.01$). HFnu showed the highest correlations with IF, amongst training data.

**Mood and training load**: Mood state fluctuations were observed in response to training loads, with negative mood scores being significantly elevated on mornings following high-intensity training reflected in IF ($p < 0.01$).

**External and internal training load:** RPE was positively associated with all power data (NP, TSS and IF; $p < 0.001$ in all cases).

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# Heart rate variability, mood and performance: a pilot study on the interrelation of these variables in amateur road cyclists

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## ABSTRACT

**Objective:** The present study seeks to explore the relationship between measures of cycling training on a given day and the heart rate variability (HRV) and mood states obtained the following morning. The association between HRV and mood state is also studied, as is the relationship between internal and external measures of training.
**Methods:** During a 6-week period, five recreational road cyclists collected 123 recordings of morning HRV and morning mood, and 66 recordings of training power and rate of perceived exertion (RPE). Training power was used as an external measure of performance and RPE as an internal measure of performance. The HRV parameters used in the study were the mean of RR intervals (mean RR) and the standard deviation of all RR intervals (SDNN) as time domain analysis, and the normalized high frequency band (HFnu), normalized low frequency band (LFnu) and the ratio between low and high frequency bands, as frequency domain analysis. Mood was measured using a 10-point cognitive scale.
**Results:** It was found that the higher the training power on a given day, the lower the HFnu and the higher LF/HF were on the following morning. At the same time, results showed an inverse relationship between training and mood, so the tougher a training session, the lower the mood the following day. A relationship between morning HRV and mood was also found, so that the higher mean RR and HFnu, the more positive the mood ($r = 0.497$ and $r = 0.420$ respectively; $p < 0.001$). Finally, RPE correlated positively with external power load variables (IF: $r = 0.545$; $p < 0.001$).
**Conclusion:** Altogether, the results indicate a relationship between training of cyclists on a given day and their morning HRV and mood state on the following day. Mood and HRV also seem positively related. It is argued that developing a monitoring system that considers external and internal training loads, together with morning mood, could help understand the state of the individual, enabling feedback to athletes to facilitate the adaptation to training and to prevent problems associated with overtraining. However, more research is needed to further understand the association between the different variables considered.

**Subjects** Neuroscience, Cardiology, Kinesiology, Psychiatry and Psychology
**Keywords** Heart rate variability, Mood, Performance, Training load, Athletes, HRV

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## INTRODUCTION

To build fitness, an individual needs to apply a stress to the body, and then through recovery, the body adapts and is able to accommodate greater stress in the next round of training. Strategies to control the adequate amount of stress and recovery are essential to facilitate the adaptation of athletes to training and to ameliorate performance (*Morales et al., 2014*; *Wallace, Slattery & Coutts, 2014*), as well as to prevent problems associated with overtraining, including injuries (*Owen et al., 2015*; *Rodas et al., 2008*).

Physical stress, or training load, is the dose of training completed by an athlete during an exercise bout and is in part responsible for fitness gains. Too much of it can result in overtraining and loss of fitness, whereas too little can result in no improvement. Training load can be quantified by a variety of methods, divided into external or internal. External methods include measures about the training itself, such as distance, speed or power and their recording is facilitated by the emergency of gadgets such as GPS devices (*Buchheit et al., 2010*; *Wallace, Slattery & Coutts, 2014*). In cycling, Normalized Power (NP) is the most used reading. NP is measured in watts and it is the estimate of the force that the individual can maintain for a given physiological cost if this force was constant during a given period of time (*Wallace, Slattery & Coutts, 2014*). Other external metrics are the intensity factor (IF) and training stress score (TSS), which estimate the overall physiological stress created by a training session, and which have been reported appropriate for monitoring and quantifying training load in cycling (*Wallace, Slattery & Coutts, 2014*).

Internal methods record the athlete's response to training and include biomarkers such as heart rate (HR), as well as subjective questionnaires including the rating-of-perceived-exertion (RPE) (*Lambert & Borresen, 2006*). RPE is a well-known and accepted scale for monitoring training, as it incorporates the relative psychophysiological stress imposed on the athlete (*Foster et al., 2001*; *Viru & Viru, 2000*). Apart from HR, another internal biomarker which has been gaining attention in the last decade is heart rate variability (HRV) (*Plews et al., 2013*). HRV is the variation in heartbeats (RR interval) within a specific timeframe and within the analysis of consecutive circadian periods, and can be measured by time or frequency domain methods. The statistical analyses of the length dispersion of RR intervals around a mean is the basis of time-domain indices. Differently, the spectral analysis of different components of the RR curve is the basis of frequency-domain parameters (*Xhyheri et al., 2012*). In medical research, HRV is being used as an objective and non-invasive tool to assess cardiac autonomic activity (*TFESC, 1996*) and in the athletic context, HRV is thought to serve as a marker for the adaptation of athletes to training (*Kiviniemi et al., 2007*; *Rodas et al., 2008*). HRV monitors the autonomic control on the cardiac system, describing the capacity of the organism, and specifically of its cardiovascular system, to alter the HR beat to beat to adapt to external and internal demands such as those imposed by training (*Morales et al., 2014*; *Ortega & Wang, 2018*). Previous studies show that when training load increases, HRV, measured in the morning, once a day, decreases. A reduction in resting HRV, has been related to fatigue, overtraining and the inability of the cardiovascular system to adjust to increasing levels of training, resulting in reduced performance (*Dishman et al., 2000*; *Garet et al., 2004*). Conversely, increase in performance, for example during competition, corresponds to positive changes in sympathetic and vagal activity (*Buchheit et al., 2010*; *Cervantes, Rodas & Capdevila, 2009*; *Ortigosa-Márquez et al., 2017*).

At the same time HRV has also been related to emotional responding. Changes in the Autonomic Nervous System (ANS) are reflected in HRV and are thought to indicate the ANS's ability to adjust arousal of an individual to the demands of the environment. *Wheat & Larkin (2010)* showed that high HRV responds to activation of the ANS to suit the demands of the stressful situation, whereas low HRV shows poor responsiveness of the ANS. In the general population, high HRV is related to more context-appropriate motivational responses, better executive attention and better working memory performance (*Gillie, Vasey & Thayer, 2014*) than low HRV, and it has also been related to reported feelings of relaxation amongst healthy participants (*Lin, Tai & Fan, 2014*). In the area of sports, low levels of HRV are associated with psychoemotional states including anxiety and a difficulty to face competition (*Kindermann, 1986*; *Kleiger, Stein & Bigger, 2005*; *Lee, Wood & Welsch, 2003*). When using the profile of mood states (POMS) questionnaire, Vigor and Fatigue subscales strongly correlated to changes in HRV, in particular to changes in the LF/HF balance (*Moreno, Parrado & Capdevila, 2013*). Moreover, altered Fatigue scores on the POMS also correlated to symptoms of overtraining or staleness, suggesting that emotional state could in turn be an indicative of athletic performance (*Moreno, Parrado & Capdevila, 2013*).

In summary, there are two main approaches to assess the amount of stress and recovery that athletes undergo: external methods give an insight into the characteristics of the training sessions, whereas internal methods inform about the physical and psychological responses of the individual to that session. Multiple studies suggest that measures of both internal and external methods relate to one another, as well as with emotional states. Understanding these associations is relevant to monitor training and to determine the balance of stress-recovery that each athlete needs to improve performance and prevent injuries. Following this line of research, the present study seeks to investigate the relationship between the psychophysiological state of cyclists in the morning and their training from the previous day. It also investigates the relationship between HRV and mood from the same day, and between internal and external training data. In particular, the study will look into the relationship between morning HRV, as indicator of the physiological condition of the athletes, morning mood, as indicators of their psychological state, and the previous day's training power output and RPE, as external and internal indicators of performance, respectively.

## MATERIALS AND METHODS

### Sample

Five recreational road cyclists volunteered to participate in this study. All were males with an average of 31.6 ± 3.4 years, had at least 6 years of experience riding and completed at least two training sessions per week for the duration of the study. Each cyclist was fully informed of potential risks and benefits associated with participation. Written informed consent was obtained from each participant. The study was conducted according to the Local Ethics Commission for Human Experimentation of the Autonomous University of Barcelona (protocol code CEEAH-5745).

## Instruments

### *Anthropometric data and training indices*

Age, height, weight and body mass index (BMI) were collected as anthropometric data. Functional threshold power (FTP) and watts/kg were used as fitness indices. This data was provided by the cyclists at the beginning of the study.

### *Mood state*

Mood was measured upon waking up using a 10-point cognitive scale, as has been used in other recent studies (*Perez-Gaido et al., 2021*). Cyclists responded to the question "How do you feel right now" (1–sad to 10–happy).

### *HRV recordings*

Upon waking up, and prior to any movement or ingest, participants were asked to remain in supine position in bed and record HRV data continuously for 3 min of natural breathing. Participant's beat-to-beat cardiac intervals (RR) were recorded using a Polar H7 chest band (Polar Oy, Polar Electro, Kempele, Finland). The accuracy and reliability of the Polar Band H7 was previously tested with the gold standard based on the ECG (*Parrado et al., 2010*). RR intervals with a resolution of 1 ms were sent by Bluetooth (BTv4) to the FitLab App (HealthSportLab.com, Barcelona, Spain), which was downloaded into a mobile device (iOS, Apple) in order to record the RR series. This application was connected *via* wireless to a remote server for analysing HRV parameters. The system allows performance of individual HRV recordings in each session and checks data quality in real time.

### *External training load*

External training load was studied using normalized power (NP), intensity factor (IF) and training stress score (TSS). NP is an estimate of the power that the athlete can maintain for a physiological cost if power is constant during a given period of time. IF is the ratio of the NP to the rider's functional threshold power. It gives a relative intensity in relation to threshold power, making IF a convenient way of comparing the relative intensity of training within or between riders. TSS is calculated based on IF and takes into account the intensity, duration, and frequency of a workout to estimate the overall stress created by that training session, as defined by TrainingPeaks (TrainingPeaks, Louisville, KY, USA). The single value of IF or TSS can represent how hard an athlete worked out, with the higher the numbers, the harder the training session. TSS and IF allow to quantify and compare workout between athlete because these values are relative to each individual's threshold, so that a 100 TSS points earned by a pro is relatively the same as 100 TSS points earned for a beginner (TrainingPeaks, Louisville, KY, USA).

All data was recorded during training sessions and obtained through each cyclists' TrainingPeak's profile. Power data was obtained using a power meter Assioma Duo (Favero Electronics SRL, Italy).

### *Internal training load*

Internal training load was studied using the Rate of Perceived Exertion (RPE) scale to measure perceived effort. The athletes had to rate the intensity of the entire training session using a category ratio scale CR10 of *Borg (1985)*, from 1 to 10, where "1" corresponds to no exertion, and "10" to maximal exertion. RPE data was taken 30 min following the completion of the cycling session to ensure the cyclists reported perception for the entire training session.

## Procedure

A longitudinal case study design was used to compare HRV and performance responses of the volunteers during a 6-week period. All eligible participants attended a first face-to-face interview individually in which demographic and fitness indices were collected.
The protocol of the study was explained. After the first interview, two sets of data were recorded, according to the individual training planning of each cyclist:

a) Training data: during the 6-week period, each participant trained individually, following their own training plan, which consisted of riding road bikes at least twice a week. The study didn't interfere with their training routine. For each training session, power data was recorded and was used to calculate TSS and IF using a power meter. RPE was also recorded. Data was saved and processed using the app TrainingPeaks.
b) Morning data: After days of training, at home on their own, upon waking on the morning, in a supine position in bed, and prior to any movement or ingest, each participant answered a 10-point mood scale. Immediately afterwards, maintaining the supine position in bed, each participant was required to complete a 3 min HRV test. Data was collected and analysed with the FitLab® system (HealthSportLab.com, Barcelona, Spain).

Participants were asked to complete the maximum number of training sessions per week possible, followed by recording morning data the day after. A total of 123 morning registers (mood and 3 min HRV test) and a total of 66 training registers were recorded. A total of 57 HRV morning recordings were not preceded by a road training the day before. During the 6-week study period, each participant completed an average of 25 morning registers (4 per week) and 12 training registers (2 per week).

## HRV data analysis

HRV analysis was performed for RR intervals in 3 min periods, as carried out in other field studies where it was required to interfere as little as possible in the training routines of athletes (*Martín-Guillaumes et al., 2018*). Ultra-short-term HRV analysis (30 s or 60 s) was recommended at rest condition (*Wu et al., 2020*), with a minimum of 120 s needed to record low frequency components (*Munoz et al., 2015*).

HRV data was obtained from the FitLab system. All RR intervals obtained were filtered and records exceeding an error rate of 11% were not considered for analysis. The mean of signal error for all recorded RR was 0.91%. Matlab's scripts (MathWork, Portola Valley, CA, USA) were used for error correction, as developed and validated in previous publications (*García-González et al., 2015*; *Parrado et al., 2010*). The error correction of RR series was applied as defined by *García-González et al. (2015)*. HRV analyses were performed following the recommendations of the Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology (*TFESC, 1996*). HRV parameters were calculated as defined by *Escorihuela et al. (2020)*: for time domain analyses, mean of RR intervals (mean RR) and the standard deviation of all RR intervals (SDNN) were calculated, and for frequency domain analysis the power in the low frequency (LF) band (0.04–0.15 Hz) and the high frequency (HF) band (0.15–0.40 Hz) were used. Additional calculations included the normalized LF and HF values (LFnu and HFnu, respectively), and LF/HF parameters.

### Statistical analysis

Analyses were carried out with all recordings for the five cyclists. Descriptive data are presented as mean ± SD. Pearson correlation analyses were performed in order to show bivariate relationships between HRV, mood, RPE, and external training load parameters. Multiple regression analysis was applied for explaining mood and HRV as a function of training parameters from the previous day, as well as mood as a function of resting HRV parameters in the same morning session. The regression method used was stepwise. G*Power (v3.1; Heinrich-Heine-Universität Düsseldorf, Düsseldorf, Germany) was used to analyse statistical power and effect size for regression analysis (*Faul et al., 2009*). Other statistical analyses were performed using IBM SPSS Statistics Package for Mac OS (version 28.0; SPSS Inc., Chicago, IL, USA). Statistical significance was set at $p < 0.05$. All data are presented as mean ± SD unless otherwise stated.

## RESULTS

### Description of anthropometric data and training indices

The cycling group consisted of five male recreational road cyclists. Anthropometric characteristics and training indices are shown in Table 1.

### Description of the main parameters analysed in the study

Table 2 shows means and standard deviations for the parameters analysed in the two situations under study, Training and Morning.

### Correlation coefficients and regression analyses

The following tables show the correlation between variables registered in the morning and those during training completed on the previous day.

**Table 1** Anthropometric characteristics and training indices.

| | P1 | P2 | P3 | P5 | Mean | SD |
|---|---|---|---|---|---|---|
| Age | 35 | 34 | 29 | 27 | 31.25 | 3.3 |
| Height | 180 | 172.5 | 179 | 186 | 179.38 | 4.8 |
| Weight | 74 | 62 | 64 | 68 | 67 | 4.6 |
| BMI | 22.8 | 21 | 20 | 19 | 20.7 | 1.4 |
| FTP | 330 | 242 | 340 | 325 | 309.25 | 39.2 |
| Watts/kg | 4.46 | 3.90 | 5.31 | 4.78 | 4.61 | 0.5 |

**Note:**
Summary of participant's anthropometric data and training indices. P1, P2, P3, P4, P5 stands for participants 1, 2, 3, 4 and 5 respectively. Height is expressed in centimetres; weight is expressed in kilograms; Body Mass Index (BMI) is expressed in kilogram by heigh in meters squared (kg/m$^2$); Functional Threshold Power (FTP) is expressed in watts; resting HR is expressed in beats per minute. Average data is expressed as mean (SD).

**Table 2** Means and standard deviations for all training and morning parameters.

| Morning data ($n$ = 123) | RRmean | SDRR | LF/HF | LFnu | HFnu | Mood |
|---|---|---|---|---|---|---|
| Mean (SD) | 1,262.46 (179.3) | 118.16 (36.3) | 1.40 (1.3) | 51.61 (16.6) | 48.39 (16.6) | 5.80 (2.5) |
| **Training data ($n$ = 66)** | **NP** | **TSS** | **IF** | **RPE** | | |
| Mean (SD) | 189.35 (40.1) | 120.48 (83.86) | 0.65 (0.2) | 5.50 (2.2) | | |

**Table 3** Pearson correlation coefficients between morning parameters (mood and HRV), and training variables from the day before ($n$ = 66 recordings).

| | NP | TSS | IF | RPE |
|---|---|---|---|---|
| Mood | −0.259 | −0.091 | −0.416** | −0.062 |
| RRmean | −0.171 | −0.201 | 0.041 | 0.276* |
| SDRR | 0.153 | 0.086 | 0.270* | 0.357** |
| LF/HF | 0.264* | 0.302* | 0.256* | 0.156 |
| LFnu | 0.385** | 0.299* | 0.421** | 0.212 |
| HFnu | −0.385** | −0.299* | −0.421** | −0.212 |

**Notes:**
* Significant correlation at 0.05 (bilateral).
** Significant correlation at 0.01 (bilateral).

## MOOD AND HRV AS A FUNCTION OF YESTERDAY'S TRAINING

Table 3 illustrates the correlation between external training load and the following morning's general emotional state and HRV variables. The training variable IF negatively correlated with Mood ($r = -0.416$; $p < 0.01$) and HFnu ($r = -0.421$; $p < 0.01$), and positively with LH/HF ($r = 0.256$; $p = 0.034$) and Lfnu ($r = 0.421$; $p < 0.01$). A multiple regression analysis was performed, but there was no significant equation that explained resting HRV or mood from a lineal combination of training parameters from the previous day.
All significant relationships between variables can be explained by simple correlations illustrated in Table 3.

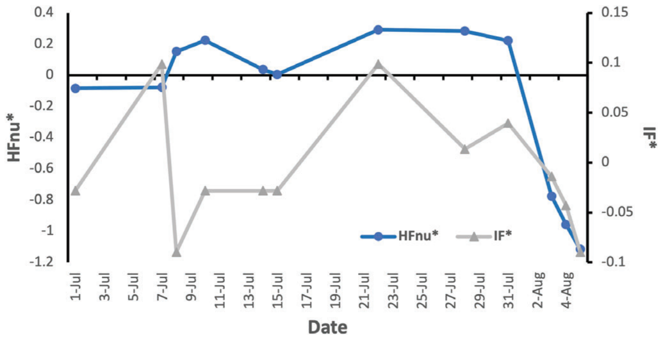


**Figure 1 Representation of data points obtained from Participant 1.** The graph illustrates the relationship between external training load (IF) and cardiac variability the next morning (HFnu), for 12 training recordings obtained from this participant. HFnu* = (HFnu − x̄HFnu)/HFnu; IF* = (IF − x̄IF)/IF. Full-size DOI: 10.7717/peerj.13094/fig-1

**Table 4 Pearson correlation coefficients between morning mood and HRV parameters from the same session ($n$ = 123 recordings).**

| | RRmean | SDRR | LF_HF | Lfnu | Hfnu |
|---|---|---|---|---|---|
| Mood | 0.497* | −0.367* | −0.331* | −0.420* | 0.420* |

**Note:**
* Significant correlation at 0.001 (bilateral).

**Table 5 Multiple regression equation to explain morning mood as a function of morning HRV ($n$ = 123 recordings).**

| Dependent variable | Independent variable | Non-standardised equation | Standardized coefficients (β) | $R^2$ | Sig. |
|---|---|---|---|---|---|
| Mood | RRmean<br>SDRR<br>Hfnu | Mood = −1.842 + (0.007 * Rrmean) − (0.026 * SDRR) + (0.034 * Hfnu) | 0.515 (Rrmean)<br>−0.381 (SDRR)<br>0.229 (Hfnu) | 0.492* | <0.001 |

**Note:**
* Effect size: $f^2$ = 0.968 (large > 0.35); Statistical power: $\pi$ = 1.00 (for $n$ = 123), three predictors and $R^2$ = 0.492.

Figure 1 illustrates a case example of the relationship between external training load (IF) and cardiac variability the next morning (HFnu). IF and HFnu are chosen as the external load and HRV parameters, respectively, because they showed the highest correlation between sets of variables (Table 3). In Fig. 1, data points are represented in relation to the overall average values obtained from the participant in question.

## MORNING MOOD AND HRV

Table 4 shows that general emotional state, as recorded by Mood, significantly correlates with all HRV parameters registered in the same morning session ($p < 0.001$, in all cases). Moreover, Mood was studied as a function of HRV indices, and the resulting model shows that morning mood can significantly be explained by a lineal combination of RRmean, SDNN and Hfnu (Table 5). This combination of HRV parameters explains 49.2% of the mood variability. The effect size ($f^2$ = 0.968) is large for a $R^2$ = 0.492, $n$ = 123, and three

**Table 6** Pearson correlation coefficients (r) between RPE and external load parameters in the same session ($n$ = 66 recordings).

| | NP | TSS | IF |
|---|---|---|---|
| RPE | 0.553* | 0.531* | 0.545* |

**Note:**
* Significant correlation at 0.001 (bilateral).

predictors ($f^2 > 0.35$). In the same way, the statistical power ($\pi = 1.00$) is also large ($\pi > 0.80$; *Faul et al., 2009*).

## TRAINING RPE AND POWER DATA

Table 6 shows a significant correlation between the internal and the external load variables measured in the study, and in particular between the subjective RPE and the power data (NP, TSS and IF; $p < 0.001$ in all cases). In this way, a higher training power, meaning a higher training load, is reflected in a higher perfection of effort.

## DISCUSSION

This study analysed the relationship between morning mood and HRV with regards to training load variables from the previous day. The association between morning mood and HRV on a given day, and between external and internal load variables was also studied. Correlation analyses were used to find association between variables and regression analyses was performed to try to explain mood and HRV as a function of training parameters from the previous day, and for explaining mood as a function of resting HRV parameters in the same morning session the day after training.

### Yesterday's training correlates with this morning's HRV

The current study indicated a relationship between morning HRV and training from the previous day. Specifically, Table 3 showed an inverse relationship between IF and HFnu, and a positive relationship between IF and LF/HF. Figure 1 illustrates, for Participant 1, the joint evolution over a month of the transformed parameters HFnu and IF. It can be seen, for example, that both pieces of data have an upward trend between 15-Jul and 23-Jul, a downward trend between 31-Jul and 4-Aug, and an opposite trend from 7-Jul to 8-Jul. The remaining training parameters under study, including NP and TSS, followed the same pattern as IF ($p < 0.01$), but with a lower significance ($p < 0.05$). Since Hfnu is considered a modulation index of the ANS parasympathetic branch (*Burr, 2007*), the results suggested that a higher training load one day (higher IF) correlated negatively with the activation of the vagal nerve the following morning, in favour of the SNS. This is in line with other studies, showing that parasympathetic power, indicated by HF, is able to reflect the recovery status hours after training (*Chen et al., 2011*; *Seiler, Haugen & Kuffel, 2007*), and that increased exercise intensity and/or duration cause delayed recovery of nocturnal cardiac autonomic modulation (*Myllymäki et al., 2012*).

As mentioned below (see Future Research), it would be interesting to track HFnu at regular hours and days post-exercise to help determine whether training was well-tolerated by the athlete, and in particular, to identify at what point the ANS switched from a sympathetic to a parasympathetic dominance. This is because the speed at which ANS recovers after exercise seems to be determined by fitness levels, with more rapid recovery in highly trained than in trained subjects after high-intensity exercise (*Seiler, Haugen & Kuffel, 2007*). Also, an increase of the parasympathetic branch following exercise is suggested to indicate the readiness of the ANS to take on strain again (*Kiviniemi et al., 2007*; *Mueck-Weymann, Janshoff & Mueck, 2004*) and is associated with improved athletic performance (*Buchheit et al., 2010*; *Garet et al., 2004*).

## Yesterday's training correlates with this morning's mood

Results showed an inverse relationship between IF and mood, so that the tougher one training session, the lower the mood of the following day (Table 4). This is contrary to the popular belief and most research on the topic, which argues that that exercise improves mood. However, such belief and research look at mood minutes, not days, after physical activity (*Hansen, Stevens & Richard Coast, 2001*; *Lane & Lovejoy, 2001*; *Walters & Kearsley, 1993*). Research looking at wellness scores the following day of exercise concluded that the greater the training load, the worse the wellness measures (fatigue, sleep quality, soreness and stress) (*Buchheit et al., 2013*). This goes in line with the results in Table 3. Other studies looking at mood over longer periods of time indicate that mood is affected by intense physical training in a dose-dependent manner, so that mood disturbances, as measured by the Profile of Mood States (POMS), increase in athletes during high-volume training sessions, in proportion to the training stimulus, and return to baseline during recovery (*Gross et al., 2016*; *Purvis, Gonsalves & Deuster, 2010*). At the same time, an impaired mood state and subjective complaints have mostly been described as sensitive and early markers of overtraining (*Morgan et al., 1988*; *Urhausen & Kindermann, 2002*), but not in all cases (*Walters & Kearsley, 1993*). While there is no clear way to define or diagnose overtraining, it is mostly characterised by 'sports-specific' decrease in performance, accompanied disturbances in mood state, including increase in fatigue, confusion, tension, depression, anxiety and lack of motivation and irritability, amongst others, persisting despite a period of recovery lasting several weeks or months (*Meeusen et al., 2013*; *Stone et al., 1991*; *Walters & Kearsley, 1993*).

In the present study it was found that the tougher one training session, the lower the mood of the following day, but it cannot be stated whether the change in mood was due to the intensity level of the training sessions nor from a state of overtraining. However, this is certainly a topic to be explored in future lines of research. Understanding short and long-term changes would be of interest to establish under which circumstances mood may be reliable and efficient to monitoring overtraining.

## Morning mood as a function of HRV

Findings in the current study indicate a relationship between morning mood and HRV, consistent with the idea that emotions that humans experience are associated with varying degrees of physiological arousal (*Levenson, 2003*). It was found that RRmean, SDNN and HFnu, in conjunction, explain 49.2% of mood variability of the same day (Table 5). Table 4 showed that mood correlated positively with RRmean and HFnu, and inversely with LFnu, LF/HF and SDRR ($p < 0.005$). Consistent with the idea of Hfnu as an index of the PNS (*Burr, 2007*), the results suggested that the more relaxed or recovered the nervous system, the more positive the emotional state. The findings are in line with other studies indicating a positive correlation between mood and HRV (*Kindermann, 1986*; *Kleiger, Stein & Bigger, 2005*; *Koval et al., 2013*; *Lee, Wood & Welsch, 2003*; *Sakuragi, Sugiyama & Takeuchi, 2002*). *Geisler et al. (2010)* supports the idea that HRV is associated with subjective well-being, whereas reduced HRV can be used as a predictive factor of the development of negative moods after situations such as deprivation of exercise (*Weinstein, Deuster & Kop, 2007*). However, it is interesting to note that most studies that found a significant correlation between mood and HRV were exclusively considering positives moods, including vigour and situations that trigger laughing, instead of negative moods (*Sakuragi, Sugiyama & Takeuchi, 2002*; *Yoshino & Matsuoka, 2011*). This could be due to the fact that positive emotions have a strong but transient effect on the ANS, while sadder moods have moderate but sustained effect (*Sakuragi, Sugiyama & Takeuchi, 2002*). Therefore, it would be interesting to study the relationship between morning HRV and mood not only on the same day, but also in consecutive days.

## RPE as an indicator of internal load

RPE, an internal load variable, correlated positively with external load variables such as NP, TSS and IF ($p < 0.005$). In this way, tougher workouts (higher power output) are reflected in higher RPE, supporting RPE as a significant measure of strain. This is consistent with other studies showing that session-RPE can be considered a valid, reliable and consistent indicator of global internal load (*Coutts et al., 2003*; *Haddad et al., 2017*; *Impellizzeri et al., 2004*; *Impellizzeri, Rampinini & Marcora, 2005*). This method was initially proposed by *Foster et al. (1996)* for monitoring internal training load in endurance athletes, but more recently is has also been proven to be applicable to other sports and physical activities with both men and women of different age and among different levels of experience (*Haddad et al., 2017*; *Lupo, Ungureanu & Brustio, 2020*; *Wallace, Slattery & Coutts, 2009*).

## Limitations

The main limitation of the current study is that despite having a number of recordings of $n = 123$ for Morning data and $n = 66$ for Training data, it only corresponds to five cyclists. A larger number of participants would be required in order to minimize individual differences and to increase the percentage of variability explained by the models of correlations and regression. Moreover, the lack of repeated measures fails to detect changes in HR and mood across different training situations, and future studies could include a follow-up assessment to capture the effects of different situations on the athletes, as proposed by *Olmedilla et al. (2018)*. Another limitation of the study is the use of a non-standardized scale to measure morning mood. A reduced relationship between mood in regard to HRV and/or performance could come from the poor measurement reliability of such scale. Other scales might be more appropriate for monitoring mood, such as the POMS (*Wallace, Slattery & Coutts, 2014*). Finally, HRV, mood states and performance are variables that can be influenced by factors unrelated to training (*Ortigosa-Márquez et al., 2017*), such as food and drinks, medications, stress, etc. (*Rodas et al., 2008*). It would be interesting to record and analyse how these factors may interact with the parameters analysed and affect training.

### Future research

The aim of this research is geared towards developing a predictive system to assess training adaptations, which could help guide load distribution and detect and prevent overtraining. For such a system, and to accurately track fitness and fatigue, it is proposed to use a combination of subjective and objective variables, both from psychophysiological data and from external and internal load parameters (*Haddad et al., 2017*). The current study indicates a relationship between variables of internal (RPE) and external (IF) training parameters, subjective psychological states (Mood) and objective physiological data (HRV), but the relationships could be further explored. In particular, it would be of interest to look into the variations of HRV and mood at different points in time (hours and days) following training. This is because, as mentioned above, the relationship between training and HRV, or training and Mood, varies as time goes by. Tracking changes in HRV and mood in the long-term is also relevant because fitness has a longer time constant than physical and mental fatigue, meaning it asymptotes at a higher level and a later time (*Morton, Fitz-Clarke & Banister, 1990*), so only variations in HRV and/or mood over several weeks, rather than consecutive days, can help interpret changes in training. The study of long-term tendencies of HRV and mood as a determinant of training has already been proposed (*Buchheit et al., 2010*; *Plews et al., 2013*), but more research is still needed to consider the effectiveness of these variables for assessing training adaptation.

## CONCLUSIONS

An array of studies has recently shown an association between HRV and other internal and external measures of performance, performance and emotional states, and HRV and emotional states. In the current article, the aim was to explore the relationship between training of one day and general mood and HRV parameters of the following morning. The relationship between HRV and mood, and between internal and external approached to measure training, was also explored.

After recording morning HRV, morning mood, and training data of five amateur road cyclists during a 6 weeks period, the main results indicated a relationship between morning HRV at rest and training, so that training of one day correlated with HFnu of the following morning, with tougher training sessions (higher IF) leading to lower morning HFnu and higher Lfnu and LF/HF, suggesting reduced PNS in favour of SNS activity. Higher IF sessions also resulted in lower moods on the following morning, indicating a relationship between training and mood on consecutive days. The study also found that mood can be explained as a function of HRV at rest, such that the higher HFnu on a given day, the more positive the mood. Finally, the study found a significant correlation between external variables of training, including TSS and IF, and the internal RPE, supporting the role of subjective measures as viable indicators of training load.

Overall, the study explored the relationship between indicators of morning psychophysiological state of cyclists and training. Despite the need for further studies, it is advocated the potential of combining HRV, mood markers and internal and external load training data to provide insights into the pychophysiological state of the individual, their ability to improve performance, and the ability to detect and prevent overtraining.

## ADDITIONAL INFORMATION AND DECLARATIONS

### Funding

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### Competing Interests

The authors declare that they have no competing interests.

### Author Contributions

- Carla Alfonso conceived and designed the experiments, performed the experiments, analyzed the data, prepared figures and/or tables, authored or reviewed drafts of the paper, and approved the final draft.
- Lluis Capdevila conceived and designed the experiments, authored or reviewed drafts of the papers, analyzed the data, and approved the final draft.

### Human Ethics

The following information was supplied relating to ethical approvals (*i.e.*, approving body and any reference numbers):

The study was conducted according to the Local Ethics Commission for Human Experimentation of the Autonomous University of Barcelona (protocol code CEEAH-5745).

### Data Availability

The following information was supplied regarding data availability:

The raw measurements are available in the Supplemental File.

### Supplemental Information

Supplemental information for this article can be found online at http://dx.doi.org/10.7717/peerj.13094#supplemental-information.

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## 3.3 Article 3

Alfonso, C., Clarke, D. C., Capdevila, L. (Accepted). Individual training prescribed by heart rate variability, heart rate and well-being scores in experienced cyclists. *Scientific Reports.*

Note: Attached below is the Accepted Manuscript (posprint) version of the article. The article has been accepted and is in press. The journal's acceptance email is **also** included.

### *Aim and results*

Article 3 aimed to evaluate the effectiveness of training protocols guided by different combinations of psychophysiological data in cyclists. It also explored the daily data collected.

The results were the following:

**Recordings:** A total of 28 trained cyclists participated and were monitored over a 40-day period. During this period, participants manually entered their RHR, RMSSD and WB values into a custom app developed for the study using AppSheet (Google LLC, CA, USA). See **Annex 3** for a screenshot of the app. For 31 of the 40 days, the app provided daily training recommendations, which participants were instructed to follow. On average, participants completed between 11 and 12 high-intensity sessions, 12 to 14 low-intensity, and 6 to 8 rest days. Group 2 completed the highest number of low-intensity sessions.
Note that participants were recruited via social media using a poster, provided in **Annex 4**. Following the campaign, 179 individuals expressed interest via email.

**Cycling performance outcomes:** When considering all 3 groups of the study, significant increases in performance were observed for 1-min, 5-min, 20-min, FTP$^{TM}$ and FTP$^{TM}$/kg variables ($p < 0.05$). When considering the groups individually, Group 1 (vmHRV-only) did not show significant improvements in any cycling performance test. Group 2 (vmHRV+WB) exhibited significant 1-min and 5-min power improvements, and Group 3 (vmHRV+WB+RHR) demonstrated the greatest performance gains, with significant increases in 5-min, 20-min, FTP$^{TM}$, and FTP$^{TM}$/kg efforts. All post-intervention values were consistently higher than pre-intervention values.
A one-way ANOVA revealed statistically significant differences between groups for 1-min and 5-min tests, with post-hoc Bonferroni analysis confirming that Group 2 outperformed Group 1 in 1-min efforts, and Group 3 outperformed Group 1 in 5-min efforts. Pmax did not improve significantly across any group.

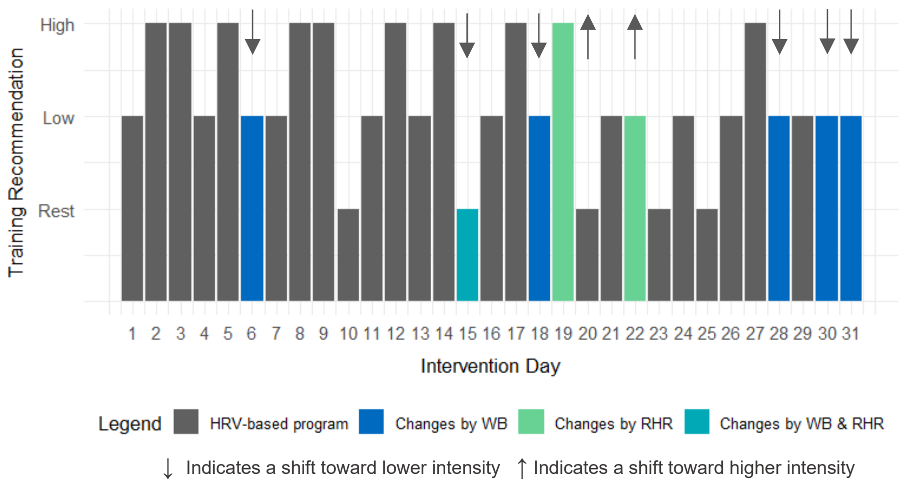
**Daily HRV, RHR, and WB parameters:** The analysis of daily vmHRV, RHR, and WB scores revealed that RMSSD and RHR were negatively correlated in 82% of participants ($r = -0.65$ to $-0.90$, $p < 0.05$), positively with WB scores in 4 participants ($p < 0.05$), with additional correlations observed for fatigue ($n = 6$), DOMS ($n = 5$), and sleep quality ($n = 4$). While some participants exhibited strong RMSSD-WB correlations, others displayed weak or even negative relationships, highlighting individual variability.

Regarding results from the ACF analyses, perceived stress displayed the strongest day-to-day autocorrelations (Lag 1 autocorrelation: $r = 0.67$, $p < 0.01$), whereas WB and RHR exhibited more sporadic patterns.

**Program performance:** As additional information, an analysis was conducted to compare the performance of each training recommendation program. In this context, “program” refers to the algorithm used to generate the training recommendations. Program 1 refers to the algorithm used for Group 1, Program 2 to that of Group 2, and Program 3 to that of Group 3. The aim was to compare how each program performed, compared to the other two, by evaluating how many daily training recommendations differed between programs when identical input data were applied over a 30-day period. For example, if on day 3, with identical input data, Program 1 recommended “High” intensity training and Program 2 recommended “Rest”, this accounted as a discrepancy. If both programs had recommended “High”, there would be no discrepancy. This comparison was calculated individually for each participant. Then, for all participants, the average of discrepancies between pairs of programs was calculated.

In total, results showed that Programs 1 and 2 differed on an average of 6 days, Programs 1 and 3 on 9 days, and Programs 2 and 3 on 4 days. Figure 7 illustrates an example of how the inclusion of WB scores in Program 2 and both WB and RHR variables in Program 3 can alter the recommendations provided by Program 1.

**Figure 7.** Example of training recommendation for Participant 16.




Using a same set of data, the figure shows how recommendations differ based on the different training programs. Grey bars represent the recommendations made by Program 1 (HRV-based only). Blue bars indicate recommendations modified by the inclusion of WB scores (Program 2). Green bars reflect changes due to RHR. Turquoise bars show recommendations influenced by both WB and RHR (Program 3), which on Intervention Day 15 lowered from "High" (hypothetical recommendation from Program 1) to "Rest" (influenced by both WB and RHR). Arrows indicate whether WB and/or RHR forced the program to recommend a more intense (↑ arrow) or a less intense (↓ arrow) workout. For example, Day 6 (in Blue), has an arrow pointing down, meaning that WB scores forced to recommend a "Low" intensity workout instead of the "High" intensity workout that would have been recommended if using an HRV-only-based training program.

Finally, at the end of the intervention of Article 3, individualized dashboards were created and shared with each participant as a summary of their personal data and study outcomes, and as a thank you for their participation. An example of a dashboard can be found in **Annex 5**. Additionally, several participants provided feedback regarding their experience taking part in the study. Some examples can be found in **Annex 6**.

Outlook

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# Individual training prescribed by heart rate variability, heart rate and well-being scores in experienced cyclists

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## Abstract

**Purpose:** Optimizing the training of endurance athletes involves the nuanced balance between overload and recovery. Monitoring recovery effectively requires integrating multiple variables. This study evaluates the efficacy of training protocols guided by vagally-mediated heart rate variability (vmHRV), resting heart rate (RHR), and subjective well-being (WB) scores in enhancing cycling performance. It also explores the relationships between physiological and subjective measures.

**Method:** Twenty-eight experienced male cyclists were divided into three groups: vmHRV-only (Group 1), vmHRV+WB (Group 2), and vmHRV+WB+RHR (Group 3). Over 40 days, participants recorded daily vmHRV, RHR, and WB scores and followed customised training protocols. Pre- and post-intervention cycling tests assessed maximal power (Pmax), 1-min, 5-min, 20-min, and functional threshold power (FTP™). Daily data analysis included correlation and autocorrelation function (ACF) assessments to evaluate trends and individual variability.

**Results:** Across all groups, significant performance improvements were observed for 1-min, 5-min, 20-min, FTP™, and FTP™/kg. Group 3 showed the greatest improvements, particularly in 5-min and 20-min efforts (310.5$\pm$60 to 337.9$\pm$71 watts, and 260.9$\pm$55 to 284.5$\pm$64 watts, respectively). ACF revealed stress as having the highest day-to-day consistency among subjective measures. Individual correlations revealed diverse strengths of the relationships between physiological and subjective markers.

**Conclusion:** Combining vmHRV, RHR, and WB offers a more nuanced assessment of athlete readiness and enhances training outcomes compared to vmHRV-only guidance. The study underscores the value of integrating physiological and subjective measures for personalising training protocols and highlights future directions for improving monitoring systems with advanced analytics.

**Keywords:** HRV, fatigue, recovery, psychophysiology, autonomic nervous system, periodization

**Abbreviations:** HRV Heart Rate Variability
vmHRV Vagally-Mediated Heart Rate Variability
RHR Resting Heart Rate
RMSSD Root Mean Square of Successive Differences
HR Heart Rate
WB Well-being

## 1. Introduction

How athletes respond to training and competition is complex [1]. Placing enough stress on the athlete primes the body for improvement, but such stress must be followed by periods of recovery to allow fitness adaptations to occur and to, importantly, avoid overtraining. Unfortunately, the boundary between successful training and overtraining is unclear, partly due to individual variability in the training response, since an appropriate load for one athlete may cause overtraining in another [2]. To address these challenges and monitor training and performance readiness, a myriad of psychological and physiological markers has been proposed. Of these, heart rate variability (HRV), resting heart rate (RHR), and well-being scores (WB) are commonly used in practice to guide endurance training.

HRV is defined as the variation in the time interval between consecutive heartbeats, and is used as a non-invasive marker of autonomic nervous system (ANS) regulation of cardiac function. It reflects the dynamic interplay between the parasympathetic and the sympathetic branches of the ANS, which promote recovery and stress responses, respectively [3], [4]. A key physiological mechanism influencing HRV is baroreflex sensitivity, a mechanism through which blood pressure changes are buffered via autonomic control. This reflex operates via negative feedback loops, modulating heart rate in response to fluctuations in blood pressure. Higher baroreflex sensitivity is associated with greater parasympathetic tone and improved cardiovascular and autonomic health [5]. Specifically, vagally-mediated HRV (vmHRV) reflects the activity of the parasympathetic nervous system, which is largely regulated by the vagus nerve, the tenth cranial nerve and main afferent pathway of the parasympathetic system [6], [7]. Since the parasympathetic system promotes homeostasis, recovery, and energy conservation, vmHRV provides insight into the body's capacity to adapt to external and internal demands, such as those imposed by training [8], [9].
HRV is measured by time- or frequency-domain methods, with the time-domain Root Mean Square of Successive Differences (RMSSD) being the most frequently used parameter to estimate vmHRV [3], [4]. In athletes, reduced resting RMSSD has been associated with fatigue, overtraining and reduced performance [10], [11], [12], [13].

Additionally, several studies have successfully used vmHRV indices to prescribe endurance training in different sports, by individualizing the timing of high-intensity sessions [14], [15], [16], [17], [18], [19]. For instance, Kiviniemi et al. [16] found that HRV-guided training significantly improved maximal running velocity.

Another key physiological marker in monitoring training is resting heart rate (RHR), a well-established indicator of an athlete's physical status [20]. Elevated RHR has traditionally been associated with accumulated fatigue or illness and the need for recovery [21], [22]. Interestingly, research highlights the interplay between RHR and HRV, emphasizing that HRV is inherently influenced by average heart rate due to physiological and mathematical factors. Normalizing HRV by average HR is essential to reduce mathematical bias and improve interpretation, particularly in populations with varying HR [23], [24]. Building on this foundation, the combination of RHR and HRV has been used to distinguish overtraining from recovery states in high-training load athletes, with promising potential for capturing subtle changes in fitness and fatigue [12], [21]. This combination shows potential for improving training precision, although further research is needed [25], [26].

Beyond physiological markers, subjective variables also provide valuable insights into athlete's states. Psychological factors such as impaired mood state, fatigue, insomnia or irritability are highly sensitive and early indicators of overtraining, often appearing before a drop in performance [27], [28], [29], [30]. They have also shown to provide information about the intensity of output that can be expected when training [31], [32], [33]. WB scores, derived from self-reported ratings of quality of sleep, fatigue, stress, and muscle soreness, provide a particularly efficient means of monitoring overtraining and recovery [34], [35], [36], [37].

Despite the value of both psychological and physiological tools in monitoring and predicting overtraining or readiness, neither provides the desired insights when used in isolation [38]. Psychological stressors, for example, can impact performance even in sports that require minimal physical exertion, like golf [39], and alterations in mood can occur in the absence of changes in performance [1]. Similarly, physiological markers like HR cannot inform of all aspects of fatigue or performance [21]. Consequently, research increasingly supports integrating both approaches, because subjective parameters can reinforce and contextualize HRV data [13], [21], [34], [40]. As Bourdon et al. [31] mentions, the combined approach balances athlete perception and quantifiable practice. Given the complexities of athlete performance, combining markers could improve the precision of training recommendations [12], [41].
Moreover, individual differences play a critical role in the integration and interpretation of combined approaches. Research indicates that under similar training load conditions, athletes may exhibit different HRV responses due to variations in autonomic regulation and recovery capacity [19], [21]. Likewise, subjective variables can be influenced by

psychological resilience or external stressors, leading to varied perceptions [27], [39]. These differences underscore the need for individualized monitoring strategies, as population-level trends may obscure significant personal variability, potentially reducing the precision of training guidance [18].

The present study aims to compare interventions that combine vmHRV (RMSSD), RHR, and WB scores (based on fatigue, DOMS, stress, and sleep quality) to guide the intensity of training sessions for endurance athletes. The primary aim is to determine the extent to which combination approaches yield greater performance improvements compared to using each metric in isolation. Additionally, the study seeks to explore the shared and unique information contributed by these measures by assessing correlations and temporal patterns between the physiological and subjective markers.

# 2. Method

## 2.1 Participants

Participants were recruited through social media networks (Twitter and Instagram) and an advertisement published in HRV4Training's monthly newsletter. A total of 119 individuals initially expressed interest in participating in the study. Participation was voluntary and anonymous, and each cyclist was informed that they could withdraw at any time. Written informed consent was obtained from each participant and ethical approval was granted by the local ethics committee from the Universitat Autònoma de Barcelona (protocol CEEAH-5745).

***Final sample and dropout description:*** Of the 119 individuals who initially enrolled, 3 were excluded during screening due to pre-existing medical conditions (asthma, diabetes, or cardiovascular pathologies), resulting in 116 eligible participants. These participants were randomly allocated into one of three training groups before the start of the intervention. Over the course of the study, 88 participants did not complete the protocol. Specifically, 23 withdrew due to illness or physical injury, including infections, musculoskeletal injuries, or bike accidents. Another 66 participants voluntarily discontinued participation, with some of the reasons provided including loss of interest, competing training commitments, or work scheduling conflicts. Two participants were excluded due to excessive time between baseline testing and program start, which compromised the study protocol. The final sample therefore consisted of 28 participants who completed the study, with 8 participants in Groups 1 and 3, and 12 in Group 2. The uneven distribution across groups reflects the observed attrition that occurred during the study. A summary of anthropometric and training characteristics for the final sample is provided in Table 1.

**Table 1.** Anthropometric and training characteristics of participants.

| | Group 1<br>*n = 8* | Group 2<br>*n = 12* | Group 3<br>*n = 8* |
|---|---|---|---|
| Age | 39.6 (10.0) | 47.7 (15.7) | 49.5 (10.3) |
| Age range | 29-55 | 27-69 | 37-65 |
| Height | 175.4 (9.3) | 182.1 (8.3) | 181.3 (5.9) |
| Weight | 71.2 (8.6) | 76.8 (9.3) | 83.1 (10.6) |
| BMI | 23.8 (5.4) | 23.8 (1.) | 25.3 (2.7) |
| Cycling experience (years) | 18.3 (7.0) | 18.8 (19.4) | 20.5 (13.8) |
| Current hours/week training | 9.4 (4.1) | 11.3 (5.7) | 10.0 (4.1) |
| Current days/week training | 4.3 (1.8) | 5.3 (1.6) | 5.1 (1.3) |

Group 1: vmHRV-based training group. Group 2: vmHRV and WB-based training group. Group 3: vmHRV, WB and RHR-based training group. BMI: Body Mass Index. Height is expressed in centimetres, weight in kilograms, cycling experience in years and current training in hours and days per week; and age range as years old. Data are expressed as mean and standard deviation (SD).

## 2.2 Instruments

***Athlete Burnout Questionnaire (ABQ).*** The ABQ was developed by Raedeke & Smith [42] and is a self-reported inventory that addresses classic symptoms of burnout, including reduced sense of athletic accomplishment, devaluation of sports participation and emotional/physical exhaustion. In this study, both the English and the Spanish [43] versions were used. The questionnaire consists of 15 items and uses a Likert scale from 1 (“almost never”) to 5 (“almost always”). The higher the scores in all items (except 1, 11 and 15), the higher the burnout. Following a total sum of items, higher scores on the ABQ indicate that athletes are high in burnout. Scores over 70 are interpreted as burnout, while those below 50 are interpreted as no risk of burnout.

***Oura ring, Whoop strap, smartphone with HRV4Training or EliteHRV*.** The vmHRV parameter of RMSSD was obtained using either an Oura ring (Gen3, Oulu, Finland), a Whoop strap (Whoop 4.0, Boston, USA) or the phone apps HRV4Training [44] or EliteHRV [45] linked to a cardiac chestband. The tools used have been previously validated [46], [47], [48], [49].

***Well-being (WB) questionnaire***. The WB questionnaire consisted of four questions regarding perceived sleep quality, fatigue, muscle soreness (DOMS) and stress. This questionnaire is custom-made, based on the recommendations of [35] for monitoring well-being in athletes. Each question was scored from 1 to 7 (with 1 and 7 representing lowest and highest ratings, respectively). A daily WB score was determined by summing sleep quality and subtracting fatigue, DOMS and stress. The maximal and minimum WB scores were 10 and -20 arbitrary units, respectively.

***Power meter.*** A power meter was used to collect data pertaining to pre- and post-intervention performance, as well as daily training sessions. Each cyclist used their own power meter, such as Assioma Duo (Favero Electronics SRL, Italy), or similar. Data were uploaded to each participant's TrainingPeaks account [50]. For the tests, the variables obtained included maximal power (Pmax), 1-min maximal power (1min), 5-min maximal power (5min), 20-min maximal power (20min) and Functional Threshold Power$^{TM}$ (FTP$^{TM}$), which is the highest power that the rider can sustain for one hour [51]. Power was measured in watts. For the training sessions, the power meter was used to measure the Intensity Factor$^{TM}$ (IF $^{TM}$), which reflects the relative intensity of a session in relation to the rider's FTP$^{TM}$ [51]. IF$^{TM}$ was used to define the intensity of each training session (see Supplementary Material A).

## 2.3 Procedure

**Inclusion and exclusion criteria:** Eligibility was assessed using an initial screening questionnaire that included questions about daily habits (e.g., smoking, medication use, pathologies) and cycling experience (e.g., years of cycling, training days per week, hours training per week). Participants also completed the ABQ. All candidates reported being injury-free, not taking medication, and not experiencing symptoms of burnout at the time of enrolment [3].

**General procedure:** Individuals eligible for the study then signed a written consent and proceeded to perform the initial power tests on the bike. These tests were performed on their own bicycles using their own power meters. Participant weights were measured on the day of the tests. The participants then proceeded with a 40-day study period: 9 days to establish the baseline of the program followed by 31 days of intervention. Every morning upon waking up, participants recorded vmHRV (RMSSD) and their perceived WB. Participants using an Oura Ring or a Whoop Strap obtained the vmHRV values automatically from the device's app. Those using the HRV4Training or EliteHRV platforms measured vmHRV for 3 minutes using the cardiac chest band, first thing in the morning, in a seated position, before any other movement, and in a fasted state. Participants registered their vmHRV and WB data into the program and during the 31-day intervention period, they followed the program's training recommendations, which advised them to train "High" or "Low" intensity, or to "Rest" (see Supplementary Material A). The procedure is illustrated in **Fig. 1**. The app used to record the data was AppSheet [52], an application that enables the creation of mobile applications from other sources.
Participants were randomly allocated to one of three groups: vmHRV-guided group (Group 1), vmHRV-WB-guided group (Group 2) and vmHRV-WB-RHR group (Group 3). Group 1 was advised to train low, high or rest based on their daily vmHRV, whereas Group 2 had an advice based on vmHRV and WB, and Group 3 based on vmHRV, WB and RHR (see Supplementary Material A). In all cases, training sessions were registered and

uploaded to TrainingPeaks and training intensity was measured using IF™. Participants exercised at the time of day that was most convenient for them. At the end of the 31 days, participants performed another set of power tests on the bike and registered their weight on the day of the tests. Participants were instructed to follow the program as closely as possible. If participants did not follow the program for 10 days or more in total (across the 31 days of intervention), they were excluded from the study.

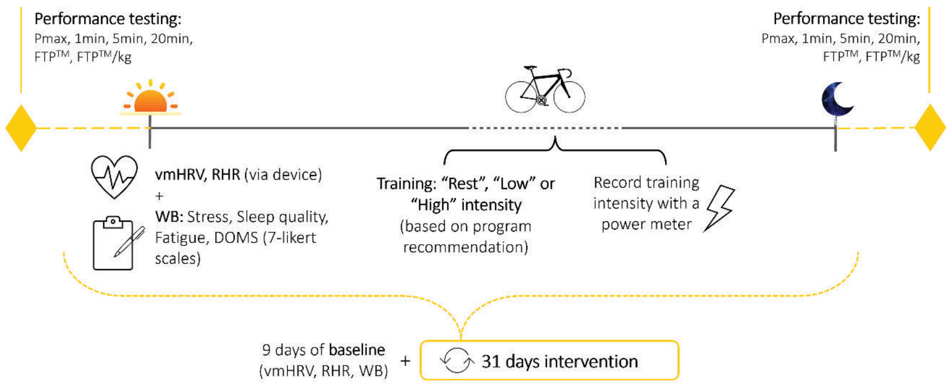



**Fig. 1** Illustration of the general procedure. During the 9-day baseline period, participants trained freely. During the 31 days of intervention, they followed individualized recommendations

**Pre and post power cycling tests**: The first day of testing consisted of a 15-min warm-up, followed by 2 x 1 min of riding at maximal power with 7-min recovery in between, followed by three maximum-effort sprints of about 15 seconds separated by7-min recovery, and a cool-down. The riders were instructed to do the tests standing and in a climb. The second day of testing consisted of a 15-min warm-up, 3 × 1-min intervals at a cadence over 100 rpm with 1 min recovery, 5 min of easy riding, 5 min at maximum intensity, 10 min of easy riding, 20 min at maximum intensity, and cool-down [53], [54], [55]. The riders were instructed to do the tests in a climb with a constant grade [56]. Participants were familiar with these testing procedures, as such protocols are routinely incorporated into training programs and have demonstrated high reliability in previous research [57]. Participants were free to choose whether to perform the tests indoors or outdoors but were instructed to maintain consistency by using the same setting for the post-test as they had used for the pre-intervention test.

## 2.4 Statistical analysis

Descriptive statistics are reported as mean ± standard deviation (SD) for each measure and subgroup, unless otherwise stated. A 3x2 multivariate analysis of variance (MANOVA) was performed to analyse the differences between pre- and post-intervention for each cycling power parameter, comparing the results between the three intervention groups. The non-parametric Wilcoxon test was used to detect

changes between the initial and final power tests, for each group separately. Mean data for each participant were used to calculate the percentage change between the initial and final tests (Post-Pre), then averaged for each group. A one-way analysis of variance compared the percentage changes across the three groups. Omnibus tests that achieved statistical significance were followed by Bonferroni post-hoc tests to compare pairs of groups. Effect sizes for one-way analyses of variance were reported using partial-eta squared ($\eta_p^2$), with values of 0.01, 0.06, and >0.14 indicating small, medium, and large effects, respectively [58]. For post-hoc pairwise comparisons, effect sizes were reported as Cohen's *d*, with values of 0.2, 0.5, and 0.8 indicating small, moderate, and large effects, respectively [59].
Correlations between daily vmHRV, RHR and WB parameters were calculated using Spearman's rank correlation test, because the data did not meet the assumptions of normality, as revealed by a Shapiro-Wilk test. Daily vmHRV, RHR and WB parameters were also analysed as a time series using Autocorrelation Function (ACF) analysis to assess temporal consistency, which is the persistence of patterns or dependencies within a time series. Daily data were computed for 24 participants, instead of the total sample of $n = 28$, because some participants in Groups 1 and 2 did not provide complete RHR data. All statistical analyses were performed using IBM SPSS Statistics Package for Mac OS (version 28.0; SPSS Inc., Chicago, IL, USA). The threshold for statistical significance was set at $p < 0.05$. The raw data supporting the findings of this study are available on the Open Science Framework (OSF) repository.

## 3. Results

The results are subdivided into two sections. First, pre- and post-performance tests were used to evaluate changes in physical performance before and after the intervention. Second, daily data of vmHRV (RMSSD), RHR, and WB scores were examined, providing insights into their trends and interplay during the study.

### 3.1 Training and cycling test performance

Over the 31-day training period, athletes from Groups 1, 2 and 3 trained an average of 11 days of high intensity, 12, 14 and 12 of low intensity and 8, 6 and 8 of rest days, respectively. A MANOVA indicated no significant differences in the pre-intervention power data amongst groups for any of the tests, showing that the cyclists were at a comparable level when starting the intervention. Wilcoxon tests were then applied to detect changes between the initial and final power tests, for each group separately. The results are shown in Table 2. For Group 1, no significant difference between Pre and Post results for any of the tests. For Group 2, there were significant differences in 1min and 5min. For Group 3, significant differences were found for 5min, 20min, FTP™ and FTP™/kg. When considering all groups together, the most significance was found for

1min, 5min, 20min, FTP™ and FTP™/kg. In all cases of significance, post-intervention values were higher than in the initial tests.

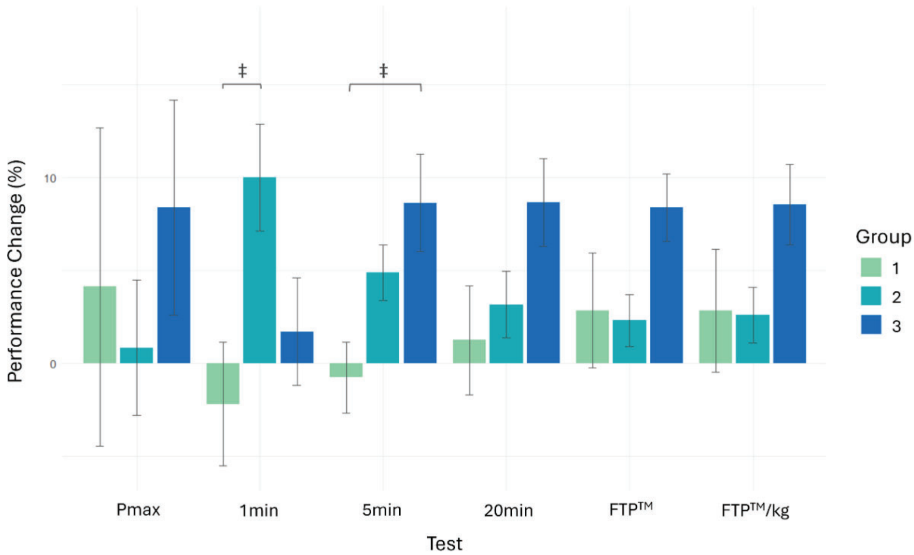
**Table 2.** Results of tests Pmax, 1min, 5min, 20min, FTP™ and FTP™/kg pre- and post-intervention for Group 1 (n=8), Group 2 (n=12), Group 3 (n=8), and the Total average from the three groups.

| | **Pre** | **Post** | ***p*-value** | $\eta_p^2$ |
|---|---|---|---|---|
| **Pmax** | | | | |
| *Group 1* | 961 ± 150.86 | 979.13 ± 160.43 | *ns* | |
| *Group 2* | 1016.67 ± 233.77 | 1014.92 ± 216.39 | *ns* | |
| *Group 3* | 954.5 ± 242.32 | 1008.38 ± 175.62 | *ns* | |
| *Total* | 983 ± 210.42 | 1002.82 ± 184.35 | *ns* | .025 |
| **1min** | | | | |
| *Group 1* | 480.38 ±77.53 | 474.00 ± 103.84 | *ns* | |
| *Group 2* | 509.50 ±105.12 | 557.75 ± 114.60 | .003ǂ | |
| *Group 3* | 475.88 ± 89.52 | 487.50 ± 110.59 | *ns* | |
| *Total* | 491.57 ± 91.60 | 513.75 ± 113.36 | .027ǂ | .180 |
| **5min** | | | | |
| *Group 1* | 312.88 ± 58.84 | 311.38 ± 64.20 | *ns* | |
| *Group 2* | 334.58 ± 52.57 | 352.25 ± 66.05 | .003ǂ | |
| *Group 3* | 310.50 ± 60.34 | 337.88 ± 70.96 | .012ǂ | |
| *Total* | 321.50 ± 55.69 | 336.46 ± 66.70 | .001ǂ | .357 |
| **20min** | | | | |
| *Group 1* | 259.63 ± 44.13 | 262.75 ± 46.58 | *ns* | |
| *Group 2* | 284.17 ± 43.01 | 293.75 ± 51.46 | *ns* | |
| *Group 3* | 260.88 ± 54.72 | 284.50 ± 64.39 | .012ǂ | |
| *Total* | 270.50 ± 46.70 | 282.25 ± 53.75 | .002ǂ | .315 |
| **FTP™** | | | | |
| *Group 1* | 244.75 ± 39.96 | 252.13 ± 47.08 | *ns* | |
| *Group 2* | 270.50 ± 44.93 | 277.25 ± 50.93 | *ns* | |
| *Group 3* | 248.75 ± 52.63 | 271.00 ± 62.65 | .018ǂ | |
| *Total* | 256.93 ± 45.83 | 268.29 ± 52.58 | .000ǂ | .406 |
| **FTP™/kg** | | | | |
| *Group 1* | 3.48 ± 0.70 | 3.57 ± 0.79 | *ns* | |
| *Group 2* | 3.65 ± 0.76 | 3.67 ± 0.81 | *ns* | |
| *Group 3* | 3.00 ± 0.63 | 3.26 ± 0.71 | .018ǂ | |
| *Total* | 3.41 ± 0.73 | 3.53 ± 0.77 | .020ǂ | .198 |

*ns*: non-significance; ǂ Post > Pre; $\eta_p^2$ : partial-eta squared

Fig. 2 presents the percentage difference between the initial and final tests (Post-Pre) for each group. A one-way analysis of variance indicated significant differences in the results of 1min ($F(25,2)=4.499$, $p=0.021$, $\eta_p^2 = 0.265$ [large effect]) and 5min ($F(25,2)=5.082$, $p=0.014$, $\eta_p^2 = 0.289$ [large effect]) between groups and tendency to significance for FTP™ ($F(25,2)=2.541$, $p=0.099$, $\eta_p^2 = 0.169$ [large effect]). Bonferroni test showed statistically significant differences between groups 1 and 2 for 1min ($p=0.025$, $d = 9.72$ [large effect]) and between groups 1 and 3 for 5min ($p=0.012$, $d = 6.47$ [large effect]). Individual pre- and post-test values, along with percentage changes for each participant, are provided in Supplementary Material B.

**Fig. 2** Percentage change (Post-Pre) and standard error of the performance tests




‡: significant difference between pairs of groups (Bonferroni, $p<0.05$).

## 3.2 Daily data analyses

### *3.2.1 Individual correlation from daily data*

Correlation coefficients of vmHRV (RMSSD) with RHR, and with WB variables for each athlete are shown in Table 3. The correlations were calculated individually for each participant by averaging the values across the 40 days of the study. RMSSD and RHR present significant negative correlation in 82% of the cases. Positive correlations between RMSSD and subjective variables were observed in a limited number of participants: WB in 4 individuals, fatigue in 6, DOMS in 5, sleep quality in 4, and stress in 1.

**Table 3.** Spearman correlation coefficients between RMSSD and RHR, sleep quality, DOMS, fatigue, stress and WB, calculated individually for each athlete using their average daily data across the study period.

| | ID | RHR | Sleep Quality | DOMS | Fatigue | Stress | WB |
|---|---|---|---|---|---|---|---|
| **RMSSD** | 2 | -0.65** | 0.22 | -0.44* | -0.49* | -0.32* | 0.47* |
| | 3 | -0.76** | 0.40* | -0.16 | -0.20 | -0.10 | 0.26 |
| | 4 | 0.46* | 0.21 | 0.06 | -0.04 | -0.04 | 0.14 |

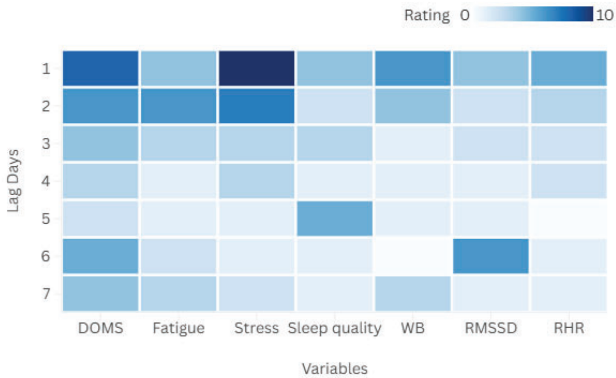
| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 7 | -0.41* | 0.03 | 0.16 | 0.15 | 0.09 | -0.13 |
| | 8 | -0.90** | 0.24 | -0.21 | -0.42* | -0.01 | 0.37* |
| | 9 | -0.48* | 0.24 | -0.34* | -0.36* | -0.31 | 0.43* |
| | 10 | -0.61** | 0.02 | 0.12 | 0.01 | -0.23 | 0.05 |
| | 12 | -0.47* | 0.12 | -0.06 | -0.05 | 0.13 | 0.01 |
| | 13 | -0.58** | 0.30 | -0.04 | 0.00 | -0.28 | 0.22 |
| | 16 | -0.70** | 0.08 | -0.22 | -0.26 | -0.13 | 0.24 |
| | 17 | -0.56** | -0.05 | -0.22 | -0.13 | -0.12 | 0.17 |
| | 18 | -0.86** | 0.41* | 0.17 | -0.03 | 0.06 | 0.17 |
| | 19 | -0.18 | 0.09 | -0.07 | 0.02 | -0.02 | 0.05 |
| | 20 | -0.63** | -0.04 | 0.02 | 0.08 | 0.17 | -0.06 |
| | 22 | -0.11 | -0.15 | 0.03 | -0.35* | -0.15 | -0.03 |
| | 28 | 0.01 | 0.22 | -0.22 | -0.18 | -0.21 | 0.27 |
| | 29 | -0.81** | 0.15 | -0.14 | -0.26 | -0.17 | 0.21 |
| | 31 | -0.76** | -0.02 | 0.11 | -0.24 | -0.15 | 0.06 |
| | 32 | -0.08 | 0.03 | 0.32* | 0.34* | 0.29 | -0.27 |
| | 33 | -0.68** | 0.36* | 0.38* | 0.03 | 0.13 | -0.02 |
| | 35 | -0.47* | -0.02 | -0.28 | -0.31 | -0.20 | 0.30 |
| | 36 | -0.54** | 0.34* | -0.34* | -0.32* | -0.11 | 0.40* |

The analysis included 22 participants, with data points for each variable collected over 40 days (n=40). Spearman significance: *p<0.05 and **p<0.001. Participants 23, 30, and 36 were excluded as their stress values remained constant across all 40 days of the study, preventing meaningful correlation calculations.

### *3.2.2 Autocorrelations from daily data*

Autocorrelation Function (ACF) analysis was used to detect patterns and temporal consistency for DOMS, fatigue, stress, sleep quality, WB, vmHRV (RMSSD), and RHR, recorded daily, across all groups. The ACF measures the correlation between a variable's values on one day and its values at prior time points (lags). For example, Lag 1 represents the correlation between the values of a variable on one day and the preceding day, Lag 2 represents the correlation with two days prior, and so on. The heatmap in Fig. 3 visualizes these correlations, with darker colours indicating stronger autocorrelations for a given variable and lag. Notably, a high autocorrelation in stress at “Lag Day 1” suggests that stress levels on one day are closely related to those on the previous day, reflecting day-to-day consistency. Sleep quality and RMSSD also exhibit moderate autocorrelations at specific lags (e.g., Lags 1 and 5), suggesting recurring trends over time. In contrast, WB and RHR display consistently low autocorrelation values, indicating more variable or sporadic patterns over the study period.

**Fig. 3** Heatmap of ACF ratings by daily lag and variable




The heatmap displays ACF ratings across multiple lags (days 1 to 7) for each variable. Each lag represents the correlation of a variable's values with its values from previous days. Rating 0-10: Darker colours indicate stronger autocorrelations. The analysis included 24 participants, with data points for each variable collected over 40 days (n=40).

# 4. Discussion

The goal of the present study was to assess the effectiveness of training protocols guided by vagally-mediated heart rate variability (vmHRV, referring to RMSSD), well-being (WB), and resting heart rate (RHR) on cycling performance. The intervention was divided into three groups depending on the variables that guided training: vmHRV-only (Group 1), vmHRV+WB (Group 2), and vmHRV+WB+RHR (Group 3). Across all groups, improvements were observed in several performance metrics, with Group 3 exhibiting the most consistent performance gains. Daily data were also analysed to explore individual correlations and temporal patterns between WB and physiological markers. Significant correlations were observed between vmHRV and RHR, while correlations between vmHRV and the subjective-report variables were less consistent. ACF revealed strong day-to-day trends for stress, moderate for vmHRV and sleep quality, and sporadic for WB and RHR.

## 4.1 Changes in cycling performance

### *4.1.1 General improvements in performance*

Participants showed significant improvements in 1min, 5min, 20min, FTP™, and FTP™/kg ($p < .05$) when considering all groups collectively. These findings align with previous research, where cyclists who trained based on vmHRV showed enhanced ventilatory thresholds and performance in a 40-min time trial, compared to block-periodization training [15], [60]. Similar results have been reported in endurance runners, for whom vmHRV-based training improved maximal running velocity [19], and countermovement jump height [17].

### *4.1.2 Comparison between groups: the role of well-being in performance gains*

Comparison between groups revealed that Groups 2 and 3 showed larger improvements in 1min and 5min, respectively, compared to Group 1 ($p < .05$). These results may underscore the importance of integrating WB scores into training recommendations. In Groups 2 and 3, high-intensity sessions were performed only when both vmHRV and WB scores were within or higher than their baseline, whereas a drop in those values triggered adjustments to "Low" or "Rest" days (see Supplementary Material A). This protocol aligns with evidence suggesting that pre-training wellness correlates with external training output, as WB appears to indicate the quality of the training output that might be produced on the day [33], [35]. In runners, a reduction in WB had likely negative to very likely negative impact on the ability of players to fulfil high-intensity efforts [61], suggesting that higher WB scores reflect increased readiness and predisposition for exertion.

Importantly, the combination of vmHRV and subjective variables may enhance training monitoring by contextualizing vmHRV trends. This is because increases in vmHRV can indicate both optimal training adaptations and the onset of fatigue or overreaching, so adding WB markers help contextualize these changes, allowing for better interpretation [9]. As [21] emphasized, measures of HR cannot fully inform on all aspects of wellness and fatigue, highlighting the importance of combining vmHRV with psychometric assessment for a more holistic view of athletes' readiness to train.

The WB factors evaluated in the study -fatigue, stress, DOMS and sleep quality- are all known to influence performance. Stress, for example, impacts the ability to perform high efforts [62], by reducing concentration and vigour [63], while fatigue questionnaires has been nominated as the most sensitive tool to variations in training load and performance [64]. DOMS, caused by eccentric muscle activity [65], is associated with a reduction in performance, as it impacts cycling economy, glycogen repletion and the intensity of subsequent training sessions [65], [66]. Finally, sleep quality, asides from being essential for health and emotional regulation, cognition and quality of life, is directly linked to athletic performance [67], [68], with poor sleep quality predicting worse changes of winning in elite athletes [32], [69], as well as impaired speed, endurance, attention, and memory [67]. Despite this, many athletes fail to sleep enough for their activity levels and also fail to recognize the impact of sleep deprivation on performance [67], [68], reinforcing the importance of tracking and integrating sleep metrics into training plans. Overall, the findings support the value of self-reported WB assessments in optimizing training schedules and improving athletic performance.

### *4.1.3 Comparison within groups: the role of RHR in performance gains*

Within-group analyses revealed that Group 3 presented the greatest improvements from pre- to post-intervention, particularly in 5min, 20min FTP$^{TM}$ and FTP$^{TM}$/kg. This suggests that combining RHR with vmHRV and WB scores provided valuable additional information for guiding training. Two key mechanisms may explain these findings. First, the inclusion of vmHRV and RHR in Group 3's training recommendations addressed potential distortions caused by HRV's dependence on average HR. HRV, typically measured via R-R intervals, is influenced by average HR due to physiological and mathematical relationships. Normalizing HRV with respect to R-R intervals (the inverse of HR) mitigates this bias, allowing HRV to better reflect autonomic changes [24]. Second, combining HRV with RHR helped mitigate HRV saturation, a phenomenon observed at high training loads or fitness levels. HRV saturation occurs when vagal tone is already elevated, reducing HRV's sensitivity as a marker of parasympathetic activity, since it plateaus even as HR continues to decrease [12]. This can complicate the differentiation between recovery and fatigue. For instance, a high HRV and low RHR typically indicate recovery, whereas stable HRV with elevated RHR may signal fatigue or overtraining [21]. The addition of RHR to the guide-training recommendations may help address this limitation by providing context for HRV changes [21]. Additionally, the use of rolling averages further enhances the utility of HRV and RHR in guiding training. RHR exhibits lower day-to-day variation than HRV, making it a practical measure for assessing training adaptation in real-time, while HRV is more sensitive to longer-term fatigue and fitness trends [70]. Notably, averaging HRV and RHR over a week provided stronger correlations with fitness improvements, such as 10-km running performance, than daily measures alone [70]. Our study adopted a similar approach, using weekly averages to capture a more reliable picture of training adaptations.

Overall, while vmHRV alone is useful in detecting nonfunctional overreaching, combining it with RHR may provide a more comprehensive view of an athlete’s condition [12], [71]. In this context, the greater performance improvements of Group 3 could stem from the combined use of RHR and vmHRV. However, more research is needed to refine these tools, as limitations in using HRV ratios have been noted [9].

#### *4.1.4 Lack of changes in performance*

Interestingly, no significant improvements were found in Pmax across or within groups, and while Group 3 showed a tendency for improvements in 20min, FTP$^{TM}$, and FTP$^{TM}$/kg compared to Groups 1 and 2, these differences were not statistically significant. A possible explanation is the reliance of these metrics on neuromuscular effort [72], [73] and cycling economy [74], [75], respectively, both of which are influenced by targeted strength training. For instance, enhancing Pmax typically required targeted strength training to increase muscle cross-sectional area and fibre composition [76], which endurance alone may not achieve effectively [74], [77]. Since participants in this study did not incorporate strength training, this may have contributed to limited improvements observed in both short-term power (Pmax) and longer endurance efforts (20min, FTP$^{TM}$). Additionally, the intervention period of four weeks may have been insufficient to detect changes in peak power, as studies such as [78], have observed increases in peak power only after an eight-week training period. Another possible explanation is the high baseline fitness of the participants. Given the homogeneity in pre-training levels across groups, the observed differences in response to training programs are unlikely to result from initial disparities in pre-intervention levels [79]. Experienced athletes often display limited improvements in endurance performance due to already optimized physiological characteristics, such as high blood volume or red blood cell counts [80], while less trained individuals tend to show greater responses to high-intensity interval and volume training [81]. Thus, the participants' advanced training status may have constrained the potential for further performance enhancements in Pmax, 20min and FTP$^{TM}$ efforts.

Additionally, while analysing within-group differences, Group 1 showed no significant improvement in performance. This finding is surprising, as vmHRV-only guided protocols have previously led to better performance [14], [15], [16], [17], [18], [19]. Asides from supporting the role of RHR and WB scores as markers to refine guided-training, discussed above, another explanation possible explanation for the lack of significant improvements in Group 1 could lie in methodological differences in how vmHRV is measured. For instance, while other studies such as [16] used an orthostatic test to assess vmHRV, our study measured RMSSD in a supine or seated position. Since body position can significantly influence HRV readings, this may account for differences in findings [9], [21], [82]. Furthermore, whereas other studies have analysed high-frequency (HF) power, this study used RMSSD due its lower sensitivity to breathing rate [83] and its reliability in short-term recordings [84], [85]. Additionally, although a logarithmic transformation of RMSSD (lnRMSSD) was not applied in the present study, this approach may help normalize the distribution and stabilize variance of RMSSD, reducing the influence of extreme values and enhancing comparability across individuals [13], [86]. Future research could explore different methodologies for HRV-guided training, including alternative parameters such as lnRMSSD and variations in recording positions.

## 4.2 Analysis of daily data: tailoring training recommendations

ACFs are used to examine the degree of correlation between a variable and its previous values over time, identifying trends of fluctuations. This is particularly useful tool for monitoring training and recovery, where both physiological (e.g., vmHRV) and psychological (e.g., stress, fatigue) markers can vary due to external and internal factors. In this study, ACF analysis revealed that stress had the highest autocorrelation at lag-1, indicating greater day-to-day consistency than the other studies variables. This temporal stability suggests that, in this sample, stress reflected a more persistent internal state. This consistency does not necessarily imply usefulness for guiding training, since the marker could remain the same regardless of training load (e.g., a daily rating of 5 within a 7-Likert scale). Still, stress may remain a relevant variable, as previous findings suggest that perceived stress can negatively affect performance and recovery and can be an early sign of overreaching [87]. In contrast, DOMS, fatigue, sleep quality and WB showed more erratic ACF values. While some consistency emerged at short lags, such as around day 2, the irregularity of these variables highlights their susceptibility to daily fluctuations. For instance, [65] emphasized the need to carefully manage recovery when DOMS is elevated, recommending training cessation until it subsides. The instability of DOMS observed in this study underscores its potential limitations as a predictor of recovery and its critical role in overtraining prevention. Moreover, although physiological measures like HRV are often expected to show more predictable linear or quadratic patterns [88], the findings here showed only moderate correlations on certain days, such as days 1 and 5. This suggests that HRV might reflect longer-term adaptations rather than daily variability. Collectively, the results emphasize the importance of individualized monitoring, as athletes' recovery responses can vary based on their unique physiological and psychological profiles. Moreover, the findings underscore the need to consider not only the day-to-day stability of each variable, but also its sensitivity to training load, when determining its usefulness for guiding training decisions.

Individual correlation analyses further revealed considerable variability in physiological and subjective responses. As expected, vmHRV presented a strong negative correlation with RHR for most participants, consistent with its calculations from R-R intervals [24]. However, correlations between vmHRV and subjective WB variables were considerably less consistent. While several participants displayed significant negative correlations between vmHRV and fatigue or DOMS, as suggested by previous research [34], [89], [90] these patterns were not universal. Similarly, some individuals exhibited positive correlations between vmHRV and WB, suggesting a link between better autonomic function and subjective well-being, as noted before [91], [92], as well as vmHRV and sleep quality [93], [94], [95], but it was not the case for all participants.

Overall, these results highlight the need for personalized training programs that monitor key metrics based on an athlete's unique profiles. In this study, all subjective variables were equally weighted in calculating perceived morning WB. However, the observed variability in correlations suggests that a uniform approach may not adequately capture individual needs, as suggested recently by [41]. While vmHRV may be more closely tied to recovery in some individuals, other factors, such as sleep quality, may play a larger role in others. Moving forward, it would be valuable to identify which variables have larger coefficient of variation for each subject and refine the formula to respond to individual dynamics.

### 4.4 Limitations

A main limitation of the study is the small sample size, which reduces the predictive power of the results [59], [96]. Although the findings are promising, high attrition led to a reduced final sample. While attrition does not inherently invalidate study outcomes if transparently reported and accounted for [97], the findings should be interpreted with caution until replicated in larger, adequately powered studies. Additionally, the sample only consisted of male athletes, as only three women showed interest, potentially biasing results due to gender differences in HRV and subjective variables [98], [99],

[100]. Another limitation involves the training structure. Participants followed training instructions to perform sessions labelled "High," "Low," or "Rest," which allowed for autonomy but introduced variability in training execution. While this design reflected real-world practice, a more structured plan with prescribed intervals or strength work could have led to more consistent performance outcomes. In this context, training intensity was monitored using IF™, a measure of external training load [51]. While IF™ provides an objective indication of work, it does not capture internal physiological strain. Future studies could benefit from integrating alternative parameters such as percentage of maximal heart rate (%HRmax), used in previous studies (e.g., [16]), to balance external and internal load markers.

In terms of instrumentation, data collection relied on a variety of validated consumer-grade tools (e.g., Oura, HRV4Training) to help increase accessibility and recruitment, but which potentially introduced heterogeneity in the data. Future research may benefit from standardising devices across participants to improve inter-device reliability and data consistency. Finally, the protocol of this study was entirely self-administered to replicate real-world training conditions. Although participants received detailed instructions and were in regular contact with the research team, the absence of direct supervision limited the ability to ensure uniform implementation of the protocol. Prior studies have shown that unsupervised training protocols may result in lower adherence rates and less consistent performance outcomes compared to supervised interventions [101], and thus future research could consider supervised assessments or hybrid study designs (combining in-person and remote components).

## 4.5 Future directions

This study used physiological and psychological indicators to guide training intensity. In the future, it would be interesting to introduce and investigate more subjective parameters, such as mood, as well as biomarkers like cortisol or hormone levels to further refine monitoring systems. To our knowledge, this is the first study using RHR as a metric to guide training, and given its potential, more research is encouraged, for instance exploring guided-training by LnRMSSD in a ratio with R-R, instead of RMSSD, as did [12].

Additionally, expanding the participant base to include both novice and elite athletes would improve the generalizability of results. Future research should also consider including formal familiarization sessions prior to testing, to improve reliability and reproducibility of performance data [102], a step that was not included in this study. Moreover, retention strategies could also be considered to mitigate high dropout rates, a common challenge in applied longitudinal research [99]. Approaches such as structured onboarding, app-based reminders, and community engagement may help improve adherence and data quality. In these future studies with larger and more diverse populations, demographic factors such as age or BMI should be assessed as potential confounders, as they have shown to influence HRV parameters [103].

In terms of tools, these monitoring systems should be incorporated into non-invasive, not expensive, time-efficient devices, that could be used by athletes [21]. Advances in methods such as time series analysis or machine learning could be pivotal in understanding the complex interactions between training load, recovery, and the prediction of performance outcomes [31], [41], [104]. For instance, in this study, these methods could help to uncover how daily fluctuations in data affected post-intervention performance, or which variables were most relevant for each athlete. Such insights could help assign differential weights to each well-being component based on their impact on performance. Ultimately, these advances will enable a more individualized approach to athlete management, particularly critical during training and competition phases, when athletes need to perform at their best.

## Conclusion

Designing optimal training strategies for endurance athletes is complex. This study evaluated the efficacy of combining vagally-mediated heart rate variability (vmHRV, particularly RMSSD), resting heart rate (RHR), and subjective well-being (WB) scores, including fatigue, stress, DOMS and sleep quality, to guide training recommendations for cyclists. The results showed significant performance improvements, with the combination of vmHRV, RHR, and WB metrics yielding the greatest gains in key performance efforts. Additionally, analysis of daily data revealed stress as a potential predictor of training readiness. However, other individual variability in correlations between vmHRV, RHR, and subjective WB variables underscored the importance of personalized training protocols. Overall, the findings reinforce the value of an integrative approach, where vmHRV, RHR, and WB are used collectively to enhance the precision of training recommendations, with WB scores providing essential context for interpreting vmHRV trends. Such an approach offers a tailored interventions to optimize performance while minimizing the risk of overtraining. Future research should validate these results in larger populations and utilize advanced analytics to further personalize training methodologies.

### Statements and Declarations

**Conflict of interest:** All authors have no competing interests to declare that are relevant to the content of this article.

**Ethical approval:** This study was performed in line with the principles of the Declaration of Helsinki. Approval was granted by the Ethics Committee of Universitat de Barcelona (No. CEEAH-5745)

**Consent to participate** Informed consent for participation in this study was received from all subjects.

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**Data availability:** The datasets generated during and/or analysed during the current study are available in the Open Science Framework repository,
[https://osf.io/w6bzq/?view_only=98c801b0c06a439e9f479f76fabd147a]

**Authors contributions:** Conceptualization: CA, LlC; Methodology: CA, LlC; Formal analysis and investigation: CA, LlC; Writing - original draft preparation: CA; Writing - review and editing: CA, LlC, DC; Funding acquisition: LlC; Supervision: LlC

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## 3.4 Article 4

Alfonso, C., Garcia-Gonzalez, M. A., Parrado, E., Gil-Rojas, J., Ramos-Castro, J., & Capdevila, L. (2022). Agreement between two photoplethysmography-based wearable devices for monitoring heart rate during different physical activity situations: a new analysis methodology. *Scientific reports*, *12*(1), 15448. https://doi.org/10.1038/s41598-022-18356-9

### *Aim and results*

Article 4 aimed to assess the agreement between two PPG-based wearable devices for monitoring HR across different conditions, with an ECG as a gold-standard reference. The article also proposed a new methodology to synchronize and compare HR data from devices with different sampling rates.

The results were the following:

**Participants:** A total of 18 university students (10 males, 8 females, 22 ± 2.45 years old) participated in the study.

**Agreement Between Wearable Devices and ECG:** HR values differed across activity levels, with higher discrepancies observed as movement intensity increased, particularly between PV and the ECG.

- **Comparing HR during a 5-min mean interval:** Overall AW maintained high agreement with ECG across all activities, with correlations above r = 0.998. In contrast, PV showed a progressive decrease in agreement as activity levels increased, with the lowest correlation found while walking (r = 0.677). ANOVA analyses confirmed that AW had consistently higher accuracy than PV.
- **Comparing HR at different time intervals**: The study tested how the devices recorded HR averaging readings from 5 to 60 seconds. In the same line as the 5min intervals, Bland-Altman analyses demonstrated that both devices aligned well with ECG while lying down, with small biases and narrow limits of agreement. However, as movement increased, PV showed larger discrepancies from ECG, particularly when walking. Averaged over longer time intervals (30-60 seconds), HR agreement improved for both devices, with AW showing a consistent reduction in bias (to -0.18 bpm at 60s) and PV remaining more variable (-2.34 bpm at 60s). Inversely, averaging over shorter periods (5-30 seconds) showed greater variability in agreement. Moreover, the spreading of the differences was also higher in the PV compared to the AW, increasing with greater movement.

**Methodological Considerations and Synchronization Strategy:** A new methodology was developed in the study, which allowed to synchronized HR values from wearables with ECG, allowing comparisons across different time scales. For example, it allowed to synchronize the ECG with the PV, which provides HR every 1 seconds, and AW, which provides HR at unstable times from 1 to 9 seconds. Notably, the proposed synchronization procedure does not require interpolation of time series data, improving precision and reliability.

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# Agreement between two photoplethysmography-based wearable devices for monitoring heart rate during different physical activity situations: a new analysis methodology

Carla Alfonso[1,2,4], Miguel A. Garcia-Gonzalez[3,4], Eva Parrado[1,2], Jessyca Gil-Rojas[3], Juan Ramos-Castro[3] & Lluis Capdevila[1,2]✉

**Wearables are being increasingly used to monitor heart rate (HR). However, their usefulness for analyzing continuous HR in research or at clinical level is questionable. The aim of this study is to analyze the level of agreement between different wearables in the measurement of HR based on photoplethysmography, according to different body positions and physical activity levels, and compared to a gold-standard ECG. The proposed method measures agreement among several time scales since different wearables obtain HR at different sampling rates. Eighteen university students (10 men, 8 women; 22 ± 2.45 years old) participated in a laboratory study. Participants simultaneously wore an Apple Watch and a Polar Vantage watch. ECG was measured using a BIOPAC system. HR was recorded continuously and simultaneously by the three devices, for consecutive 5-min periods in 4 different situations: lying supine, sitting, standing and walking at 4 km/h on a treadmill. HR estimations were obtained with the maximum precision offered by the software of each device and compared by averaging in several time scales, since the wearables obtained HR at different sampling rates, although results are more detailed for 5 s and 30 s epochs. Bland–Altman (B-A) plots show that there is no noticeable difference between data from the ECG and any of the smartwatches while participants were lying down. In this position, the bias is low when averaging in both 5 s and 30 s. Differently, B-A plots show that there are differences when the situation involves some level of physical activity, especially for shorter epochs. That is, the discrepancy between devices and the ECG was greater when walking on the treadmill and during short time scales. The device showing the biggest discrepancy was the Polar Watch, and the one with the best results was the Apple Watch. We conclude that photoplethysmography-based wearable devices are suitable for monitoring HR averages at regular intervals, especially at rest, but their feasibility is debatable for a continuous analysis of HR for research or clinical purposes, especially when involving some level of physical activity. An important contribution of this work is a new methodology to synchronize and measure the agreement against a gold standard of two or more devices measuring HR at different and not necessarily even paces.**

Wearable technology uses smart electronic devices that are worn close to or on the surface of the skin, to detect and analyse body signals and/or ambient data and transmit it to the phone[1]. In the last decade, wearable devices have become more comfortable, lightweight, and cost-effective for assessing health behaviour, and at present,

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they have shown potential applications in personal recovery, sleep and fitness, as well as medical surveillance, non-invasive medical care, and mobile health-wellness monitoring[2]. With an expected number of connected wearable devices of more than one billion by 2022[3], the number of companies developing such technology is growing speedily, and the need to test the accuracy of data collected by these devices increases accordingly. The physiological signals recorded by wearables can have immediate clinical, research and practical impact in the monitoring of fitness and medical conditions, so there is a need to determine whether their measurements are within clinical limits of agreement[4]. One of the physiological parameters those wearable devices measure, and whose validity has been tested compared to a gold standard, is heart rate (HR).

HR is a measure of cardiac activity usually expressed as the number of beats per minute (bpm). The current gold-standard method for assessing HR is the standard 12-lead electrocardiogram (ECG), while HR measurements from wrist-worn wearables are predominantly obtained from photoplethysmography (PPG). PPG is an optical measurement technique that allows to collect volumetric changes in blood perfusion under the skin using a light emitter and a photodetector. HR research has been limited by the lack of ecological validity, inability to collect data during a representative time span and the obtrusiveness of the HR measurements. Fortunately, the present irruption of wearables has the potential to increase and improve the research on HR provided that the measurements are valid. In the future, continuous wearable-based technology has great potential for helping users to monitor their health, as well as impacting clinical and research settings, by guiding healthcare decisions and medical interventions. For this reason, it is important to prove the accuracy and suitability of wearables for the assessment of HR. To date, studies exploring the accuracy of wearables' HR compared to ECG indicate that, on average, wearables slightly underestimate absolute HR[5–7] with the Apple Watch having slightly greater accuracy than other devices such as Fitbit[4,8]. The intensity of body movement seems to affect the detection of HR, as well as the position where devices are worn, with the wrist being particularly susceptible to movement and to corrupting the PPG signal and affecting the accuracy of the estimation[9]. Overall, it is known what PPG lags behind ECG when it comes to HR detection[10], yet it is still interesting to keep testing the accuracy of PPG because it is less intrusive, low cost and convenient way to detect cardiac changes than ECG[11].

The accuracy of HR in situations that involve movement seems to depend on two factors: motion complexity and level of physical activity[4]. Wearables are more accurate during rest, low intensity exercise[7,12] and locomotor activities characterized by repetitive movements (eg, cycling, walking or running)[7,12–14]. Some research shows that absolute error during activity is higher with resistance training exercises, with inherently more complex movements, being more inaccurate (35% accuracy) compared to aerobic exercise (92% accuracy)[15,16].

Recent guidelines and recommendations complain that there is a lack of transparency from manufacturers on describing the underlying signal processing and on disclosing the HR data measured by their devices[4,17]. This lack of information complicates the comparison procedure among wearables of different manufacturers. To validate a wearable, comparisons among two or more time series quantifying the HR in a selected time scale must be made. For the sake of comparison, the time series must be properly synchronized and represent the HR at some time scale (i.e. by averaging the sampled data during the same time span). For the sake of automatic synchronization and validity assessment, the majority of validation studies include an interpolation procedure to resample the information of the devices to be compared at the same sampling frequency[17]. Moreover, a large proportion of studies only compare the average of the HR of the overall recording. Hence, they use a time scale of some minutes (often 5 min) losing the opportunity to check if the wearable can correctly track variations of HR along the recording. Interpolation adds fictitious data to the sparser sampled time series (generally, to the time series obtained from the wearables) while measuring at only one time scale narrows the scope of the validation procedure.

The aim of this study is to determine the validity of the measured HR, as a key health and fitness measurement, from two of the most popular wearables: the Apple Watch and Polar Vantage, under different activities. The study will compare these devices to a gold-standard ECG in different positions to account for motion complexity and level of physical activity. Moreover, the study proposes a new methodology for validity testing that can be employed to gain more insight on signal processing differences among devices. The proposed methodology avoids the interpolation of the HR data to compare with the gold-standard measurements and it advocates for the device's comparison over different time scales to track variations of HR along the recording.

## Materials and methods

For this study, two heart rate photoplethysmography-based wearable measurement devices were compared against the beat-to-beat heart rate obtained by a reference ECG system. The two wearable devices were the Apple Watch S6 (Apple, Cupertino, CA, USA) (AW) and the Polar Vantage M2 (Polar Electro Oy, Kempele, Finland) (PV). The ECG was acquired using a Biopac MP36 data acquisition system (Santa Barbara, CA, USA) using a sampling frequency of 1 kHz and limiting the bandwidth of the amplifier between 0.5 Hz and 150 Hz. The accurate beat-to-beat heart rate obtained with this system was the gold standard measure (GS) for comparison against the other systems. Both AW and PV provide estimates of HR obtained by filtering and processing the detected heartbeats using photoplethysmographic techniques and non-disclosed and proprietary algorithms. The PV provides HR updates each second while the AW provides HR samples at more unstable times, typically ranging from 1 to 9 s.

**Participants.** Twenty participants started the study but 2 were rejected due to poor quality of the ECG signal. Hence, eighteen university students (10 males, 8 females), with a mean age of $22 \pm 2.45$ years, were included in the study. All participants were volunteers and provided written consent. Descriptive statistics of the participants are shown in Table 1. Privacy was assured for all participants as regards all data collected. The study was

| | Mean ± SD |
|---|---|
| Age (years) | 22 ± 2.45 |
| Height (cm) | 172.21 ± 8.95 |
| Women | 165.5 ± 7.18 |
| Men | 176.9 ± 6.97 |
| Weight (kg) | 65.0 ± 9.99 |
| Women | 57.25 ± 9.21 |
| Men | 71.2 ± 5.16 |

**Table 1.** Descriptive statistics for participants.

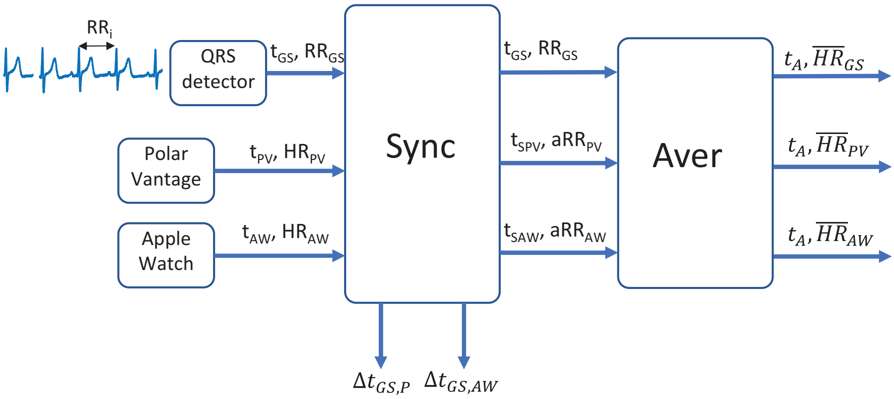


**Figure 1.** Signal processing stages. The Sync block synchronizes the time stamps of the point heart rate estimates for the alternative measurement methods while the Aver block provides an average of point estimates for each method at the same reference time stamp. See text for further details.

conducted according to the guidelines of the Declaration of Helsinki and approved by the local Ethics Commission for Human Experimentation of the Autonomous University of Barcelona (protocol code CEEAH-5745).

**Procedure.** A within-subject design was used in this study. Participants were contacted via email or Twitter. The study was conducted in one session. Before starting the session, participants completed an informed consent form. Weight and height were measured before starting the HR recordings.

The measuring HR devices (GS, AW and PV) were placed on each participant. The ECG electrodes for GS measurement were attached near the clavicula (one at each end), while the reference electrode was placed at the jugular notch, ensuring an ECG signal good enough for proper QRS detection while allowing the movement of the participants from place to place according to the measurement protocol. The AW was placed on the right wrist and the PV on the left wrist. Each participant was asked to remain in a lying position for 5 min (lying activity), then to seat on a chair for 5 min (sitting activity), stand for 5 min (standing activity), and finally walk on a treadmill without inclination at a speed of 4 km/h for another 5 min (walking activity). When moving from one position to another, 30 s were allowed to let the signal stabilize. The researchers manually annotated the starting and ending times of the activities.

The HR series of the PV device were downloaded from the Polar Account webpage after syncing the PV device with the Polar Flow service. The data format was a text file with two columns for each session (timestamp and HR data). For the HR series of the AW, the AW was automatically synced with an iPhone 10. All health data of the iPhone was exported to an .xml file and the HR series were extracted from the file with a short script written in Matlab.

**Signal processing.** Figure 1 shows the main stages of the signal processing procedure. A QRS detector detects the R peak locations from the ECG of the GS system. These locations are used to generate a timestamp and a gold standard RR time series ($t_{GS}$ and $RR_{GS}$, respectively). On the other hand, the PV and AW systems provide their timestamps ($t_{PV}$ and $t_{AW}$) in correspondence with their point estimates of HR. These estimates are easily converted to average heart periods ($aRR_{PV}$ and $aRR_{AW}$). The first step is to synchronize the timestamps of the studied measurement systems with respect to the gold standard. This procedure estimates the delay between $t_{GS}$ and $t_p$ or $t_{AW}$ by minimizing the error between the point estimates and the $RR_{GS.}$ Synchronization creates new timestamps for the PV and AW systems ($t_{SPV}$ and $t_{sAW}$). After synhronization, the averaging block identifies the $RR_{GS}$ intervals and $aRR_{PV}$ and $aRR_{AW}$ point estimates that lie inside a certain interval of length $t_s$ (averaging time), compute their mean values and converts them to mean HR estimates. Because these estimates are obtained at the same temporal location ($t_A$), these values can be directly compared to measure the agreement with respect to the GS.

The QRS complexes were detected using the same procedure described in[18] that starts with a first estimation of the QRS locations using a Pan-Tompkins QRS detector[19]. The QRS locations are further refined using a matching pattern technique. After QRS detection, the QRS locations were further refined by looking for outliers and correcting them using the same approach of[20]. See a more detailed description of the QRS detection and outlier detection and correction in Appendix A1 in the supplementary materials. At last, the QRS detector, including the artifact correction, provides the $RR_{GS}$ time series and its corresponding timestamps $t_{GS}$ time series for each volunteer.

AW and PV systems provide their heart rate time series ($HR_{AW}$ and $HR_{PV}$) expressed in beats per minute (BPM) at different interval times (not necessarily regular) as measured by their timestamps ($t_{AW}$ and $t_{PV}$) in milliseconds. Because timestamps for the gold standard are referred to the beginning of the ECG recording, the first manipulation of the $t_{AW}$ and $t_{PV}$ time series was subtracting to every timestamp the initial timestamp corresponding to the first provided HR measurement.

Note that at this stage, the three different timestamp time series are differently sampled and they can include significant delays due to different starting measurement times, clock errors and delays introduced by each measuring system. The synchronization procedure estimates these delays and it is described in detail in Appendix A2 in the supplementary materials. The output of this procedure performs an straightforward transformation of the $HR_{AW}$ and $HR_{PV}$ time series to averaged RR period time series ($aRR_{PV}$ and $aRR_{AW}$) and provides new timestamps ($t_{SPV}$ and $t_{SAW}$) synchronized with $t_{GS}$.

$$AWaRR(j) = \frac{60000\, ms/minute}{AWHR(j)} \tag{1}$$

After synchronization, time series are split in four parts corresponding to the four different activities (lying, sitting, standing and walking). The partition is made considering the manual annotations and starts at 10 s after the annotation of the beginning of the activity and ends 10 s before the annotation of the end of the activity.

The first approach to assess the agreement compares the mean HR for each activity and devices obtained from the average the RR time series against the HR obtained from the GS for the same individual and activity. Hence, after activity partition, mean HR in beats per minute (BPM) were obtained for each device, activity and subject as

$$mHR_d^{s,a} = \frac{60000}{mRR_d^{s,a}} \tag{2}$$

where $mRR_d^{s,a}$ is the mean RR time series (in ms) averaged using all the available samples for subject $s$ during activity $a$ while measuring with device $d$ (averaging time series $aRR_{PV,}$ $aRR_{AW}$ or $RR_{GS}$ for PV, AW or GS systems respectively). Each of these averages covers a time interval of around 5 min.

These mean HR values were analyzed with the IBM SPSS Statistics package for Mac OS (version 25), and the significance threshold was set at $p<0.05$. First, the Kolmogorov–Smirnov test was applied to prove that all HR values presented normality of the distributions, for all activities. Analysis of variance (ANOVA) for repeated measures was applied to compare the averages of HR values on approximately 5 min periods between the three different devices for each situation. Bonferroni contrast tests for repeated measures was applied to compare the differences between HR mean values and to calculate the 95% confidence interval. The effect size for ANOVA (repeated measures) was also analyzed from the parameter partial eta-squared ($\eta_p^2$); benchmarks provided by[21] were used to define small ($\eta^2=0.01$), medium ($\eta^2=0.06$), and large ($\eta^2=0.14$) effects. G*Power (v3.1; Heinrich-Heine-Universität Düsseldorf, Düsseldorf, Germany) was used to analyse statistical power for analysis of variance (ANOVA) for repeated measures. To calculate the statistical power, we considered an $n=18$, four factors of repeated measurements (lying, sitting, standing and walking), the overall effect size calculated for all factors and the lowest correlation observed between devices for that factor. Pearson correlation analyses were performed to test HR bivariate associations between pairs of devices for each situation.

Because the $RR_{GS}$ time series reflects the beat-to-beat variability of the heart rate while $aRR_{AW}$ and $aRR_{PV}$ have some kind of filtering and averaging, in order to provide a fair agreement measurement, including the tracking of HR changes, the three RR time series were smoothed by averaging their samples using different averaging times ($t_s$). The averaging procedure for each subject, device and activity looks for the timestamps of the three systems ($t_{GS}$, $t_{SAW}$ and $t_{SPV}$) that are included in the interval $[t, t+t_s]$ and outputs the mean value of the RR time series (either for $RR_{GS,}$ $aRR_{AW}$ or $aRR_{PV}$) that correspond to these timestamps. The procedure considers as the starting time ($t_o$) the first timestamp of the $t_{GS}$ that corresponds to the beginning of the activity under study. In this work we have considered averaging times from 5 to 60 s (in steps of 1 s). This procedure provides estimates of the averaged RR time intervals at the same instants for the three systems. Because AW and PV provide their measurements as heart rate in BPM, for each subject ($s$), activity ($a$) and averaging time ($t_s$) the following three time series were obtained:

$$\overline{HR_{GS}^{s,a,t_s}}(m) = \frac{60000}{\overline{aRR_{GS}^{s,a,t_s}(m)}} \tag{3}$$

| Activity | Biopac (GS) | Apple Watch (AW) | Polar Vantage (PV) | ANOVA (*p*) |
|---|---|---|---|---|
| Lying | 62,92 ± 10,72 | 62,62 ± 10,59** | 61,87 ± 10,68*** | < .001 |
| Sitting | 71,18 ± 12,39 | 70,94 ± 12,40 | 69,95 ± 12,36 | .278 |
| Standing | 77,10 ± 12,97 | 76,92 ± 13,10 | 72,95 ± 14,10* | .019 |
| Walking | 86,48 ± 13,37 | 86,76 ± 13,24 | 90,91 ± 19,42 | .358 |

**Table 2.** HR mean obtained from GS, AW and PV (mean ± SD) in bpm. *p < .05; Significance is shown according to Bonferroni contrast tests applied to compare the differences between HR mean values from an ANOVA analysis between wearables. **p < .01; ***p < .001. Significant difference compared to GS (Bonferroni contrast test for repeated measures). Statistical Power: $\pi = 0.99$.

$$\overline{HR_{\mathrm{AW}}^{s,a,t_s}}(m) = \frac{60000}{\overline{aRR_{AW}^{s,a,t_s}}(m)} \tag{4}$$

$$\overline{HR_{\mathrm{PV}}^{s,a,t_s}}(m) = \frac{60000}{\overline{aRR_{PV}^{s,a,t_s}}(m)} \tag{5}$$

where $\overline{aRR_{GS}^{s,a,t_s}}(m)$, $\overline{aRR_{AW}^{s,a,t_s}}(m)$ and $\overline{aRR_{PV}^{s,a,t_s}}(m)$ are the mean value of the $RR_{GS}$, $aRR_{AW}$ and $aRR_{PV}$ time series in the interval $[t(m), t(m)+t_s]$ being $t(m) = t_o + (m\text{-}1)\cdot\Delta t$ for subject $s$ and activity $a$. In this work we have chosen $\Delta t$ as 1 s. If for a certain combination of $t_s$and $\Delta t$ there is a device that does not have any timestamp inside the interval, the computation in this interval is skipped. The Appendix A3 in the supplementary materials shows and example on how the averaging procedure is made. Note that this methodology can be easily modified to allow for other location statistics such as the median or the mode of the time series by simply computing these statistics in the intervals of length $t_s$ instead of the arithmetic mean. The averaging for longer $t_s$allows to study the agreement of the devices when mean heart rate is the target indicator by smoothing all causes of heart rate variability (HRV). Analysis using shorter $t_s$allows to study how fast the devices can track changes in heart rate. Nevertheless, for short $t_s$the normal heart rate variability of the subject will reduce the agreement between devices.

Now that the three time series are sampled at the same intervals, agreement analysis for different averaging times can be performed. Results are based on quantifying Bland–Altman plots[22,23] by comparing the samples of either AW or PV with the GS. These plots change with activity, subject and averaging time and are scatterplots where each point corresponds to:

$$\left(x(m), y(m)\right)_{ts}^{s,a} = \left(\frac{\overline{HR_{\mathrm{GS}}^{s,a,t_s}}(m) + \overline{HR_{\mathrm{DEV}}^{s,a,t_s}}(m)}{2}, \overline{HR_{\mathrm{GS}}^{s,a,t_s}}(m) - \overline{HR_{\mathrm{DEV}}^{s,a,t_s}}(m))\right) \tag{6}$$

and $\overline{HR_{\mathrm{DEV}}^{s,a,t_s}}(m)$ can be either $\overline{HR_{\mathrm{AW}}^{s,a,t_s}}(m)$ or $\overline{HR_{\mathrm{PV}}^{s,a,t_s}}(m)$ depending on the systems intended to be compared. BA will be computed by pooling the data for every subject and for different averaging times. Because the differences between systems $(y(m))$ may be not symmetrically distributed, the percentiles 2.5% and 97.5% of the differences were computed for the pooled Bland–Altman for each activity and averaging time as surrogate measures of the limits of agreement (LoA) of the BA. It is expected that the dispersion of BA, measured as the difference between percentiles, will decrease by increasing the $t_s$because of the progressive smoothing of heart rate variability and random noise.

The median of the differences was employed as a quantifier of the bias between measurements. Statistical significance of the difference between biases when comparing different devices, averaging times or activities were assessed using the non-parametric Wilcoxon Rank Sum Test[24].

Statistical significance of differences in the spreading of the BA when comparing different devices, averaging times or activities were assessed by comparing the standard deviations of the differences using the non-parametric Ansari-Bradley Test[25] after removal of the median value of the difference for each BA.

Synchronization, averaging of time series and BA plot analysis and their associated statistical tests were performed with MATLAB® (R2021 Update 3 for 64 bits Windows).

**Institutional review board statement.** The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the local Ethics Commission for Human Experimentation (protocol code CEEAH-5745).

**Informed consent.** Informed consent was obtained from all participants involved in the study.

## Results

Table 2 shows the results of analysis of variance (ANOVA) for repeated measures, comparing 5-min mean HR between devices as defined in (1), in the different situations (lying, sitting, standing and walking). Bonferroni contrast tests was applied to compare the differences between pairs of devices regarding HR mean, as well as to calculate the 95% confidence interval when ANOVA shows significance.

The differences of HR mean values between devices can be calculated from the data in Table 2. Figure 2 represents a summary of the results of Bonferroni contrast tests comparing these differences and calculating

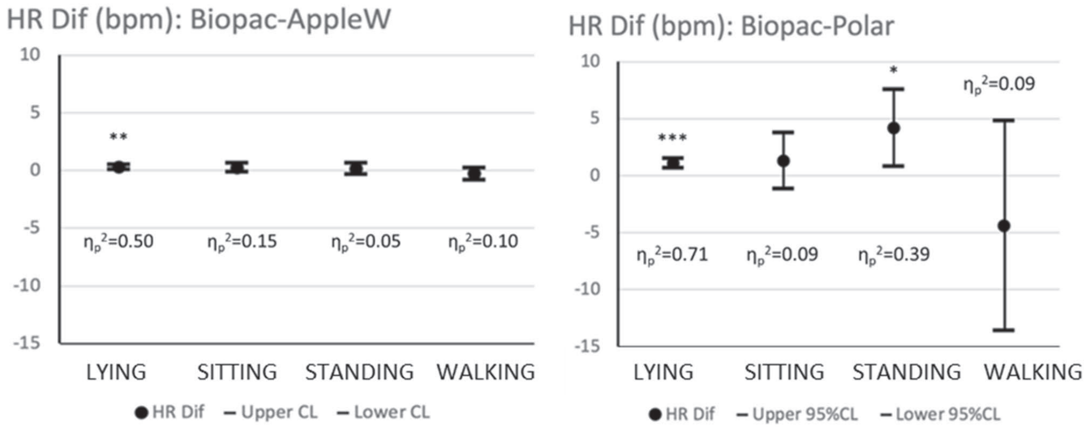


**Figure 2.** Differences of HR mean values between GS and the other devices. The mean value of the differences and their 95% confidence interval are represented as well as the significance of Bonferroni Contrast Test *$p<.05$; **$p<.01$; ***$p<.001$ and the $\eta_p^2$ measuring the effect size.

| Activity | Lying | | Sitting | | Standing | | Walking | |
|---|---|---|---|---|---|---|---|---|
| Wearable | Apple (AW) | Polar (PW) | Apple (AW) | Polar (PW) | Apple (AW) | Polar (PW) | Apple (AW) | Polar (PW) |
| Biopac (GS) | 1.000** | .998** | .999** | .950** | .998** | .925** | .998** | .652* |
| Apple (AW) | – | .998** | – | .960** | – | .929** | – | .677* |

**Table 3.** Pearson correlation coefficients (r) of HR mean values between Biopac (GS), Apple Watch (AW) and Polar Vantage (PV) systems for the four activities ($n=18$). Significant differences: *$p<.01$; **$p<.001$**

the 95% confidence interval. The effect size for ANOVA is also analyzed. The statistical power for this analysis was $\pi=0.99$, considering $n=18$, four factors of repeated measurements (lying, sitting, standing and walking), an overall effect size of 0.37 and the lowest correlation observed between devices of 0.652.

Table 3 shows that AW presents a high correlation of HR mean values with the GS in all situations (always higher than 0.998), while the correlation of PV and GS decreases as the level of physical activity increases.

In Appendix B1 can be consulted the BA plots defined by (5) and obtained for each activity by averaging in time intervals of length $t_s$ (using a $\Delta t=1$ s to update the limits of the time intervals) and by pooling all the subjects for selected averaging times are shown. Nevertheless, all these results can be summarized in Fig. 3 that shows how the limits of agreement (LoA), defined as the percentiles 2.5% and 97.5% of the differences with respect to the GS, evolve with the averaging epoch length ($t_s$) for the AW (in black) and the PV (in red). As seen in Fig. 3, the AW has generally tighter LoA than the PV for every averaging time. For the AW, as the averaging time increases, the limits of agreement narrow, whereas for the PV, the dependency of the LoA with the averaging time is not so noticeable, especially while walking.

Figure 4 shows the median differences of the BA when comparing the AW or the PV against the GS for the different activities (lying, sitting, standing and walking) and two averaging times (5 s and 30 s). The figure also shows the statistical significance of the differences in median when comparing the biases of AW and PV against the GS for the different averaging times and activities. All the comparisons show significant differences ($p<0.001$, ‡). Note that except while walking, the median differences for AW and PV have opposite sign and that the median difference is always negative for AW. This is a seemingly surprising result considering that results in Fig. 2 predict a statistically significant positive mean difference when averaging for around 5 min. Nevertheless, this sign difference may be attributed to the asymmetrical distribution of averaged HR differences.

Figure 5 shows the standard deviation of the differences of the BA to assess the spreading of the differences as well as the statistical significance of the difference between spreads of the BA when comparing the AW and PV against the GS. All the comparisons show significant differences ($p<0.001$, ‡) except when comparing AW with PV while lying and when averaging for 30 s ($p<0.05$, †). At Appendix B2two tables comparing the bias and spread for the same measuring device during different activities and during different averaging times are provided, also using the Wilcoxon Rank Sum Test and the Ansari-Bradley Test.

Figures 4 and 5 show that when walking while wearing the PV, the median difference change of sign and the standard deviation of the differences increases disproportionately for both averaging times (5 s and 30 s). On the other hand, Fig. 3 shows that when walking, the decrease of the LoA for PV with the averaging time is negligible. That might mostly influenced by the outlier measurements for one of the subjects. Results for walking by removing this subject are shown in Appendix B3.

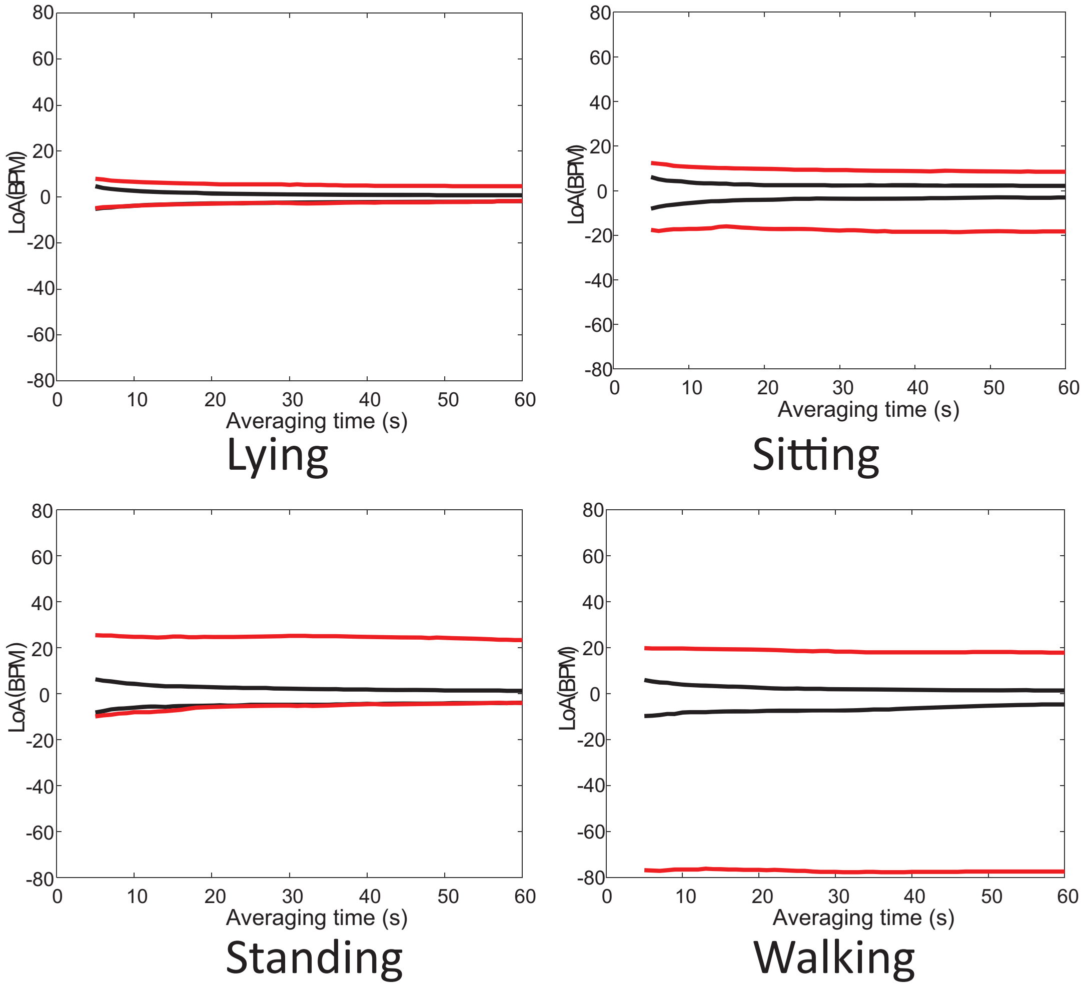


**Figure 3.** Change in the Limits of agreement (LoA) with 2.5% and 97.5% percentiles of the Bland–Altman plots with respect to the averaging time (from 5 to 60 s) for the four activities. Red and black lines correspond to the PV and AW devices respectively.

## Discussion

The first aim of this study was to determine the validity of HR measured by two of the most popular wearables in the market: the Apple Watch and the Polar Vantage, under different levels of activity, compared to a gold standard. Sections "HR agreement by averaging during the whole activity to "Agreement assessed by BA" discuss the Results found regarding this aim. A second goal of the study was to propose a new methodology for testing the validity of HR measurements, which is discussed in Section "Methodology for HR validation".

**HR agreement by averaging during the whole activity.** For each activity, mean HR values were obtained and compared between devices. As presented in Fig. 2 and Table 3, mean HR differences between wearables and the GS increased as levels of physical activity rose. Such increase was more evident for the PV than for the AW. That is, the AW values correlated to the GS in all situations (always higher than 0.998), while the correlation of PV and GS decreased as the level of physical activity increased. The Pearson correlation coefficient are in accordance with previous studies[7,27–29]. Other studies comparing watches to ECG found that the accuracy of real-time HR monitoring also reduced as exercise intensity increased[30,31]. For all the wearables and every activity, the correlations were statistically significant.

For reference, lying down was the position in which there were fewer differences between the GS and the other two devices. Nevertheless, while lying down, the biases of mean HR couldn't be assumed to be zero as pointed by the Bonferroni contrast test for repeated measures, because both the PV and AW provided mean HR

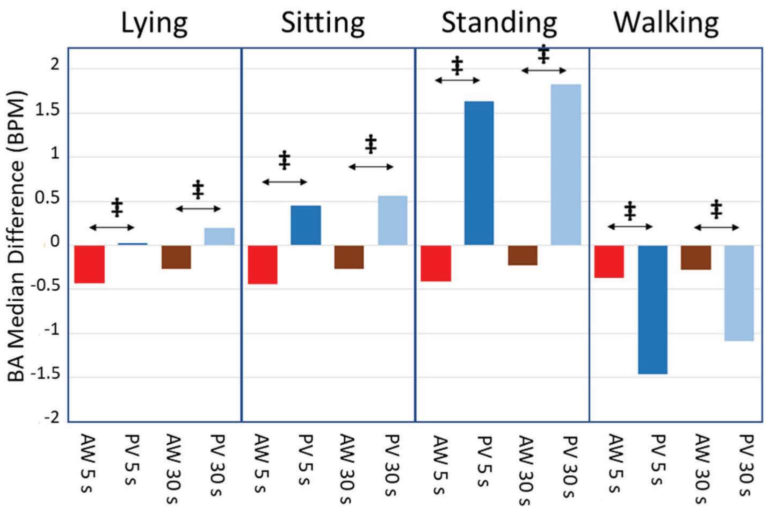


**Figure 4.** Median differences of the Bland–Altman for the AW and PV devices for 5 s and 30 s averaging time and for the four activities. Red bars are for AW device and 5 s averaging time, dark blue are for PV device and 5 s, brown are for AW device and 30 s and light blue are for PV device and 30 s. Wilcoxon Rank Sum Test results are also shown comparing the median values of differences for both devices. Significant differences: ‡ $p < .001$.

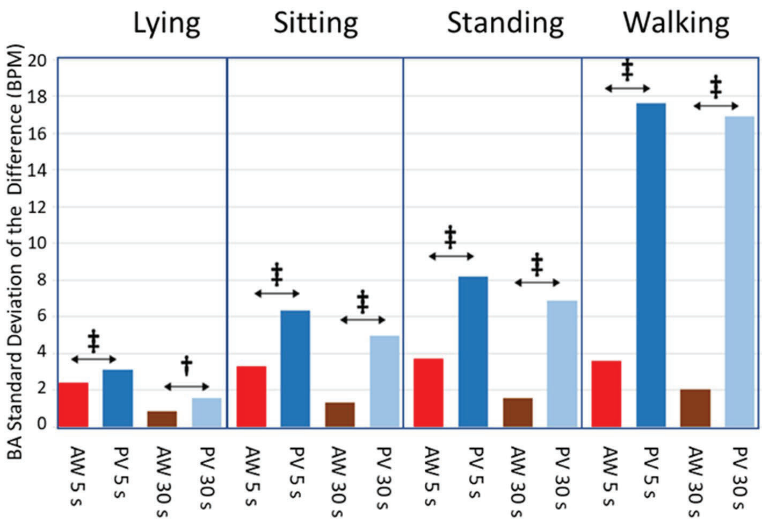


**Figure 5.** Standard deviation of the differences in the Bland–Altman for the AW and PV devices for 5 s and 30 s averaging time and for the four activities. Red bars are for AW device and 5 s averaging time, dark blue are for PV device and 5 s, brown are for AW device and 30 s and light blue are for PV device and 30 s. Ansari-Bradley Test results are also shown comparing the spread of the differences for both devices. Significant differences: ‡ $p < .001$; † $p < .05$.

significantly lower than the GS. These results are in agreement with[5] who analyzed people while sleeping, and with[6] who measured intensive care patients. Both studies reported that wearables tended to slightly underestimate HR at rest. Nevertheless, the differences in mean HR values change from subject to subject in agreement with[26] and also change when the activity level changes, as can be seen by the different widths of the confidence intervals. Overall, the interindividual differences have more dispersion as the level of activity increases. In this sense, as Table 2 shows, the standard deviations (SD) of the mean values increased as the level of physical activity also increases, being the highest SD (19.42) for PV device in the situation of walking. This is in line with the results of previous studies[7,12]. This rise in dispersion can explain why the Bonferroni contrast test does not provide significant differences for most activities but while lying.

**Agreement assessed by BA.** "HR agreement by averaging during the whole activity" Sect. discusses the accuracy of the devices when providing values of HR averaged along the whole duration of each activity (around 5 min) but doesn't explain how the devices perform for different averaging time intervals, nor their ability to adapt to HR changes throughout the recordings. Figures B1 and B2 in the Appendix B1 shows the BA for averaged HR between pairs of devices, recorded while the volunteers were lying and walking, respectively. Both figures show that the higher the averaging time ($t_s$), the lower the spread of dots is. This means that the agreement between devices increases for larger averaging times. That is reasonable because the longer the averaging the lower the impact of the heart rate variability and noise on the result. The results are summarized in Fig. 3.

Overall, and as expected from results in Fig. 2, the differences between the devices and the GS, especially for PV, are much bigger while walking than when lying, showing a greater sensitivity to the movement in the detection of the HR in the PV versus the AW. This is illustrated by the evolution of the LoA with the averaging time. Figure 3 shows that AW had generally tighter LoA than the PV.

For the PV, the narrowing of the LoA with the averaging time was not so noticeable, especially while walking, meaning that averaging PV's HR values does not improve the agreement as much as in the case of the AW. This could be attributed to the tendency of the PV to provide unusually higher HR than the GS when there is a certain degree of activity and a limited capability to track changes of the HR as a response to changing physiological states. In fact, it is worth to note that for some measurements the PV was unable to correctly track HR. For example, in Figures B1c and B2d in the Appendix B1 there was an accumulation of dots around a mean value of 125 bpm and mean differences of -80 bpm that corresponded to the results of one of the measured subjects. For this subject, the PV provided readings around 80 bpm higher than the true HR. These readings can be treated as outliers and the origin may be attributable to a modulation of the received light in the photoplethysmograph at twice the stepping cadence associated to the arm's movement as identified in previous works[15].

Figure B3 in Appendix B3 replicated the results of Figures B2 and 3 but removing the subject that originated the outliers. The results clearly show that the removal of the outliers mostly affected to the lower bound of the LoA. Nevertheless, the interval defined by the LoA in the PV is still wider than in the AW as seen by Figure B3c. This means that the agreement for AW is better than for PV while walking, regardless the averaging time.

Devices were also compared during different activities and at two averaging times (5 s and 30 s) of HR data obtained. Figures 4 and 5 showed the median differences and the standard deviation of the differences of the BA, respectively, when comparing the AW or the PV. Overall, the spreading of the differences was higher in PV than in the AW, as expected from Fig. 2, confirming that the agreement is better for the AW than for the PV. The dispersion of differences increases with the increase in physical activity, in line with the results of previous studies[7,12], as mentioned earlier. What was interesting here was that the dispersion reduced when increasing the averaging time. The change of the standard deviation of the differences (or the LoA in Fig. 3) as the averaging time changes is a confounding factor when interpreting the agreement of HR measuring devices. Most studies provide the agreement results when averaging HR during a long and single time (typically 5 min). The current methodology proposed in this study precisely avoids this problem by showing the agreement when averaging at arbitrary intervals: depending on how fast the HR must be updated for a certain experiment, the displayed results in Fig. 3 are useful to estimate the LoA of the measurement.

**Methodology for HR validation.** In this study, a methodology to analyze HR data from wearable devices is proposed. This methodology aims to avoid the interpolation of the HR data over longer average times, and instead advocates for a comparison over different time scales to track variations of HR along recording. Interestingly, the proposed synchronization procedure does not require any interpolation of time series, in contrast to recently proposed methods such as in[32], which promote resampling of time series for delay estimation. In Appendix A4, a study is presented assessing the effects of interpolation using the proposed methodology versus the different time series at 25 Hz as in[32]). The study shows differences in LoA lower than 2 bpm, suggesting it can be of importance only when the compared systems show good agreement.

Moreover, note that the results in this section have considered the pooling of data for every subject. Because differences of averaged HR are also affected by HRV, it is presumable to think that LoA will depend on the HRV of the measured subject. This is especially true for short averaging times. Although Fig. 3 shows the LoA for averaging times up to 60 s, the averaging for longer intervals is straightforward and likely will asymptotically reduce the LoA to values independent of the subject's HRV. Nevertheless, these values cannot be experimentally obtained due to the finite length of the experiment and the physiological non-stationarity of HR[33].

**Limitations of the study.** Arguably, the main limitation of this study is the small sample size. However, the methodological rigor with which it has been carried out has made it possible to obtain results with a large statistical power. Another limitation is that the wearables being compared were always placed on the same arm. This is a variable that could have affected the results, in that the device on the right arm could register differently from the device on the left. It would be interesting, in future studies, to randomize the positioning of the wearables.

Another aspect to take into account is that, in general, it is considered that a minimum sampling rate is necessary for clinically accurate measurements—30 Hz for HR and 200 Hz for HRV measurements[26]. Nonetheless, these numbers are not very clear, since, for example, a study in patients with cardiovascular disease conclude that the Apple Watch measures HR with clinically acceptable accuracy during exercise, while also stating that it is too early to recommend this device for cardiac rehabilitation[34]. For HR, a main issue comes from the fact that there is no standard measurement. That is: HR is measured by counting beats in a given time window, but the actual way of doing so can differ for each system or software. Given that, we propose, for comparison, to measure the agreement in temporary windows of the same size for all systems, by averaging the HR samples we have for each system within each window. Since there is no a standard of how long the average time should be, we propose to do the analysis for several times (as opposed to most analyzes that use all the observation time).

As a final remark, and despite being effective in accessing HR and HRV, the applications of PPG monitoring are limited by multiple confounders such as sensor pressure against the skin, skin tone, light intensities, and user movement leading to artefactual measurements[14,26,30]. This will have an impact on the feasibility and reliability of mobile phone–based PPG within clinical practice, and should be further explored. In future research it would be interesting to extend the study sample to a wider range of ages and races, as well as take measurements under more demanding physical activities such as running.

## Conclusions

This work analyzed the agreement in HR measurements taken by an Apple Watch (AW) and a Polar Vantage (PV), in comparison to a gold-standard electrocardiogram (ECG), at different activity levels. Results for mean HR values, and at different averaging times, clearly show that the agreement is higher for the AW than for the PV for every activity. Moreover, the best agreement corresponds to the lying position while the worst agreement is found while walking. We conclude that photoplethysmography-based wearable devices are suitable for monitoring HR averages at regular intervals, especially at rest, but their feasibility is debatable for a continuous analysis of HR for research or clinical purposes, especially when involving some level of physical activity. Additionally, this paper proposes a new methodology to synchronize and measure the agreement, against a gold standard, of two or more devices measuring HR at different, and not necessarily uniformly, spaced intervals. This methodology does not require the use of any interpolation or resampling of the data, hence avoiding the need to the unnecessary creation of artificial data and always working using the sampled data provided by the devices. The proposed method also provides an easy way to explore the agreement of the devices at different time scales, allowing to translate the results of the analysis as a function of how much time is devoted to estimate HR. Although the analysis of agreement is based on mean HR differences reported by the devices during a certain time, the extension to other analysis based on statistics such as differences in median, mode, percentiles or extreme values, is straightforward.

## Data availability

The datasets generated and/or analysed during the current study are available in the OSF repository, https://osf.io/9x7zs/?view_only=c7536f159f9c48a1ae605319eadaae4a.

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## Author contributions

Conceptualization, L.C., J.R–C. and M.A.G.; methodology, C.A., E.P., L.C., J.R–C. and M.A.G; software, L.C. and J.R–C.; validation, C.A., L.C., J.R–C. and M.A.G; formal analysis, C.A., L.C. and M.A.G.; investigation, C.A., E.P., L.C., J.R–C. and M.A.G.; resources, J.G-R. and J.R–C.; writing—original draft preparation, C.A., L.C., M.A.G. and J.G-R.; writing—review and editing, C.A., L.C., M.A.G., E.P. and J.R–C.; funding acquisition, L.C. and J.R–C. Authors C.A. and M.A.G. contributed equally to this work. All authors have read and agreed to the published version of the manuscript.

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## Competing interests

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# 4. DISCUSSION

This chapter presents a discussion of the main findings of the thesis in relation to its objectives. The central goal was to explore the role of vmHRV, RHR, and SVs in athlete monitoring, and in particular, to evaluate existing knowledge, identify methodological and practical challenges, and contribute to the development of integrated mHealth-based monitoring systems that combine physiological and subjective data to support training and recovery decisions. To achieve this, four studies were conducted, including a scoping review and three empirical studies.

The discussion is organized into four parts. The first part comprises four subsections: the first three address thesis subgoals, while the fourth provides a summary of findings across all subgoals. Note that the fourth subgoal is discussed throughout this first part. The second part highlights the practical contributions of the thesis, connecting the findings to established training frameworks, and also introducing a new perspective to view the results. The chapter finishes by discussing limitations and future directions.

## 4.1 Objectives and article contributions

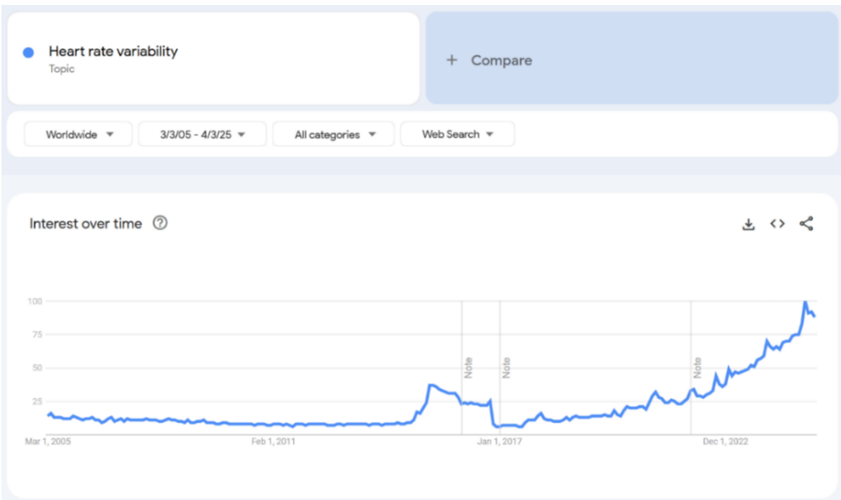
### *4.1.1 Objective 1*

**The first subgoal of the thesis was to synthesise the existing literature on vmHRV and SVs in athletes**. This involved identifying reported associations, specific variables assessed, and prevailing methodological practices. This goal was mostly addressed in Article 1, a scoping review, with additional empirical support from Article 3. The section is organized into three parts: one sets context, another focuses on findings regarding RMSSD-SVs correlations, and the third discusses methodological practices.

**Growing popularity of the field**

To illustrate the need for the first sub-goal, and before diving into the results, it is important to recognise the **rising interest in HRV among both researchers and practitioners**. When working on the review, an initial observation was the high volume of articles retrieved in the search (>9000), mostly from year 2009, reflecting an interest in the psychophysiological monitoring in sport science, as noted in previous research (Schneider et al., 2018). Public interest has grown as well: a quick search on Google Trends (*Google Trends*, 2025) shows a rise in interest starting in 2014 and later in 2017 with a steady increase until present (Figure 8). This interest in HRV applied to training was also evident anecdotally during the recruitment process for Article 3, where 179 individuals expressed interest purely through a single advertisement via a newsletter.

**Figure 8.** Screenshot from Google Trends




Search for “heart rate variability”, from March 2005 to March 2025, worldwide.

Moreover, in the scoping review, the 31 included studies investigated a diverse range of sports, from football and CrossFit to dance, highlighting the widespread applicability and perceived value of HRV across multiple disciplines.

Taken together, these observations reflect a growing interest in the use and application of HRV and SVs, particularly in sport. Importantly, this surge among athletes and researchers underscores the need for a systematic synthesis of existing knowledge about HRV and SVs, as well as advancing towards clear implementation and reporting standards (Subgoal 1).

**Findings about the relationship between RMSSD and SVs**

Focusing on the correlation between RMSSD-based vmHRV and SVs, a key question was whether the direction of these correlations was consistent across studies, for example whether higher fatigue would be mostly correlated with lower RMSSD, as previously suggested (e.g., Srinivasan et al., 2024) and as expected based on the Neurovisceral Integration Model (NIM; Thayer & Lane, 2000) and the Vagal Tank Theory (VTT; Laborde et al., 2018).

In Article 1, **correlation analyses revealed a tendency** for higher RMSSD to be associated with lower fatigue, lower perceived stress, better sleep and improved recovery, as expected. **However, the direction of these associations varied considerably across studies, and the strength was often weak.** For instance, fewer than 40 % of studies observed the expected negative correlations between fatigue and vmHRV, less than one third found significant associations with mood, and perceived stress showed negative correlations in 38% of cases and no association in 42%. In the same line, only 27% of studies reported positive correlations between vmHRV and sleep quality, while another 60 % found no association.
Notably, this heterogeneity was also present in Article 3, which revealed inconsistent relationships between RMSSD and SVs in cyclists. That is, while some athletes presented significant correlations between RMSSD and fatigue, perceived stress, sleep quality or well-being, others exhibited none.

**At a theoretical level,** these inconsistencies carry important implications because much of HRV research –including this thesis– rests on the NIM and the VTT. The NIM posits that cardiac vagal tone, indexed by vmHRV, indicates the functional integrity of a distributed prefrontal–subcortical network that coordinates autonomic, cognitive and emotional processes. Within this network, information flows bidirectionally, such that prefrontal inhibitory circuits modulate cardiac output, while vagal afferents influence higher-order cognition and emotion. Building on this, the VTT conceptualizes cardiac vagal activity as a finite resource for self-regulation, with vmHRV indicating how efficient these resources for self-regulation are mobilised and used for goal-oriented behaviours. From their perspective, higher vagal tone is expected to be associated with greater emotional stability and reduced perceived stress (Thayer et al., 2012).

Given this theoretical grounding, the heterogeneity in the present findings – where correlations between vmHRV and SVs are mixed and weak– may seem contradictory. However, rather than undermining the theories, these **discrepancies arguably illustrate their complexity**. For instance, the NIM emphasizes that the central autonomic network is dynamically organized and can recruit different structures depending on situational demands (Thayer & Lane, 2000). Hence, **a high vmHRV (reflecting physiological capacity) does not guarantee that an athlete will *feel* recovered** or energized. Instead, the observation that physiological capacity (e.g., high vmHRV) does not automatically translate into perceived experience suggests that physiological and subjective measures operate on different timescales and may be sensitive to different individual and contextual moderating factors such as motivation, training phase or expectations (Laborde et al., 2018). Cognitive load may also moderate the relationship between vmHRV-SVs. Fuster et al. (2021) defines cognitive load as the amount of mental resources invested in a task, noting that it is closely related to an athlete's emotional state. Prolonged cognitive effort (e.g., during periods of emotional stress) could lead to an increase in perceived fatigue even when vmHRV remained high. **In this way, autonomic output captured by RMSSD indexes the underlying capacity for self-regulation, whereas SVs reflect the conscious appraisal of one's cognitive state and affective processing.** While physiologically linked, "decoupling "between markers illustrates the complexity and flexibility of the NIM and underscores the need to consider context when interpreting vmHRV.

From a practical perspective, these insights support the integration of vmHRV and SVs for the monitoring of athletes, echoing emerging paradigms (Plews et al., 2013; Bourdon et al., 2017; Rothschild et al., 2024). It supports a multilevel approach whereby examining both physiological signals and subjective experiences allows to capture the capacity for self-regulation and the affective influences on athlete state, improving the precision of monitoring strategies. This allows to differentiate between physiological capacity and conscious appraisal; that is, between the availability of self-regulatory-capacity (RMSSD) and how the capacity is experienced or interpreted by the individual (SVs).

In sum, Article 1 synthesised the current landscape of vmHRV and SVs research in the athletic context, highlighting some expected but mostly inconsistent correlations between variables. The findings reinforce the potential of vmHRV as a psychophysiological monitoring tool, but supports the need for an integrative approach. In that sense, the findings support and extend the NIM and VTT at a theoretical level, emphasising, the importance of interpreting physiological data in light of subjective context.

**Findings about methodological practices**

In line with the first subgoal, a further aim was to examine current methodological practices in the literature, which was addressed in Article 1.

From the 31 studies analysed, the scoping review **revealed a striking diversity** in how vmHRV and SVs are assessed. To begin with, most studies reported multiple HRV parameters. More than 40 metrics were used, with vmHRV-based ones (i.e. RMSSD and HF) being the most common, coinciding with their recognition as key indicators of parasympathetic regulation and autonomic flexibility (Task Force, 1996; Thayer et al., 2012). In the same line, protocols for recording RMSSD varied considerably: most recordings were short or ultra-short in duration, taken in the morning upon waking, in a supine position, while

others included 10-min long recordings taken before or after exercise. Moreover, some studies included an acclimatization period, while others did not, and breathing control, measurement timing, and environmental conditions also differed substantially. Devices ranged from chest belts and ECGs to PPG-based wearables like HRV4Training, echoing debates around the accuracy and standardization of HRV tools in applied settings (Umair et al., 2021).
Likewise, a similar heterogeneity was evident for SVs. There was a variety of SVs used, measured by a variety of tools. Fatigue and stress were the most studied SVs, though measurement approaches were diverse, ranging from validated multi-item questionnaires to Likert-scale assessments. Moreover, some SVs were composite indices, such as well-being (WB) scores combining multiple indicators, and calculated using different formulas depending on the article, whereas others used the items individually.

Overall, the discrepancies highlight a **lack of standardised guidelines**, even more pronounced than it was suggested in the introduction. Most importantly, the discrepancies complicate cross-study comparison. That is, disparities in recording conditions, devices, analysis parameters, and synchronization protocols reduce the comparability of results and limits the generalizability of findings. Importantly, this methodological variation may partially explain the inconsistent correlations between vmHRV and SVs reported in Article 1. In this sense, the lack of methodological standardisation limits the capacity to fully conclude whether vmHRV reflects (or not) self-regulatory capacities.
In addition, the observed inconsistencies point to a **lack of theoretical grounding** in the existing literature, as also noted by Mosley & Laborde (2022). For instance, in the review, all vmHRV and SV measures were taken at rest, but the conditions under which “rest” was defined varied: while the majority of measures were recorded in the morning (63%) or at night (6%), some were taken around training or competition (20%). In some cases, studies even correlated RMSSD and SVs measured at different times of day. While all conditions are “at rest” (i.e., without movement), according to the VTT, these contexts correspond to distinct functional phases of vagal regulation (Laborde

et al., 2018). Morning or nighttime measurements might reflect baseline (tonic) vagal control, while recordings after training should instead be interpreted as indicators of recovery (phasic control). However, many studies failed to differentiate between these phases. This is important because the VTT suggests that phasic vagal responses to environmental demands, such as competition, may reveal phenomena not observable through resting measurements alone. Thus, failing to account for timing and functional phase may have also contributed to the inconsistent vmHRV–SV associations observed in the review.

Overall, the findings underscore the need for harmonized protocols across research communities. **To practically address this methodological heterogeneity, the review proposed two elements: a categorization of SVs and a methodological checklist.**

Given the broad range of SVs used across studies, it was difficult to group them under a single conceptual umbrella such as "self-regulation". To address this, the review attempted a classification, categorizing SVs into three domains based on their primary focus: fatigue–recovery indicators, psychological states, and sleep-related factors. This classification, detailed in Article 1, represents a step toward structuring the use of SVs in the athlete monitoring literature.

In parallel, the methodological checklist emphasises the importance of transparency and encourages researchers to consider and report recording conditions (e.g., posture, breathing control, time of day), vmHRV parameter selection, device validation, SVs type, and synchronisation protocols when conducting research in this field. With this, the checklist aims to enhance the rigor, comparability, and reproducibility of future studies. As such, both the SV categorization and the checklist directly informed the design of Article 3.

In summary, the review identified inconsistent methodological practices in current research, which may contribute to the weak and variable associations reported in the literature. This underscores the importance of standardised methods and theory-informed practiced in future research.

### *4.1.2 Objective 2*

The second subgoal of the thesis was to assess the application of vmHRV and SVs in training optimization. This was explored mainly in Article 3, with article 2 serving as a bridge between the theoretical synthesis of Article 1 and the intervention design in Article 3. Each article's contributions are presented below.

**Article 2**

To first investigate whether vmHRV and mood respond to training load at all in real-world settings, Article 2 was conducted. Note that Article 2 was the first empirical investigation of the thesis and served as an **exploratory study** with Carla Alfonso as a first author, providing valuable experience in planning and executing experiments, recruiting and contacting participants, as well as in handling and becoming familiar with multiple HRV parameters alongside SVs in athletes. It is important to note that the study remained a pilot because, as the thesis evolved, new understanding of the topic led to a different focus and refinement of methodology. Nevertheless, it usefully served as a foundation for the development of Article 3.

Article 2 followed five recreational cyclists over six weeks, during which they recorded morning HRV and mood concurrently with their usual training routines. The approach prioritised ecological validity while standardising key methodological elements (e.g., consistent measurement timing and posture) in line with recommendations from Article 1. With a sample of 5 participants, the results cannot be generalized, but the study nonetheless provides insights into the relationship between morning HRV and mood, and their association with training load in cyclists. It also explored the relationship between internal and external indicators of training load, though these findings lie outside of the scope of the thesis.

The main finding was that **morning mood correlated positively with vmHRV** (in this case HFnu), suggesting a link between improved mood and higher vagal activity, in line with the NIM (Thayer et al., 2012). Nonetheless, as exemplified in Figure 6 in the Results Section 3.2, the fluctuations of vmHRV (in this case RMSSD) and mood varied, suggesting that, in line with the scoping review, the relationship between vmHRV-SVs is not straightforward.

Article 2 also examined how training load influenced next-morning vmHRV and mood. A clear inverse relationship emerged between intensity factor (IF) and HFnu, suggesting that **higher training loads of one day were associated with reduced vagal activity the following morning**. This pattern aligns with prior findings on nocturnal HRV changes post-exercise. For instance, Hani et al. (2009) demonstrated that vmHRV indices were significantly reduced during the first night following supramaximal intermittent exercise, reflecting a shift in autonomic balance toward sympathetic dominance. Notably, these indices returned to baseline by the second night post-exercise, suggesting recovery of autonomic function within 36 hours. These findings had been observed in earlier studies, where high-intensity training was associated with temporary disruptions in autonomic regulation, including decreased parasympathetic tone (Lehmann et al., 1998). Similarly, an inverse correlation was found between IF and mood, indicating that **higher-intensity sessions were often followed by lower mood scores** the next day. This may reflect the short-term impact of high intensity training, compared to lower loads (Bresciani et al., 2011; Noon et al., 2018).

**From a theoretical standpoint**, the findings that intense training was followed by reduced vagal tone and lower mood align with the VTT (Laborde et al., 2018). Next-morning measures represent the resting phase of the model, and metaphorically, the declines are consistent with a temporarily “depleted tank” after training load, suggesting a reduction in the system’s regulatory capacity. That said, the correlations in the study tested a lagged relationship, linking training data from one day to next-morning psychophysiological measures. This means that it only sampled one of the VTT’s three phases (i.e., resting, and not reactivity or recovery). A more complete VTT test, in follow-up studies, would ideally add phasic assessments, including immediate measures after exercise and before bed. This would allow to examine whether transient vagal withdrawal (reactivity) and its rebound (recovery) map onto the next-day resting level, and whether mood moves in parallel across those phases.

Importantly, the findings of Article 2 led to the realization that interpretation of resting psychophysiological markers must extend beyond single events. As Hottenrott and colleagues (2019) noted, VTT focuses on single-event responses. However, endurance training produces long-term adaptations. That is, meta-analytic evidence indicates that exercise programs extending over several weeks leads to improvements in vmHRV markers like RMSSD and HF, reflecting progressive adaptation of the parasympathetic nervous system (Amekran & El Hangouche, 2024). In a similar manner, mood shows to improve over the long term with regular exercise (Arent et al., 2000; Tozzi et al., 2016). Thus, while Article 2 detected short-term “depletion” the morning following intense exercise, it is important to realize that this short-term depletion co-exists with longer-term improvements in vagal tone and mood. In practice, this argues for **tracking chronic trends over longer periods of time** to help distinguish transient from sustained psychophysiological changes.

Overall, Article 2 suggests that vmHRV and mood are responsive to training load and may serve as practical tools for daily monitoring athletes at rest, identifying “tank” states. Although limited by sample size and pilot design, the findings highlighted the need for longer-term tracking of markers to complement the single-event focus of the VTT, helping to distinguish between transient and adaptive changes. This emphasis on timescale informed the approach used in Article 3.

**Article 3**

Building upon the previous studies, Article 3 transitioned from studying correlations to **practical application**. While earlier findings showed that the relationships between physiological and psychological markers were not always consistent, Article 3 explored whether integrating these variables could improve training prescription (directly targeting Subgoal 2). Specifically, it evaluated whether a training approach guided by a combination of RMSSD, RHR and WB scores would lead to greater performance improvements in cyclists compared to RMSSD-only guided training. This design was inspired by prior research demonstrating the benefits of vmHRV-guided training in cyclists (Javaloyes et al., 2020), runners (Kiviniemi et al., 2007; Nuuttila et al., 2017), and other endurance athletes (Schmitt et al., 2018). A key innovation was the use of rolling averages rather than single-day values, as in Article 2, to better capture cumulative trends. RHR was also included in one group, acknowledging its complementary value in interpreting HRV data (Introduction, Section 1.3.3).

In Article 3, participants were randomised into three groups: Group 1 (vmHRV-only), Group 2 (vmHRV+WB), and Group 3 (vmHRV+WB+RHR). Participants tracked daily RMSSD, WB and RHR, and training intensities were adjusted accordingly. Methodological considerations (e.g., need for device validation, synchronization protocols) and theoretical underpinnings (e.g., NIM, types of SVs) were based on findings from the scoping review. Also, WB scores were calculated using fatigue, muscle soreness, perceived stress, and sleep quality, meaning that WB scores included at least one item from each of the categorization developed in Article 1, grouping SVs into fatigue-recovery indicators, psychological states, and sleep-related factors. The inclusion of multiple domains aimed for a comprehensive assessment of the individuals.

Across all groups, power output improved over the study period, in line with prior evidence that vmHRV-guided training improves performance (Kiviniemi et al., 2007; Javaloyes et al., 2020). However, performance gains were greater in **groups that integrated RHR and WB scores**, particularly for short- and mid-duration cycling efforts. Notably, this supports the hypothesis that while vmHRV is a valuable marker of ANS, it cannot fully capture all dimensions of fatigue, performance, or well-being (Buchheit, 2014). Instead, using multiple variables is useful to complement the data. Consistent with prior research, SVs proved to be sensitive indicators of training status (Saw et al., 2016), and integrating subjective and objective data seemed to enhance monitoring accuracy (Barrero et al., 2020; Bourdon et al., 2017; Leti & Bricout, 2013).

From a psychophysiological standpoint, Article 3 supports the NIM and VTT by reinforcing the role of autonomic flexibility, reflected in higher **vmHRV, as a key element in training adaptation** and resilience (Laborde et al., 2018; Thayer & Lane, 2000). Nonetheless, in line with the conclusion in Objective 1, the findings also highlight the **importance of considering SVs**, to capture affective, conscious appraisals. That is, the combined vmHRV-WB approach allowed training adjustments based not only on a physiological index, but also on how the athlete experienced or interpreted their self-regulatory-capacity to exercise.

In addition, further analyses in Article 3 underscored the need to assess SVs and vmHRV **individually**, for each person. Correlation analyses between WB and RMSSD were not consistent across individuals. While some athletes showed positive correlations between RMSSD and some of the WB markers, others exhibited weak or inconsistent patterns. This may suggest that certain variables play a more dominant role in some athletes than in others, for example fatigue in an athlete, and perceived stress in another. In practice, it also means that if some SVs move in line with vmHRV, the ones that do not could be prioritized in a monitoring system, as they would be adding complementary information about the athlete. Overall, and as suggested previously, it advocates that effective training must account for personal baselines and response patterns rather than group-level trends and generalizations (Bourdon et al., 2017; Plews, Laursen, Stanley, et al., 2013).

**Regarding RHR,** it also proved to be a useful addition to the training guidance. Its inclusion in Group 3 was associated with greater performance improvements, suggesting that RHR enhanced training decisions when combined with vmHRV and WB. Interestingly, Article 3 showed that RHR exhibited more stable autocorrelation patterns than HRV, which aligns with prior research indicating that RHR may be a better indicator of cumulative

training load, while vmHRV is more sensitive to short-term fluctuations (Buchheit, 2014; Plews, Laursen, Stanley, et al., 2013). The findings reinforce the utility of adding RHR alongside vmHRV in training programs.
From a VTT perspective, the addition of RHR is also relevant. Commentaries on the VTT note that vmHRV may saturate in well-trained athletes and suggest that measuring vmHRV with orthostatic tests can help prevent it (Hottenrott et al., 2019). Although orthostatic tests were not used in this study, integrating RHR could help address this saturation effect due to its physiological and mathematical relationship with HRV (Sacha, 2013, 2014; see Section 1.3.3).

Laborde et al. (2018) also argued that future research should explore to which extent the assumption of “the higher, the better” applies to resting cardiac vagal control and self-regulation, and under what conditions. Taking into account that this thesis focuses on resting data in healthy, well-trained adults, the findings suggest that, at least in this population, **higher vmHRV alone does not always indicate a “full tank” or a greater capacity to mobilize resources.** Instead, the interpretation **requires contextual information.** The superior performance of Groups 2 and 3 suggests that the tank metaphor may need more than one gauge, such as RHR and WB scores. These metrics can help determine how full or depleted the tank is, for instance, distinguishing whether an elevated vmHRV reflects readiness or overreaching. For instance, a high vmHRV suggests that the prefrontal–amygdala circuit can flexibly inhibit subcortical drive, but it does not necessarily mean that an athlete feels well or is ready to train. In the future, the role of potential contextual or individual factors that influence how vmHRV, RHR and SVs interact, should be further investigated.

In summary, the findings support the application of vmHRV and SVs in training to optimise the responses to it (Subgoal 2). Specifically, the findings highlight the value of incorporating RHR and SVs to contextualize data and account for individual variability. Notably, the study provides a practical, evidence-based protocol for guiding training and, in line with Articles 1 and 2, notes the importance of longitudinal monitoring.

### *4.1.3 Objective 3*

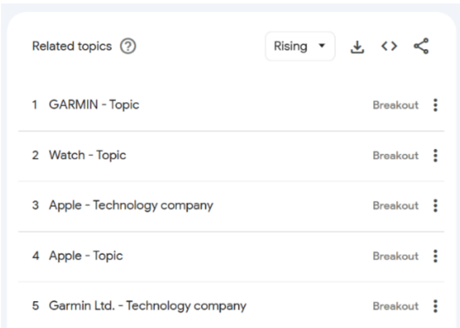
The third subgoal of the thesis was to validate the accuracy and feasibility of wearable devices for HR monitoring. This addresses a practical question: **can wearables reliably measure HR, and by extension vmHRV, in real-world settings?** While Articles 1, 2, and 3 suggested that vmHRV be useful for athlete monitoring, this is only feasible if the underlying HR data is accurate.

To investigate this, Article 4 compared HR readings from two commercially available devices, Apple Watch S6 and Polar Vantage M2, compared to a gold-standard ECG and across four conditions: lying, sitting, standing, and walking. These devices were selected based on their commercial popularity (Fuller et al., 2020) and accessibility, while the postures were chosen based on previous accuracy studies (Arunkumar & Bhaskar, 2020; Giurgiu et al., 2022).
The results revealed significant discrepancies between HR readings from the wearables and the ECG. In line with previous research, accuracy declined as activity level increased (e.g., Fuller et al., 2020; Wang et al., 2017), with the Polar Vantage M2 showing greater deviation than the Apple Watch S6, particularly during standing and walking. Also, both wearables underestimated 5-min HR intervals while lying down.

In addition to comparing 5-minute intervals, the study introduced a **multi-scale analysis** where HR agreement was evaluated across multiple averaging timescales. Findings showed that accuracy improved with longer averaging windows, whereas shorter windows (e.g., 5 to 30-sec) introduced more variability, especially in the Polar device. This suggests that validation studies relying solely on long averages may overestimate accuracy.

These findings reveal an **important challenge: a gap** between the theoretical potential of vmHRV in training monitoring, and the current limitations of wearable technology. This is relevant as coaches and athletes increasingly rely on wearables to monitor performance, partly encouraged by a rapid growth of commercial tools marketed to capture real-time, physiological data (West et al., 2021). Anecdotally, Google Trends (*Google Trends*, 2025) reflects this surge of public interest in devices to measure HRV, with the top five "Related topics" linked to "heart rate variability" featuring commercial wearables (Figure 9). As consumer enthusiasm grows, Article 4 confirms a concert stated in the introduction: that there is a real risk that mainstream wearables is outpacing scientific validation (Balagué, Pol, & Guerrero, 2019; Giurgiu et al., 2022).

**Figure 9.** Screenshot from Google Trends




Related Topics from a Google Trends search for "heart rate variability", from March 2005 to March 2025, worldwide.

At a theoretical level, **psychophysiological research relies on accurate HR-based data**. If wearables introduce significant measurement noise, the interpretations of cardiac vagal control become unreliable, as do vmHRV-based decisions. Current findings indicate that wearables are appropriate for measurements in supine positions (i.e., without movement), but require careful consideration when posture changes or movement is involved. This is relevant for protocols following the NIM and the VTT, where measures are recommended to be taken while sitting or via orthostatic tests. In such cases, wearables may serve better as tools for estimation rather than as sources of highly accurate data (as previously suggested by Altini, 2023). In the case of this thesis, all measures in Articles 2 and 3 were conducted at rest, either laying or sitting, with validated devices under these conditions of minimal movement. Their application in more dynamic contexts (e.g., standing or during exercise) would require further validation.

In practice, coaches and practitioners should **use consumer wearables with caution**, ensuring that the chosen device is validated for the intended body position and context. It should be considered that wearables may reliably track HR while laying, but their accuracy declines if moving. Consequently, if commercial mHealth devices such as the Polar Vantage are to be used to track vmHRV following specific protocols (e.g., orthostatic test), the results should be interpreted as estimates. This is particularly relevant for general users who prioritize accessibility and convenience in wearables. In contrast, in scenarios where diagnostic accuracy is critical, such as clinical settings, ECG should be favoured over PPG-based devices for tracking HR (Gagnon et al., 2022).

Beyond assessing device accuracy, Article 4 made an important **methodological contribution** by introducing an alternative approach to HR accuracy assessment. Unlike most studies that report device agreement based on a single long averaging period (e.g., 5-min), this study evaluated device agreement across multiple time scales, offering a more detailed analysis of HR. The synchronization procedure was also interesting because it avoided the need for interpolation of time-series data, providing a more precise comparison of HR measurements between wearables. This approach can serve as a tool for future studies validating HR in dynamic contexts.

In summary, Article 4 challenges the reliability of wearables, particularly for movement-based HR monitoring. To be effective, monitoring systems must provide consistent, valid data, and while useful at rest, wearables seem less reliable during movement, and values should be interpreted as estimates rather than precise metrics. The findings expose a gap between theoretical HRV applications and current consumer-grade technologies, underscoring the need for more rigorous validation before full integration into monitoring systems.

### *4.1.4 Summary of the findings*

The goal of this thesis was to explore the role of vmHRV, HR, and SVs in athletic monitoring, with a particular emphasis on the use wearable technology. The goal was driven by three gaps in the literature: (1) the need for athlete monitoring systems, (2) the lack of standardization in how metrics are measured and integrated, and (3) the insufficient validation of wearable technologies, despite their widespread use. The four studies presented in this thesis confirm these three gaps and address both the main and the specific subgoals.

**The first subgoal of the thesis was to synthesize current evidence on vmHRV and subjective measures in athletes,** including variables studied, correlations, and methodological practices being used. This was mostly addressed in Article 1. The scoping review concluded that while there is a general trend suggesting higher RMSSD is associated with more favourable subjective states (e.g., lower fatigue, better mood), these associations are inconsistent and weak. These mixed findings, echoed in the empirical Article 3, indicate the need for a more integrative approach. Interestingly, the inconsistencies between subjective and physiological data may suggest that these variables provide distinct insights into athlete monitoring.

Moreover, Article 1 also revealed substantial variability in both vmHRV and SV measurement practices, including differences in protocols, devices, analysis methods, and types of SVs. These inconsistencies limit cross-study comparisons and may contribute to the inconsistent relationships between variables. The findings highlighted the need for standardized protocols, transparent reporting of methods and theory-informed designs.

**The second subgoal aimed to assess the application of vmHRV and SVs in training responses and optimization.** This was explored through two empirical studies. Article 2, a pilot study, showed that both vmHRV and mood were responsive to prior-day training load, serving as potential tools for monitoring athletes, while also pointing that relationships between variables are not always consistent and indicating the need for long-term monitoring. Article 3 extended these findings by demonstrating that training programs incorporating WB scores and RHR alongside vmHRV produced greater performance gains than vmHRV-guided training alone. The study supports the application of physiological and psychological markers for individualized training strategies.

**The third subgoal was to validate the accuracy and feasibility of wearable devices for HR monitoring in applied settings.** Article 4 directly addressed this by comparing an Apple Watch and a Polar Vantage to a gold-standard ECG across four conditions. The results showed that while both devices were reasonably accurate while laying, their reliability declined significantly during more dynamic conditions such as standing or walking. These findings highlight a disconnect between the commercial popularity of wearables and their scientific validation, particularly in real-time, more movement-based contexts.

**The fourth subgoal was to connect the findings to existing HRV frameworks (NIM and VTT).** Collectively, the observation that vmHRV and SVs often covary but can also diverge does not directly conflict with the NIM or the VTT, which describe vmHRV as an index of the functional capacity of the central autonomic network. The contribution of the present thesis to the theoretical development of HRV research lies in emphasizing that while vmHRV provides information about the underlying capacity to self-regulate, SVs informs about how this capacity is consciously experienced. Divergence between these measures may indicate situations in which physiological resources are available but not perceived as such, or vice versa. These findings suggest that vmHRV can be a key, but not sole, indicator of self-regulation. Integrating subjective perceptions with physiological markers like vmHRV and RHR add context. This perspective expands the NIM by emphasizing that vagal tone should be interpreted in relation to both autonomic signals and conscious perceptions (e.g. perceived fatigue), reinforcing that self-regulation emerges from the dynamic interaction of multiple levels of the neurovisceral system and that a single physiological marker cannot fully capture it. In turn, the findings also refine the VTT in two ways. First, they show that elevated vmHRV can signal either readiness or overreaching, and that incorporating RHR and WB scores helps distinguish a "full" vagal tank from one that is saturated or in a state of maladaptation. Second, they emphasise that the VTT, which was originally conceived for single events, needs to consider longitudinal monitoring.

**Together, the four studies respond to the central research aim by supporting previous claims that no single marker is sufficient to monitor athletes, and instead, combining physiological (vmHRV, RHR) and subjective (SVs) measures offers a more accurate and adaptable picture of athlete readiness and recovery. A key finding is that this integration should be applied *within* a personalized and context-aware framework.**

Put into perspective, the findings build on the historical and scientific perspectives introduced earlier in the thesis. From ancient conceptions of the heart as the seat of emotion and intellect to modern insights from neurocardiology, there has been a long-standing recognition of the bidirectional relationship between cardiac and psychological processes, with the NIM offering a physiological explanation for this connection and VTT adding context. However, while vmHRV and SVs might be interrelated, they also seem to offer distinct information, and in applied sport settings then, this distinction becomes important: monitoring both domains in parallel increases the sensitivity to changes in athletes' state. Overall, the results support that an individualized, multimodal monitoring system combining vmHRV, RHR, and SVs offers a more complete monitoring approach for understanding and supporting athlete adaptation.

## 4.2 Practical contributions and theoretical repercussions for athlete monitoring

As introduced in the *Presentation*, this thesis originated from the applied field, specifically from conversations with fellow athletes who asked about the connection between data from wearables and how they felt. These recurring discussions sparked the present doctoral project. Over time, also became clearer that this origin story is not only anecdotal; it reflects a broader trend, as interest in the topic continues to grow in both research and applied contexts. Wearable devices and self-monitoring apps are also becoming increasingly popular, facilitating the collection of physiological data, in parallel to sport science moving towards individualized approached to training and recovery.

With this background, a core motivation of the thesis, outlined in *Section 2*, was to **contribute not only to theory, but also to practice**, informing both practitioners and scientists. This section outlines the practical contributions of the thesis and is divided into three parts: one highlights the direct practical tools developed during the thesis, a second interprets the findings within established training frameworks, and a third discusses the role of SVs in light of the results and ongoing advancements in wearable technology.

### *4.2.1 Practical contributions of the thesis*

There are three direct practical tools developed through the articles of this thesis. **First,** in response to the methodological inconsistencies identified **in Article 1, the thesis proposes a methodological checklist alongside a classification of SVs,** for researchers and practitioners working with vmHRV and SVs. Together, these tools aim to encourage standardization in the selection of protocols, variables, and devices, ultimately improving the reliability and comparability of studies and field applications.

**Second**, Article 3 presents a training protocol that applies an integrative approach, specifically **guiding training based on the combined input of vmHRV, RHR, and SVs**. The protocol is fully available for practitioners who

want to apply it in training, as well as for researchers who wish to further test and refine the protocol. This program directly bridges research and practice by offering a field-ready implementation of the variables under study.
Notably, after the study, some participants wrote feedback about their experience with the training program (check Annex 6). Feedback reflected interest, engagement and perceived benefit from the intervention, while also highlighting the need for improvement in the app interface, pointing to opportunities for further development in mHealth technologies.

**Third, Article 4 introduced a novel method to evaluate agreement between wearable devices**, contributing to evidence-based guidance on the use of wearable technology for monitoring systems. The analytical approach offers a scalable way to assess device reliability over time, relevant both for researchers and technology developers.

### *4.2.2 In light of performance frameworks*

Beyond these direct tools, the findings of the thesis can be discussed in light of the training frameworks outlined in the introduction: supercompensation, periodization, and IZOF. The aim is to discuss how a combination of vmHRV, RHR and/or SVs could be used in practice from a training perspective.

**Supercompensation** theory describes how performance initially declines after training, followed by an adaptive rebound, and **periodization** build on this by structuring training intensity and volume to optimise adaptation and prevent overtraining. Since effective periodization depends on balancing training load and recovery, it is essential to distinguish between transient fatigue and long-term adaptation. The findings of the thesis suggest that multi-day tracking of psychophysiological markers can help locate athletes on the fatigue–recovery continuum and time workloads accordingly.
This idea was mostly illustrated in Article 3, where rolling averages of RMSSD, RHR and WB prescribed training depending on whether the daily resting “vagal tank” was fuller and depleted. *Section 3.3* presents a comparison between the

three programs used in the study, to show how the different combination of variables can influence training prescription. The analysis compared Program 1 (HRV-only), Program 2 (HRV + WB), and Program 3 (HRV + WB + RHR). Programs 2 and 3 produced the most similar recommendations, with the largest differences observed between Programs 1 and 3. Given that Groups 2 and 3 showed greater performance improvements, the analysis suggests that even small, data-driven adjustments to training prescription, can lead to differences in performance. In other words, incorporating HRV-theory concepts (i.e. monitoring self-regulatory markers) into periodization encourages long term tracking of key variables that supports more precise training decisions.
An interesting direction for future work would be to compare the distribution of “High,” “Low,” and “Rest” training days across programs. For instance, if Program 1 recommended more “High” intensity days than Programs 2 or 3, it would suggest that incorporating WB and RHR favours more lower-intensity training. Such analyses could inform ongoing debates on whether a greater proportion of low-intensity sessions prevents overtraining (Laursen, 2010).

In turn, the **IZOF** model adds an emotional dimension, positing that each athlete has a unique emotional zone where performance peaks (Hanin, 1995). In Article 3, Groups 2 and 3 received training recommendations partly based on their morning WB scores, guiding training intensity with the athlete’s perceived state. This suggests the application of IZOF principles beyond pre-competition settings, such that training readiness, like competitive performance, may also be governed by individual perceived baselines. In this way, the thesis suggests the extension of the IZOF model from pre-competition into daily training management. Moreover, the varied correlations between RMSSD and SVs across individuals support a call for personalized profiling (Ruiz et al., 2017).

In summary, the findings support that a combination of physiological and subjective markers allows to **fine-tune periodisation, interpret supercompensation phases and align sessions** with an athlete’s individual perceived cognitive-emotional zones.

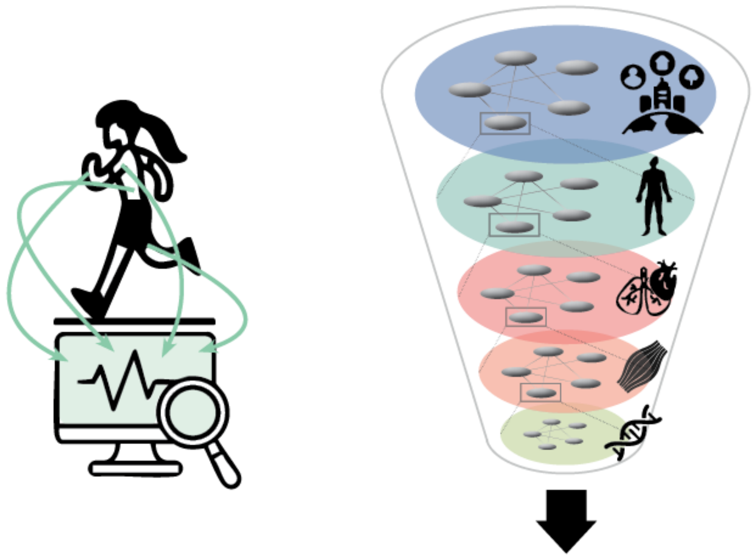
### *4.2.3 SVs as a core input: a Complex Adaptive System lens*

As outlined in the introduction, athletic performance was framed as the resulting interplay of numerous interrelated psychophysiological factors. This thesis indicates that, while SVs and vmHRV share physiological underpinnings, neither alone is sufficient for effective athlete monitoring, and that, instead, integrated systems should be prioritized. A key conclusion is that vmHRV alone cannot fully capture self-regulation, and that conscious appraisal reflected in SVs complements physiological data. This underscores the relevance of SVs, and aligns with prior research that give SVs a central role in athlete monitoring (e.g., Saw et al., 2016). But what makes SVs so essential?

A useful lens for understanding **why SVs are so informative is the Complex Adaptive Systems (CAS) framework**. CAS describes systems of interacting elements that continuously adapt and evolve in response to internal and external stimuli. Unlike traditional linear systems, driven by predictable cause-and-effect relationships, CAS exhibit emergent behaviours through the interactions of individual components. Each agent within the system adjusts its behaviour based on local interactions, resulting in patterns that are often unpredictable (Holland, 1992, 1998; Waldrop & Waldrop, 1993). In recent years, this framework has been applied to sports; in fact, much of the sport-specific CAS work appeared during the course of this thesis, which is why it is not mentioned in the Introduction. A full explanation of CAS can be found elsewhere (e.g., Carmichael & Hadžikadić, 2019), but, importantly, it offers a lens to explain how SVs capture athletes' internal state.

Based on CAS, SVs integrate **multiple streams of information**: sensory, emotional, and cognitive processes, such as proprioceptive, interoceptive, and environmental perception, providing athletes with a form of informed self-awareness that supports real-time adaptation. Figure 10 illustrates the concept.

**Figure 10.** Complex adaptive systems view of athlete monitoring




*On the left:* Objective (physiological) monitoring collects discrete sensor streams (e.g., HR, GPS, accelerometers) reported as separate metrics, fragmenting information to allow quantification. *On the right:* Subjective monitoring integrates multiscale inputs (genetic-epigenetic, biochemical, organ-system, biomechanical, social-environmental) into a single perception (athlete self-report). Adapted from Montull et al. (2022).

In a way, CAS supports that **the brain** is able to process complex, dynamic inputs in real time, which is something currently beyond the capacity of monitoring systems. That is, while wearables can capture large amounts of data, their ability to instantly quantify, integrate, and interpret multidimensional data remains limited (Montull et al., 2022). Thus, while data and wearable technology evolves, and may soon be able to effectively and reliably integrate markers in real time, SVs provide a way to capture and compute multiple data streams that operate across time and context (Pol et al., 2020).

This perspective has relevant implications for the future of wearable technology. As technology progresses, there is a risk that attention is overly directed toward objective physiological markers. However, since adaptation is the result of multiple systems, future mHealth must build systems that integrate all data, including SVs. In fact, CAS suggests that subjective input is not merely complementary, but foundational. SVs provide personal and contextual data (Carmichael & Hadžikadić, 2019), and without SVs there is a risk of accumulating volumes of data without context, leading to misinterpretation (Tempelaar et al., 2020). Moreover, self-reported subjective monitoring also supports autonomy, confidence, and self-regulation of athletes (Pol et al., 2020), and is a practical and cost-effective method for capturing continuous, actionable information (Balagué et al., 2020; Saw et al., 2015).

In summary, vmHRV and SVS may share underlying physiology pathways, but the information they provide is not redundant: vmHRV indexes autonomic regulation, whereas SVs capture conscious, affective appraisal. Their integration is essential and as wearables evolve towards validated, multi-marker technologies, SVs should be further studied and considered to **remain a core component**, providing context to physiological data.

## 4.3 Limitations

This thesis comes with several limitations that should be acknowledged, including methodological, participant-related, and theoretical aspects.

**HRV parameters and measurement consistency:** While this thesis emphasizes vmHRV, particularly RMSSD, as the primary parameter for athlete monitoring, Article 2 used a broader array of HRV parameters, including SDNN and HF. Similarly, Article 2 also focused exclusively on mood as a subjective variable, whereas the Articles 1 and 3 integrated other indicators such as fatigue or sleep quality. The absence of RMSSD and the narrow focus of SV in Article 2 limit its direct integration and comparability with the other studies. However, these choices reflect the exploratory nature of Article 2, which served as a foundation for subsequent research and also played a crucial role in the research training process. As the work progressed, the use of RMSSD and a broader range of SVs became more prominent, reflecting a growing understanding of vmHRV and SVs in sport contexts.

**Body positioning:** Another methodological limitation concerns the variability in body position during HRV recordings across studies. Article 2 used a supine position, while Article 3 used supine recordings for wearable devices (Oura, WHOOP) and seated measurements for app-based tools. These inconsistencies may have influenced the comparability and interpretation of results, as discussed in Article 1. That same article also noted the lack of consensus in the literature regarding optimal measurement protocols, although orthostatic testing is increasingly recognized as a sensitive approach for detecting subtle shifts in autonomic balance in trained athletes. The choices adopted in the present articles were intended to facilitate participant adherence and broaden inclusion criteria; however, in retrospect, standardizing body position across studies and incorporating orthostatic testing would have improved their methodological consistency and comparability of results.

**Wearable devices:** Different wearable devices were used across the four studies, including chest-strap monitors, PPG-based applications, and commercially available devices such as Whoop and Oura. In Studies 2 and 3, the use of commercially available, validated devices was intended to support ecological validity and maximize participant recruitment. Although all devices had been previously validated for RHR and vmHRV measurements, methodological variability in device type, signal acquisition, and processing algorithms may have introduced inconsistencies, limiting direct comparisons and the generalizability of findings. It is also worth noting that Oura was initially included in Article 4 but was removed following a safety-related incident. One participant experienced finger swelling that required hospital intervention to remove the ring. For safety reasons, the device was excluded from the study, and the company was notified of the incident.

**Participants:** A key limitation of the experimental studies lies in the small sample size, which may reduce statistical power and limit generalizability. This is particularly the case for the pilot study (Article 2) but also Articles 3 and 4. Overall, female representation was low (only three women expressed interest in Article 3), raising concerns about sex-based biases in autonomic markers and subjective measures. Given known differences in vmHRV and SVs responses across genders, future studies should aim to include more balanced samples.

Also, regarding level, the empirical studies included mainly amateur but experienced cyclists, whereas the scoping review encompassed athletes from recreational to elite levels. Although this diversity allows us to explore results across various athletic contexts, it also limits the ability to extrapolate findings to specific performance levels. Standardizing participant profiles in future research would improve comparability and applicability of the research.

It is also important to note that the thesis is limited to adult and healthy populations. Expanding future investigations to include youth athletes, clinical populations, or those returning from injury could also help understand how psychophysiological monitoring functions across age and health contexts.

## 4.4 Future research

The thesis highlights the complexity and individual variability in athlete monitoring and reinforces the need for integrative approaches. Several unresolved questions and challenges remain that can offer direction for future research.

First, **wearable validation, standardization and usability**: Article 4 highlights a disconnect between the rapid commercialization of wearables and the slower pace of scientific validation. Future research should ensure that the devices used are validated under the desired body position and movement condition. Consistency in protocol selection and reporting, grounded in robust theoretical frameworks, is also essential to improve comparability across studies and strengthen practical applications.
In addition, researchers should prioritize **user-friendly, intuitive tools** to support engagement and adherence to studies, a challenge faced in Article 3 despite high initial interest.

Second, **use and interpretation of SVs:** For subjective monitoring to be effective, education is crucial. Athletes and coaches must understand the purpose and value of SVs to ensure honest and meaningful engagement (Saw et al., 2015). This is because a key limitation of SVs is the sensitivity to personal biases influenced by factors such as motivation, attentional focus, values and habits (Balagué, Pol, Torrents, et al., 2019; Tempelaar et al., 2020). Athletes may, for instance, underestimate fatigue under high-intensity or prolonged exercise (Legall et al., 2024), and common tools like sRPE can be affected by peer influence or attempt to manipulate training loads (Foster et al., 2021). Thus, future work could include educational strategies to promote accurate self-assessment.

Third, **multiple biomarkers:** Future research could explore the integration of RHR, vmHRV and/or SVs with hormonal and biochemical markers (e.g., cortisol, testosterone). As outlined by previous authors (Fry et al., 1991; Heidari et al.,

2019), overtraining manifests across physiological, psychological, biochemical, and immunological domains, so identifying which biomarkers are relevant for specific athletes and sport contexts could advance athlete monitoring.
However, note that this integration warrants caution. Accumulating more data does not necessarily translate into a better understanding of athletes (Tempelaar et al., 2020). In fact, practitioners often struggle with processing and interpreting large quantities of data, and in some cases, data overload even leads to analysis paralysis rather than actionable insights (Rein & Memmert, 2016). As Albert Einstein quoted: "*not everything that counts can be counted, and not everything that can be counted counts*". So, the key challenge is to understand what each variable can bring and determine which variables matter for each athlete, including SVs.

Fourth, **individual data monitoring and interpretation:** Future research could explore individualized approaches in data selection and interpretation. For instance, while Article 3 used composite WB scores (i.e., fatigue, sleep quality, stress, soreness), this method assumes equal importance across variables, an assumption that may obscure key individual differences (Schliep et al., 2020). Different SVs may vary in relevance across individuals, suggesting a need for more personalized marker combinations. Particularly, the IZOF model states that optimal performance is not necessarily associated with uniformly "positive" emotional states, but rather with individualized patterns of emotional experiences. Some athletes may perform best under moderate stress, while others may require calmness (Ruiz et al., 2017). Thus, understanding the relevant data for each individual would improve monitoring. For this, advancements in modelling approaches may open possibilities to interpret large volumes of data and capture individual-specific patterns and its relationship with performance (Claudino et al., 2019).

Fifth, further research could explore the **relevance of markers across different sports.** Particularly given that in high-explosive or neuromuscular-demanding sports (e.g., sprinting, weightlifting), vmHRV may not correlate as strongly with readiness as in endurance sports (Coyne et al., 2018).

Sixth, **expanding HRV-based frameworks.** The thesis points to some directions for advancing psychophysiological models in athletic contexts. One area is to promote longitudinal monitoring, moving beyond single-timepoint assessments. Another is including resting, reactivity and recovery phases of autonomic regulation in future studies, to understand how vmHRV fluctuates in response to stressors (e.g., exercise). A third option would be to investigate potential moderators of vmHRV–SV associations, including age, gender, training history, and cognitive-emotional load, given that these factors may affect both the strength and direction of the relationships. Overall, the aim is to move HRV-related frameworks towards formally integrating SVs as core markers of the system.

Finally**, the findings in the thesis raise an important conceptual implication:** the variability of responses, inconsistent correlations between vmHRV and SVs, and need for individualized interpretation challenges traditional, linear models of adaptation that rely on fixed cause-and-effect relationships and isolated markers. Instead, the results suggest that athlete monitoring is a dynamic, emergent process shaped by multiple interacting factors. This view aligns with the CAS, which is likely why it has been recently cited in sports sciences. Rather than treating athletes as collections of isolated variables, CAS views them as non-linear systems composed of interdependent elements (Balagué, Pol, & Guerrero, 2019; Fullagar et al., 2019). Based on the principles of CAS, the inconsistencies seen in Articles 1, 2 and 3 illustrate core CAS principles of non-linearity and emergence, where the same input (e.g., vmHRV) cannot consistently predict a given state or performance due to the influence of other interacting variables.

At present, CAS in sports science remains largely theoretical (Gatrell, 2005), and its mention in this thesis is reflective, no empirical, intended to contextualize the findings. Nonetheless, CAS may offer a valuable lens for future research.

As technology advances, CAS-based methods such as network analysis (Ivanov et al., 2016) or fractal analysis (Gronwald et al., 2020) may help empirically test interdependencies and better capture the complexity of athlete monitoring (Montull et al., 2022). Moreover, these methods could help answer question such as: What is the optimal way to combine SVs and physiological data? How should fluctuations in vmHRV, RHR, and SV be interpreted?

In summary, future research should refine wearable validation, enhance the accuracy of monitoring, and develop individualized, multi-marker, real-time training models. These advances would enable more precise, adaptive and integrated strategies to support athletic performance, health, and long-term development.

# 5. CONCLUSION

This thesis set out to explore whether and how resting vagally-mediated heart rate variability (vmHRV), resting heart rate (RHR), and subjective variables (SVs) can be integrated into athlete monitoring.

The project was rooted in both scientific and applied needs. On the one hand, coaches and athletes increasingly rely on wearables and data-driven tools to guide performance, yet they frequently comment that physiological metrics such as HRV or RHR diverge from how athletes feel. On the other hand, scientists are calling for multimodal and personalized systems in athletic contexts. As such, the thesis set out to explore the disconnect between variables and test the feasibility of an integrated approach.

**Answering the research questions**

The thesis drew upon a combination of theoretical synthesis, empirical studies, and applied validation. The focus was on an adult, healthy and trained population.

In short, the central conclusion supports previous research: no single marker suffices to monitor or guide performance. The observation is that physiological data often diverge from perceived states, and integrating vmHRV, RHR, and SVs provides a better picture of the physical and psychological state of athletes. Such divergence is consistent with complex, context-dependent adaptation. More specifically, the thesis met its objectives across four studies.

- A scoping review (Article 1) mapped inconsistent associations between vmHRV and SVs and revealed substantial methodological heterogeneity. This led to a practical checklist to standardize variables, protocols, and devices, and suggested that inconsistencies could, in part, be contributing to variable findings across studies.
- A pilot study (Article 2) suggested that vmHRV and mood might be responsive to training load, and an intervention (Article 3) showed that

training prescriptions informed by vmHRV together with RHR and SVs outperformed vmHRV-only guidance on cycling performance, supporting a multi-marker approach for day-to-day decision-making.

- A validation study (Article 4) introduced a synchronization and multi-timescale agreement approach to compare consumer wearables with ECG, clarifying when current devices are suitable (trends at rest) and when caution is warranted (when movement is involved).

Collectively, the studies progress from synthetizing current evidence to empirical testing, practical application and technological feasibility.

**Theoretical perspective**

At a theoretical level, the thesis connects long-standing views of heart–brain interplay with contemporary models such as the Neurovisceral Integration Model (NIM) and the Vagal Tank Theory (VTT). That is, from ancient civilizations that revered the heart as the seat of intellect and emotion, to contemporary models like the NIM, the idea that physiology and psychology are deeply intertwined has long-standing roots.

With this basis, the findings advance sport science by supporting an integrated view of the athlete as a system in constant interaction with the environment, and where performance is complex, adaptive, and context-dependent. Particularly, the findings refine HRV-related theories by suggesting that vmHRV and SVs index complementary layers of self-regulation: vmHRV reflecting regulatory capacity and SVs capturing how this capacity is consciously perceived. In this way, the apparent "decoupling" between physiological and subjective markers underscores the value of multi-modal monitoring approach, and supports the notion that self-regulation emerges from a dynamic interplay of physiological and cognitive–affective processes. Using both vmHRV and SVs, together with RHR, can therefore provide a more individualized understanding of athletes' states, explaining why physiological and subjective trajectories can diverge yet both remain valid and informative.

**Practical contributions**

The thesis highlights a growing interest, both public and scientific, in the use of vmHRV, SVs and wearables in athletic contexts. In this growing field, the thesis contributes several practical tools:

- **A methodological checklist:** After identifying inconsistencies in how vmHRV and SVs are measured, a checklist is provided to standardize and improve comparability across future studies and applications. Complementing the checklist, the identified SVs were classified according to their primary focus –fatigue and recovery, psychological-, and sleep-related variables– which could be used in future research.
- **A training recommendation guide**: A protocol combining vmHRV, RHR, and SVs to inform daily training prescriptions for endurance athletes. This supports the development of individualized monitoring systems.
- **A method to evaluate wearable agreement over different averaging windows:** By proposing a new methodology, the thesis points that with adequate synchronization protocols, commercially available devices can provide sufficiently accurate HR data for athlete monitoring purposes.

Besides the practical tools, the thesis encourages coaches and sport scientists to incorporate multiple psychophysiological variables, rather than single markers, into established performance frameworks (e.g., supercompensation), as cues for adjusting load and recovery. Also, it encourages the use of commercial wearables with cautions: using validated devices, following standardized protocols, and treating outputs as estimates rather than absolutes. Finally, at a conceptual level, it assigns SVs a prominent role in performance monitoring and guidance. From a Complex Adaptive Systems (CAS) perspective, SVs integrate real-time sensory, emotional and context-dependent information, and offer a practical measure of athletes' internal state. In this view, wearable technologies should develop into tools that aggregate multiple variables around a subjective core. In such technologies: objective measures would inform about self-regulatory capacity, subjective data contextualize, and the combination drive practical, athlete-specific choices.

**Limitations and Future research**

Limitations of this thesis include small samples, uneven device/protocol standardization (e.g., body position, devices), and real-world settings that improved ecological validity but reduced experimental control.
At the same time, several avenues follow. First, future research should follow standardized protocols for vmHRV and SVs (e.g., body position, measurement timing, preprocessing, device reporting) to reduce heterogeneity and improve comparability. Second, larger-scale studies would be needed to validate the proposed training systems across different sports, age groups, levels of expertise, and under sport-specific conditions. Third, exploring additional markers (e.g., hormonal profiles) could enrich individualized models. Fourth, targeted education for athletes and staff should improve the reliability of SV collection and reduce bias. Overall, the field should pursue individualized, adaptive, integrated strategies –potentially CAS-informed– to support day-to-day decision-making.

**In summary,** thesis supports the need for athlete monitoring systems that move beyond one-dimensional metrics. By examining the combined use of vmHRV, RHR, and SVs, it shows that an integrative approach is conceptually grounded, empirically supported, and –at rest– technologically feasible with validated wearables. It also offers practitioners and sport scientists practical guidance for managing day-to-day training and recovery.

As wearable technology continues to evolve, multi-marker systems should be prioritised, with subjective monitoring remaining essential to contextualise physiological signals. When high-quality SVs are combined with validated physiological data –and collected under standardised, theory-informed protocols– training decisions are better supported, recovery is optimised, and performance and well-being are promoted. Together, these findings advance the thesis's aim of laying a foundation for structured, evidence-based athlete monitoring.

## 5.1 Closing note

This thesis set out to explore psychophysiological variables in athlete monitoring to optimize, guide and support training, performance and well-being. Revisiting the words of Aristotle –"*the whole is more than the sum of its parts*"– the findings reinforce that the true value of monitoring lies not in analysing isolated markers, but in understanding how they interact and inform each other. Just as Gestalt theory reminds us that individual components gain meaning only in relation to the whole, this research highlights the need for holistic, individualized, and dynamic systems that reflect the athlete's realities.
Similarly, this thesis is not a collection of isolated studies but a structured progression toward a deeper understanding of athlete monitoring. It aims to contribute not just data, but also direction. It offers practical tools, theoretical framing, and evidence to guide future practice in the field. Ultimately, it invites to move beyond the sum of the metrics and to see the athlete not just as a body to be measured, but as a person to be understood.

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# ANNEXES

## Annex 1. Science communication article

This science communication article was developed during the international research stay at the Deutsche Sporthochschule Köln (German Sport University Cologne), in collaboration with fellow researchers. It aims to make the concept of vagally-mediated heart rate variability (vmHRV) accessible to a broader audience, and specifically explores how Olympic athletes can use vmHRV to enhance performance by connecting mind and body, particularly in honour of the (then) upcoming Paris 2024 Olympic Games.

**Reference:** Laborde, S., Ackermann, S., Alfonso, C., Borges, U., Crone, E., Iskra, M., Jackovič, M., Haydt, V., Hunder, L., Maqsood, R., Midderhoff, F., Mosley, E., Paykoç, D., Salvotti, C., Sanden, C., Schubert, R., Schmaußer, M., & Voigt, L. (2024). Heart rate variability (HRV): How Olympic athletes can use the heart-mind connection to boost their performance. In-Mind Magazine. https://www.in-mind.org/article/heart-rate-variability-hrv-how-olympic-athletes-can-use-the-heart-mind-connection-to-boost

## Annex 2. Science communications

This section includes visual materials presented in national and international conferences where findings from the studies included in the present doctoral thesis were showcased. The communications, delivered in the form of posters and oral presentations, contributed to the scientific dissemination and peer discussion of the study results.

The following communications are presented in the order in which they appear on the next pages:

**Communication 1. Poster**

Alfonso, C., & Capdevila, L. (2024, June). *Prescripción del entrenamiento en base a la monitorización psicofisiológica: Estudio de intervención en ciclistas* [Poster presentation]. XVIII Congreso Nacional de Psicología de la Actividad Física y del Deporte, Barcelona, Spain.

**Communication 2. Poster**

Alfonso, C., & Capdevila, L. (2024, July). *Assessing the impact of psychophysiological variables on performance in recreational cyclists: A 30-day intervention study* [Poster presentation]. FEPSAC Congress 2024, Innsbruck, Austria.

**Communication 3. Symposium oral presentation.** The doctoral candidate delivered one of the four presentations included in the symposium.
Alfonso, C., Capdevila, L., Laborde, S., Welsh, M. R., Mosley, E., Day, M. C., Sharpe, B. T., Burkill, R. A., Birch, P. D., Schwalb, F., Pels, F., Javelle, F., Hartmann, U., Chermette, C., Kleinert, J., You, M., Ackermann, S., Borges, U., Dosseville, F., & Mosley, E. (2024, July). *Heart rate variability in sport & exercise psychology: Implications for training, performance, and well-being* [Symposium presentation]. FEPSAC Congress 2024, Innsbruck, Austria.

# Prescripción del entrenamiento en base a la monitorización psicofisiológica: estudio de intervención en ciclistas

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## Introducción

En deportistas, el equilibrio entre carga de entrenamiento y recuperación es clave para producir adaptaciones físicas, mejorar el rendimiento y prevenir lesiones. Este equilibrio es complejo, y se han propuesto varios marcadores para medirlo (1). Entre ellos destacan dos marcadores fisiológicos: la variabilidad de la frecuencia cardíaca (VFC) y la frecuencia cardíaca en reposo (FC) y varios marcadores psicológicos: estrés, calidad de sueño, dolor muscular, y estado de ánimo, entre otros. Además, un número creciente de investigadores, deportistas y entrenadores remarcan la necesidad de incorporar ambos tipos de marcadores para informar sobre los estados de bienestar, fatiga y rendimiento de los deportistas (2).

## Objetivo

En este estudio se realizó una intervención para:

- Aplicar planes de entrenamiento personalizados para guiar las cargas de entrenamiento en función de una combinación de datos obtenidos diariamente de VFC, FC y bienestar (WB).
- Evaluar la eficacia de los diferentes planes de entrenamiento, en base a resultados de pruebas de esfuerzo.

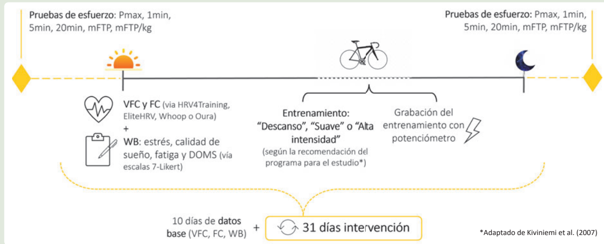
## Método

**Muestra:** Ciclistas recreativos (n=28, edad: 45,89 ± 12,84, masculinos).

**Programas de entrenamiento** personalizados*, guiados por:

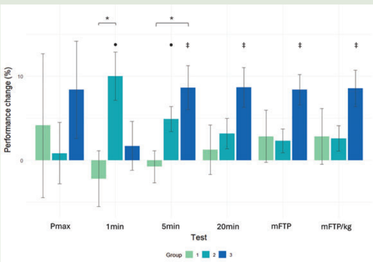
- la VFC (Grupo 1, *n = 8*)
- la VFC y la FC (Grupo 2, *n = 12*)
- la VFC, la FC y el WB (Grupo 3, *n = 8*). WB se calculó a partir de escalas de calidad del sueño, estrés, fatiga y dolor muscular (DOMS).

**Figura 1:** Proceso de recolección de datos e intervención.




## Resultados

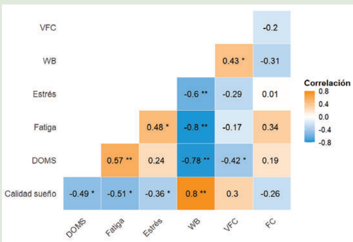
**Figura 2:** Porcentaje de cambio (POS-PRE) y error estandar entre los resultados de los test iniciales (PRE) y finales (POS).




Entre-grupo: * indica diferencia sign. (Bonferroni, p<,05).
Intra-grupo: entre datos PRE y POST (Wilcoxon):

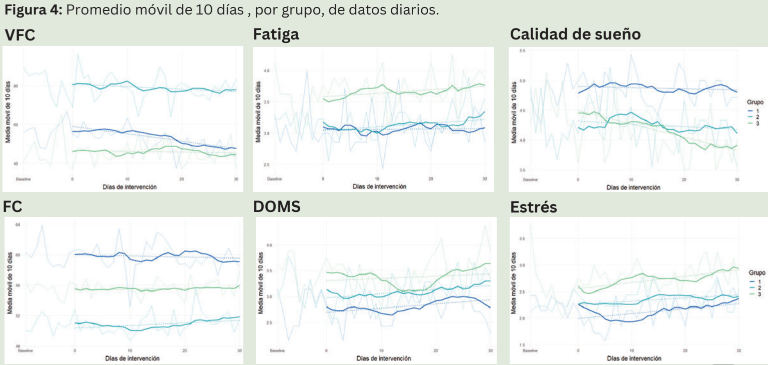
- • **Grupo 2:** 1min, 5min POS>PRE (p<,01)
- ‡ **Grupo 3:** 5, 20min, mFTP y mFTP/kg POS>PRE (p<,05)
- **Grupo 1:** no mejora significativa en ningún test

**Figura 3:** Matriz de correlación (Spearman) y significación de datos de 31 días consecutivos




- **VFC** relaciona en positivo con WB (p<0.05).
- **WB** correlaciona con todas las variables subjetivas (p<0.01).
- FC y VFC no significativos. Pero: al mirar **correlaciones individuales**, correlacionan negativamente en un 77% de los casos.

**Figura 4:** Promedio móvil de 10 días , por grupo, de datos diarios.




Se observa que todos los grupos muestran tendencias similares, excepto en:

- **VFC:** mayor bajada de VFC en el grupo 1 y 2. Grupo 3 más estable.
- **Calidad del sueño**: empeora en el grupo 3
- **DOMS:** aumento en el grupo 1, a lo largo de la intervención. Grupo 3 más alto de inicio

## Conclusiones

__Generales__: **Integrar variables psicológicas (WB) con variables fisiológicas (FC y VFC) en la planificación del entrenamiento** puede ayudar a mejorar el rendimiento, en la línea de recientes estudios (3, 4).

__**Rendimiento:**__

- El **Grupo 3**, que guió su entrenamiento en base a FC, VFC y WB, presenta mayor mejora de rendimiento: media de 7.4% entre todos los test, relevante teniendo en cuenta el nivel de los participantes (+6 años en ciclismo y +8h/semana). Versus 1.4% (Grupo 1), 4% (Grupo 2).
- El **Grupo 1 no presenta mejora** significativa en rendimiento. Sí presenta diferencias con el Grupo 2 (1min) y con el Grupo 3 (5min).
- La heterogeneidad de resultados en Pmax y 1min podría deberse a esfuerzos anaeróbicos.

__**Datos diarios:**__

- El grupo con la **VFC más estable** fue el **Grupo 3**, a pesar de que todos los grupos guiaron su entrenamiento en base a la VFC. Podría ser por haber tenido en cuenta la relación entre VFC y FC en el programa.
- El **bienestar** (así como la calidad de sueño, fatiga, DOMS y estrés) **no mejoró** a lo largo de la intervención. También en los grupos 2 y 3, a pesar de tener en cuenta WB para guiar sus entrenamientos.

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# Assessing the impact of psychophysiological variables on performance in cyclists: a 30-day intervention study

POSTER
P001

UAB Universitat Autònoma de Barcelona

FEPSAC CONGRESS 2024


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Download poster:

## Introduction

In athletes, the balance between training load and recovery is key to producing physical adaptations, improving performance, and preventing injuries. This balance is complex, and several markers have been proposed to measure it (1). Among them, two physiological markers stand out: vagally-mediated heart rate variability (vmHRV) and resting heart rate (HR), together with several psychological markers: such as stress, sleep quality, muscle pain, and mood, among others.
Recently, a growing number of researchers and coaches have highlighted the need to incorporate both types of markers in combination to assess the states of well-being, fatigue, and performance in athletes (2).

## Goal of the study

In this study, an intervention was carried out to:

- Implement personalized training plans to guide training loads, based on a combination of daily data obtained from HRV, HR, and well-being (WB).
- Evaluate the effectiveness of the different training plans based on the results of cycling performance tests.

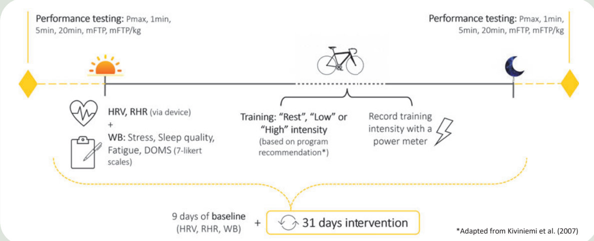
## Method

**Population:** Amateur cyclists (n=28, age: 45,89 ± 12,84, male).

**Personalized training programs*, guided by:**

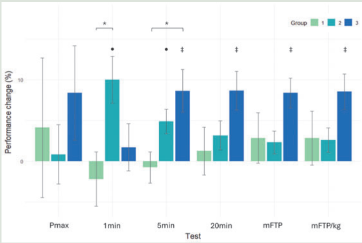
- HRV (Group 1, n = 8)
- HRV and WB (Group 2, n = 12)
- HRV, WB and HR (Group 3, n = 8). WB was calculated from scales of sleep quality, stress, fatigue, and muscle soreness (DOMS).

**Figure 1:** Data collection and intervention process.




## Results

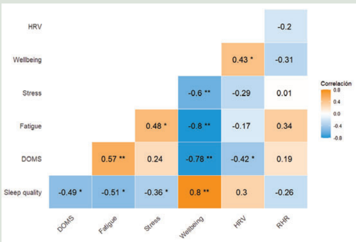
**Figure 2:** Percentage change (POST-PRE) & standard error between results of the initial (PRE) and final (POST) tests.




**Between-group**: * sign. difference (Bonferroni, p<.05).
**Within-group**: between PRE and POST data (Wilcoxon):

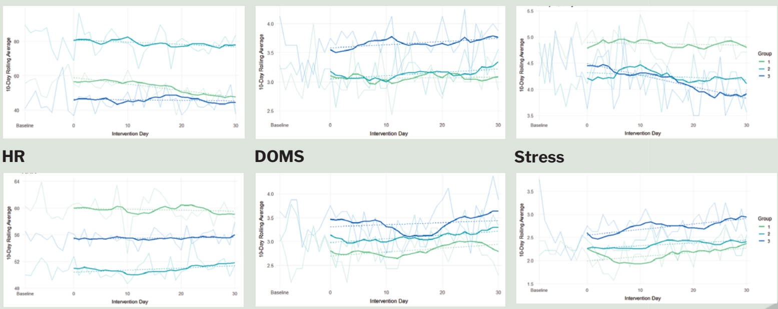
- • **Group 2:** 1min, 5min POS>PRE (p<,01)
- ‡ **Group 3:** 5, 20min, mFTP & mFTP/kg POS>PRE (p<,05)
- **Group 1:** no significant improvement in any test

**Figure 3:** Spearman correlation matrix &statistical significance of data over 31 consecutive days




- **HRV** is positively related to WB (p<0.05).
- **WB** correlates with all subjective variables (p<0.01).
- HR and HRV are not significant. However, when looking at **individual correlations**, they negatively correlate in 77% of the cases.

**Figure 4:** 10-day moving average of daily data, by group.




All groups show similar trends, except in:

- **HRV**: greater decrease in HRV in Groups 1 and 2. Group 3 remains more stable.
- **Sleep quality**: worsens in Group 3.
- **DOMS**: increases in Group 1 throughout the intervention. Group 3 starts higher.

## Conclusions

**Overall: Integrating psychological variables (WB) with physiological variables (HR and HRV) when planning training** can help improve performance, in line with recent studies (3, 4).

**Performance:**

- **Group 3,** which guided their training based on a combination of daily HR, HRV, and WB, shows the **greatest performance improvement**: averaging 7.4% across all tests,compared to 1.4% (Group 1) and 4% (Group 2). The improvement is relevant considering the participants' level (+6 years in cycling and +8 hours per week).
- **Group 1 shows no significant improvement** in performance. However, it does show differences with Group 2 (1min test) and with Group 3 (5min test).

**Daily data:**

- Group 3 presented the **most stable HRV**, despite all groups basing their training on HRV. This could be attributed to the program's consideration of the relationship between HRV and HR.
- Well-being (as well as sleep quality, fatigue, DOMS, and stress) did not improve over the course of the intervention. Also in Groups 2 and 3, despite incorporating WB into their program to guide training.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1


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UAB Universitat Autònoma de Barcelona — Deutsche Sporthochschule Köln, German Sport University Cologne

**Relationship between measures of resting vmHRV and subjective self-reported variables in athletes: a scoping review**


Carla Alfonso, Valerie Haydt, Dr. Sylvain Laborde, Dr. Lluis Capdevila


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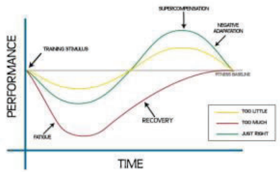
# Topic background

- We are talking about sports *performance*




Principle of *supercompensation*

How can I measure?
How/when to train/recover?

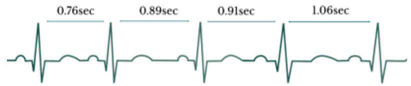
**1.** Vagally-mediated heart rate variability (**vmHRV**)

**2. Subjective variables**, e.g. fatigue, anxiety, mood, etc.

3

# 1. Heart rate variability (HRV)

Distance between heart beats:




- Higher HRV, improved performance (Stanley et al., 2013).
- Improved performance when guiding training based on HRV (Kiviniemi et al. 2007; Javaloyes et al. 2018, 2020; Nuuttila et al., 2017)

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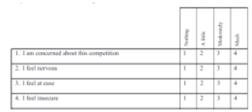
# 2. Self-reported subjective variables

- General fatigue, delayed-onset muscle fatigue (DOMS), stress, motivation, anxiety, sleep quality, amongst others.
- **Effective method to control over-training. Useful to prevent *burnout*** (Kellmann, 2010; Main and Grove, 2009; Urhausen & Kindermann, 2002)


CSAI-2 (Martens et al., 1990)

5

# Recently:

Both physiological and psychological data seem relevant to monitor training load, BUT none of the markers have a determining value on its own (Lac & Maso, 2004).

Growing need to consider, study and use both types of variables in conjunction

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## Goal of the study

Scoping Review

*Identify & synthesize* existing literature studying the *interplay of resting vmHRV & self-reported subjective variables* in the context of *performance and training*.

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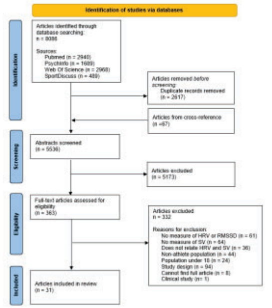
# Method

- Following PRISMA-S Guidelines (Tricco et al., 2018), bibliographic searches in PubMed, PsycINFO, WoS Core Collection & SportDiscuss.
- Keywords: "heart rate variability" AND "athlet*" AND "subjectiv*", along with synonyms.
- Search: February 2024.

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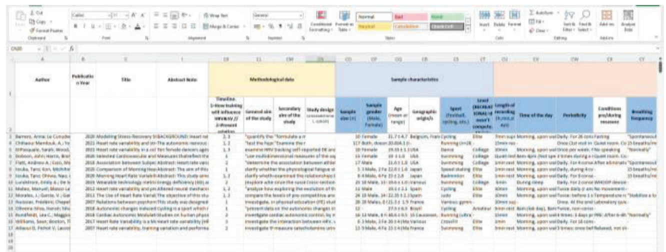
# Extraction table



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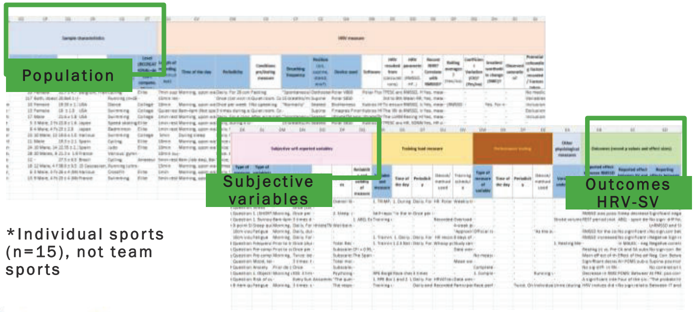
## Extraction table




*Individual sports (n=15), not team sports

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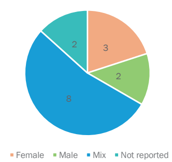
## Results: (1) Population characteristics

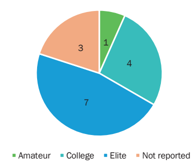
**Average age:** 23.73 ± 5.24

**Gender** (number of studies):




**Sports:** Swimming (n=4), cycling (n=3), running (n=2), power athletes, dancing, speed skating, badminton, judo, CrossFit, triathlon, various (all n=1).

**Level of the athletes** (number of studies):

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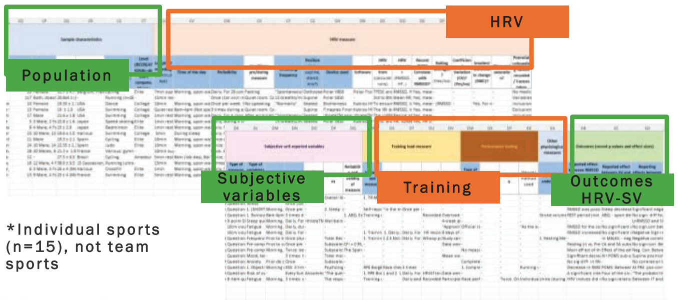
## Extraction table




*Individual sports (n=15), not team sports

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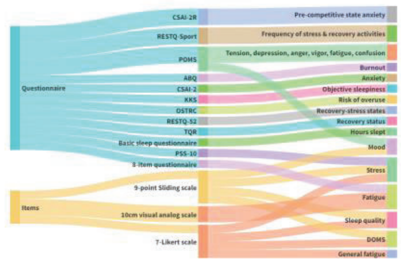
## Results: (2) Subjective variables (SV)

Varied types of SV. Varied questionnaires & items.



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## Results: (2) Subjective variables (SV)

Varied frequency of measurements.

| | | *n* studies |
|---|---|---|
| **Once** | | 4 |
| **Twice** | | 1 |
| **Three times** | Within 4 days | 1 |
| | Within 7 weeks | 1 |
| | Within 25 weeks | 1 |
| **Daily** | 2 days | 1 |
| | 4+4 days | 1 |
| | 8 days | 1 |
| | 26 days | 1 |
| | 28 days | 1 |
| **Once per week** | For 14 weeks | 1 |
| | For 16 weeks | 1 |

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## Preliminary discussion

**Goal of the study**

*Identify and synthesize* literature studying the *interplay of vmHRV & subjective variables* in *performance & training*.

**Population:** young, genders, elite/college, mix sports

**SV** (Subjective Variables)**:**

- **Mix** of tools, variables, timelines
- Most studied variables: Fatigue & Stress
- **Some SV are both sign. and non-sign.**

**Heterogeneity of results.** **<u>Cannot expect constant relationship HRV & SV</u>** –> Depends on context –> **<u>Need both types of measures to understand athlete.</u>**

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## Results: (3) SV-vmHRV

- **Table:** Method of HRV measure and correlation between HRV & SV
- **10 out of 15 articles found significant correlations** ($p<0.05$)
- **Some items are both significant and non-significant.**
- Mix of HRV (RMSSD) methods

| | | Significance | Correlation | No-significance |
|---|---|---|---|---|
| **RMSSD** | **Supine** | Fatigue | - | Fatigue (n=3) |
| | | Stress (n=2) | - | |
| | | Sleep quality | - | |
| | | DOMS | - | |
| | | Somatic anxiety | - | |
| | | Cognitive anxiety | - | |
| | | Self-confidence | + | |
| | | Vigor (Potentially-overtrained) | + | Vigor |
| | | BorgTQR (Pre-race, non-finishers) | + | |
| | | | | KSS (Sleepiness) |
| | | | | Tension (n=2) |
| | | | | Depression (n=2) |
| | | | | Anger (n=2) |
| | | | | Confusion (n=2) |
| | | | | Total Mood Disturbance (n=2) |
| | **Standing** | Fatigue | + | |
| | | Stress | - | |
| | | | | DOMS |
| | | | | Sleep quality |
| | **Ortho** | | | Fatigue |
| | | | | Stress |
| | | | | Sleep quality |
| | | | | DOMS |
| | **Seated** | | | Fatigue |
| | | | | Somatic anxiety |
| | | | | Cognitive anxiety |
| | | | | Self-confidence |
| **Whoop-RMSSD** | **Supine** | Sport-specific stress | - | |
| | | Total stress (females+males, males) | - | |
| | | General stress (males) | - | |
| | | | | General stress |
| | | | | Recovery–stress balance |
| **LnRMSSD** | **Supine** | Overuse | + (probability) | |
| | | | | General stress |
| | | | | Emotional exhaustion |
| | | | | Self-efficacy |
| | **Ortho** | Fatigue | - | |
| | | Sleep quality | - | |
| | | DOMS | - | |
| | | | | Stress |
| | **Seated** | Fatigue (n=3) | - | |
| | | Stress | - | |
| | | Sleep Quality | + | |
| | | Mood | + | |
| | | | | DOMS |

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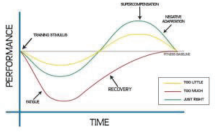
## Implications & Future directions




Contribute to the need for **integrating psychological assessment with physiological data to understand training workloads.** (HOW/WHAT)

*"player management, involves the integration of systematic monitoring (i.e., training load,...), innovative training methods (i.e., ...heat acclimatization), tailored biometric assessments (i.e., FMSTM, PHV), early fatigue detection (i.e., HRV), effective recovery strategies (i.e., temperature-based...), attention to nutrition (...), and healthy sleep hygiene (...).* (Michel et al., 2023).

→ **Guide coaches and athletes.** Effective training strategies, performance, well-being.

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## Preliminary discussion: Others

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1. n=36 studies excluded for no relating HRV & SV → They mention in goals of the study, but then only put a sentence in Discussion!
2. “Only” in 11 out of 15 studies: HRV and SV measured at the same time.
3. HRV → No methodological consensus. Eg: seating, standing, supine, orthostatic positions

→ Need a guideline for HRV studies, and HRV-SV studies

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## Thank you for your attention!

Carla Alfonso, Valerie Haydt, Dr. Sylvain Laborde, Dr. Lluis Capdevila

UAB Universitat Autònoma de Barcelona

Deutsche Sporthochschule Köln German Sport University Cologne

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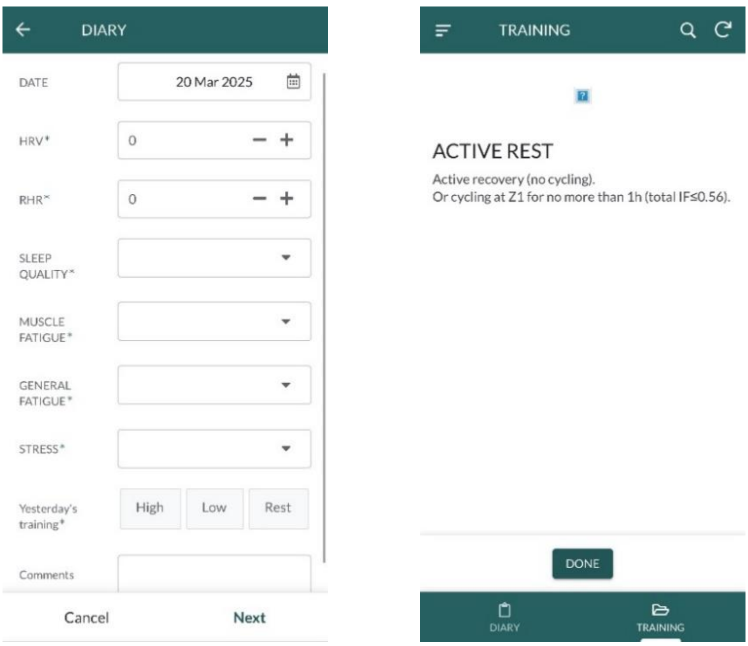
## Annex 3. Article 3 – AppSheet

The following images present screenshots of the mobile application used by participants in Article 3, developed using the AppSheet platform (*Google AppSheet*, 2020). The app allowed participants to enter data and receive training recommendation without needing to contact a researcher or log in into any other platform. Participants engaged with this app daily throughout the 40-day intervention period.

Upon opening the app, a “Diary” page appeared (upper left image). After completing the diary, participants received a personalized training recommendation, for example "Rest" (upper right). Additionally, users could also view the history of their daily logs (lower left) and training recommendations (lower right).

**Figure.** Screenshots of the application developed for Artcle 3.




Diary record
DATE HRV RHR SLEEP QUALITY
9/11/2022 77 41 5 Good
10/11/2022 214 44 6 Well rested
11/11/2022 167 47 5 Good
12/11/2022 168 40 5 Good
13/11/2022 127 50 6 Well rested
16/11/2022 210 42 6 Well rested
15/11/2022 173 43 6 Well rested
20/11/2022 271 48 7 Very well restec
19/11/2022 248 41 7 Very well restec
18/11/2022 259 44 5 Good
21/11/2022 267 43 5 Good
22/11/2022 241 40 4 Normal
23/11/2022 217 40 4 Normal
24/11/2022 270 39 5 Good
25/11/2022 182 34 5 Go
26/11/2022 182 38 5 Good
DIARY
TRAINING


Training record
Date Training
18/11/2022 EASY DAY - Keep it low intensity
21/11/2022 HARD DAY - Add high intensity or longe...
22/11/2022 HARD DAY - Add high intensity or longe...
23/11/2022 HARD DAY - Add high intensity or longe...
24/11/2022 EASY DAY - Keep it low intensity
25/11/2022 ACTIVE REST
26/11/2022 EASY DAY - Keep it low intensity
27/11/2022 ACTIVE REST
28/11/2022 ACTIVE REST
29/11/2022 EASY DAY - Keep it low intensity
30/11/2022 HARD DAY - Add high intensity or longe...
1/12/2022 HARD DAY - Add high intensity or longe...
2/12/2022 EASY DAY - Keep it low intensity
3/12/2022 HARD DAY - Add high intensity or longe...
4/12/2022 EASY DAY - Keep it low intensity
5/12/2022 EASY DAY - Keep it low intensity
DIARY
TRAINING

## Annex 4. Article 3 – Call for participants

Presented below is the advertisement used to call for participants for Article 3.

# Looking for volunteers

## TO TEST AN HRV-GUIDED TRAINING PROGRAM

## Want to participate?

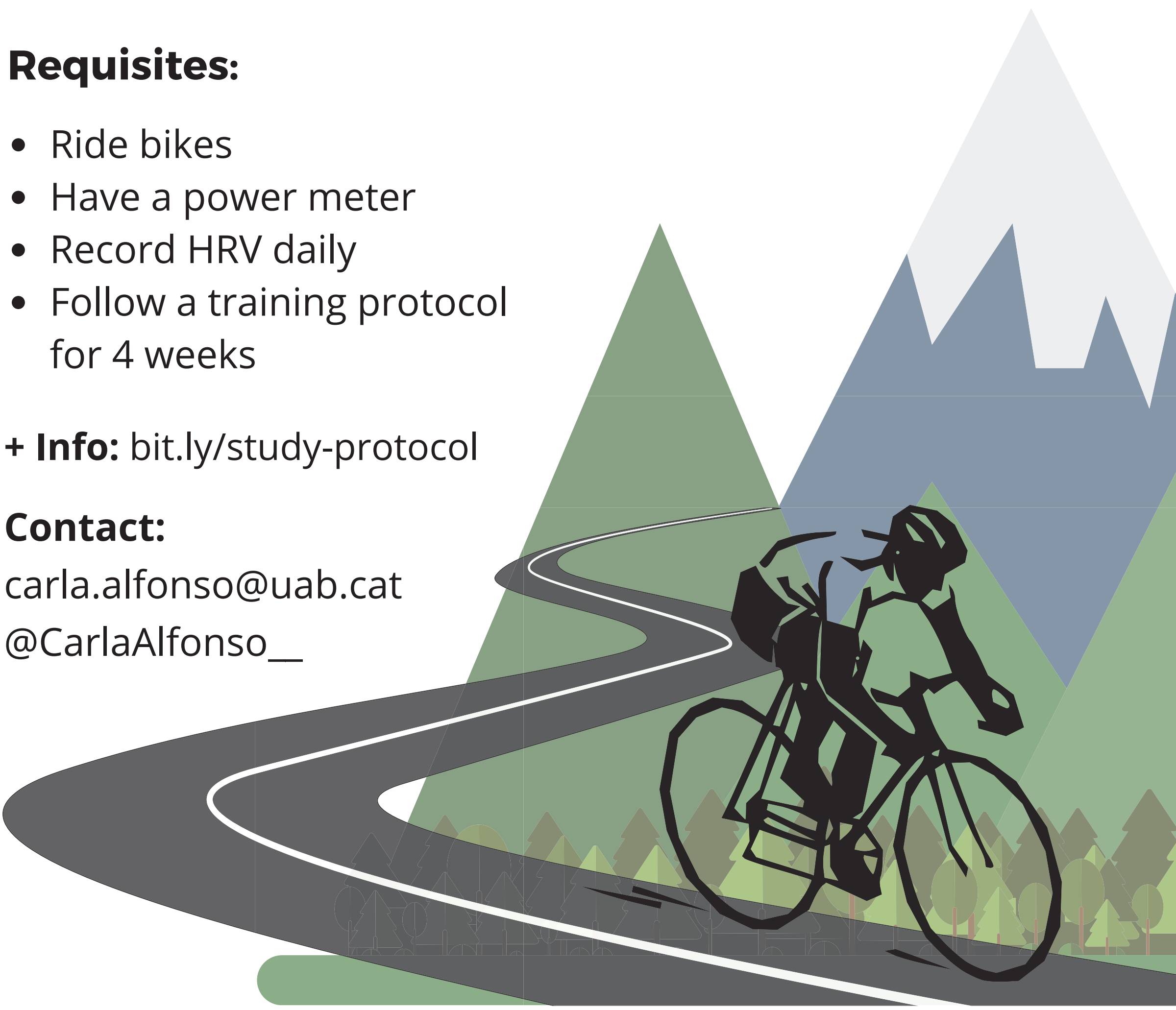
**Requisites:**

- Ride bikes
- Have a power meter
- Record HRV daily
- Follow a training protocol for 4 weeks

**+ Info:** bit.ly/study-protocol

**Contact:**

carla.alfonso@uab.cat
@CarlaAlfonso__



## Annex 5. Article 3 – Dashboard

At the end of the intervention in Article 3, individualized dashboards were created and shared with each participant as a summary of their personal data and outcomes from the study. These dashboards, developed using Tableau software (Tableau Software, LLC), included visualizations of the data regarding training days, performance test, subjective variable, heart rate data trends, and linear correlations between HRV and SVs. The dashboards also served as a thank you for participants' involvement in the study. The following document is an example of a Dashboard.

# Dashboard: individual results from the study about training based on heart rate variability, resting heart rate, and subjective variables

By Carla Alfonso Martin
Sports Psychology Laboratory, Universidad Autonoma Barcelona

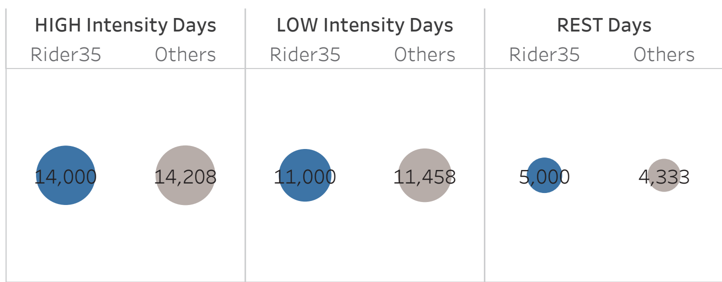
Name and Surname

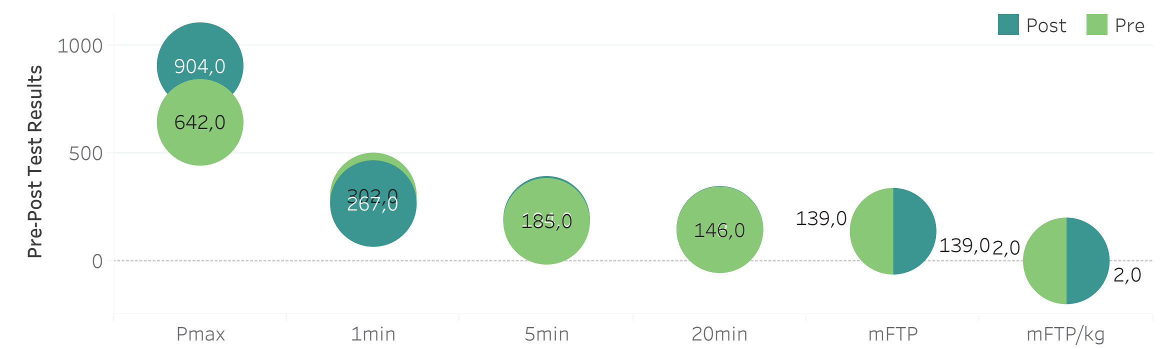
Gender: Male
Age: 38 years old (during participation)
Study group allocation: Training based on HRV, RHR & subjective variables

First thing in the morning for 40 days, the participant recorded heart rate variability (HRV) and resting heart rate (RHR) and uploaded the results onto AppSheet, where a questionnaire about sleep quality, stress, fatigue, and muscle soreness was answered. Days 1-9 established a baseline, and from day 10 to 40 the participant received an individualized recommendation to train "High", "Low" or "Rest". Recommendation were followed. Before and after the 40 days, cycling tests were carried out to measure changes in performance.

## Training

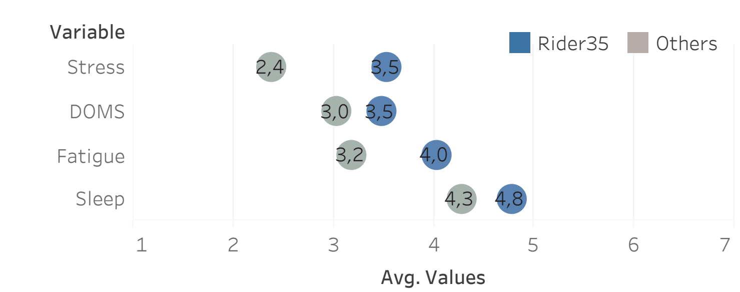
The graph on the right shows the amount of days that you (& the others) rested or trained at high and low intensity, during 30 days of recommendations. The graph below shows changes in sprints (Pmax), 1min, 5min and 20min efforts between the start and the end of the study.
Well done on the commitment & some improvements in the short time!



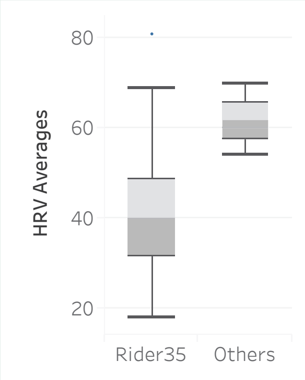



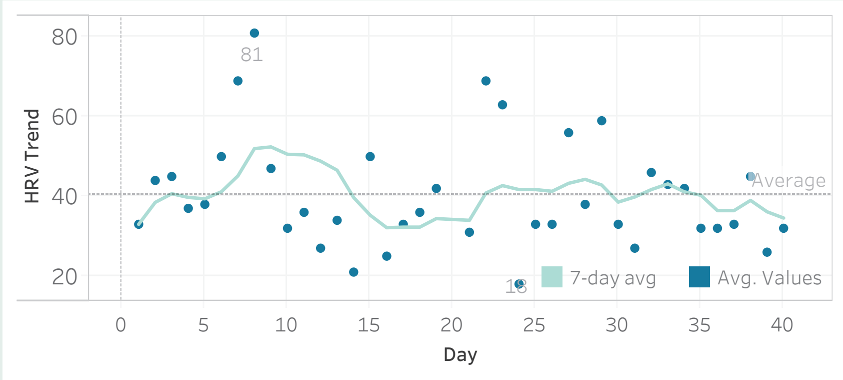

## Subjective Variables

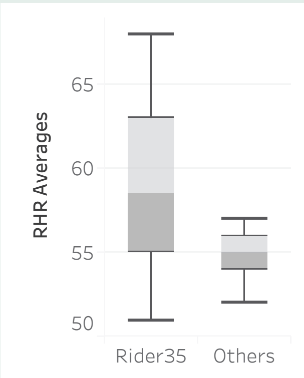
The graph shows the average punctuations for the subjective variables recorded during the 40 days of the study. In blue, your averages. In grey, the average of all other participants, for reference.
You personally scored higher in all subjective variables.

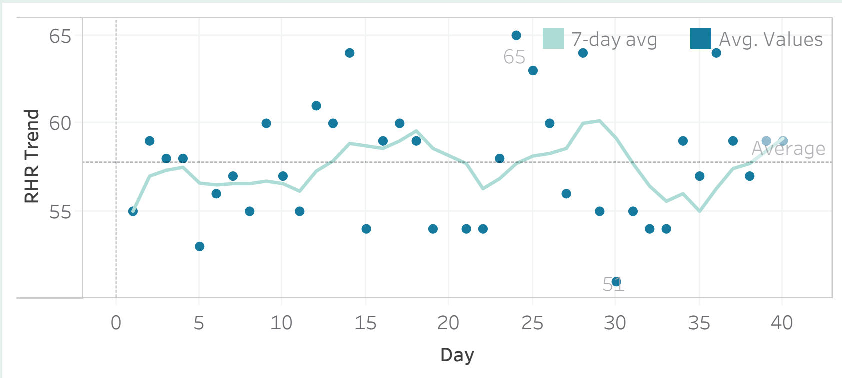


## Heart Rate Data




Note: Training recommendation started on Day 10.
Comments: Both HRV and RHR stayed pretty consistent during the study, which can be a good sign, indicating you were coping with the training. Watch out for days with high fluctuations, which could be due to changing lifestyle (sleep schedule & duration, nutrition, alcohol, hydration, training, stress,...).

## Correlations

| Variable | HRV | RHR | DOMS | Fatigue | Sleep | Stress |
|---|---|---|---|---|---|---|
| HRV | 1,00 | | | | | |
| RHR | -0,63 | 1,00 | | | | |
| DOMS | -0,35 | 0,43 | 1,00 | | | |
| Fatigue | -0,49 | 0,53 | 0,30 | 1,00 | | |
| Sleep | -0,26 | -0,03 | -0,28 | -0,11 | 1,00 | |
| Stress | -0,56 | 0,32 | -0,02 | 0,52 | 0,30 | 1,00 |

The table shows the correlations between all the variables recorded every morning during the study, including HRV, RHR, sleep quality, stress, fatigue and muscle soreness (DOMS).
A few observations:
· The higher the HRV, the lower the RHR
· The higher the HRV, the more DOMS, fatigue & stress
· The higher the HRV, the worse sleep (interesting..)
· The more stress, the more fatigue

Thank you so much for your participation in this study!!

**Questions? Comments? Contant via email: carla.alfonso@uab.cat**
**or Instagram: @carlaalfonso**

## Annex 6. Article 3 – Feedback from participants

At the end of Article 3, several participants provided feedback regarding the intervention and their experience with the application used. Some anonymous examples of this feedback are presented below, classified by topic.

**Regarding participation in the study and results:**

*"I would be really interested to read the Study when you have completed it please. I have really enjoyed being part of the Study and would like to thank you for your patience, support and understanding."*

"*Hi Carla*
*Just had to let you know I had a terrific summer of riding, I give you and the HRV guided training much credit for this.*
*Highlight of the summer was taking 2ed place silver in the Calgary 2023 Stampede Road Race Rodeo and Provincial Masters Championships. The interesting things I learned,  I did not win gold this day but the following day I did a 15 Kms ITT followed by another 45 Kms road race winning both, I was able to distance my competitors,*
*I credit this to your progressive training, I was better able to recover then the completion.*"

*"Thank you very much, I'll use the program also after conclusion of the 30 days of study. I'm curious to see what happens when stars the race season"*

"*I was able to complete (the tests), certainly better than I did them back at the end of December. There were generally  improvements in my wattage numbers.* "

**Regarding the app and/or program:**

"*In respect of app feedback I think an integration with HRV4T would save time but if that's not possible then I personally think that options for inputting Health Status and Alcohol Consumption are very important.*"

"*The use of the app was generally OK, but it was confusing at first that the workouts in the app were different than the ones I saw in Training Peaks. Also, the workouts assigned in the app didn't appear to consistently correlate to my sleep and HRV. I wondered if I was in a cohort where the workouts were randomly assigned as a control group, rather than assigned based upon the HRV/Sleep data?*"

**Regarding the interest but lack of understanding of HRV:**

"*I talked to several riding friends at a club meeting a few days ago. These are males 50 - 70 years old who are long time 'serious' cyclists. They all know about HRV - using Whoop or Garmin devices. But they don't seem to understand what a baseline, High or low HRV means. They see changes in HRV only due to how hard or easy they trained the day before - ignoring sleep, stress, alcohol and diet factors. I found that drinking two large cups of coffee in the morning- before the HRV measurement - influences the results.* "

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