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Applications of Heart Rate Variability in Monitoring Training Load and Recovery: Theoretical Foundations and Practical Implications

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Abstract: Training load–recovery management aims to dynamically align external stimuli with an athlete's adaptive capacity, yet conventional monitoring approaches remain constrained by inter-individual variability, contextual confounding, and limited comparability across time scales. Heart rate variability (HRV), conceptualized as a time-series phenotype of sinus RR-interval fluctuations, can provide a longitudinal reference of cardiac autonomic modulation—particularly vagally mediated modulation—under standardized resting conditions, thereby complementing the internal load–recovery monitoring chain. This review synthesizes the theoretical foundations, interpretive frameworks, and applied evidence of HRV in sport sciences. Mechanistically, we outline how autonomic regulation contributes to exercise stress and post-exercise re-equilibration, and we delineate the physiological meaning and inferential boundaries of time-domain, frequency-domain, and non-linear HRV indices across relevant time scales. From an applied perspective, we summarize characteristic HRV responses to acute training stimuli and to accumulated load, and we discuss sources of consistency and heterogeneity across sports and populations in fatigue identification and training adaptation assessment. We further appraise HRV-informed prescription strategies that operationalize threshold-based decision rules (e.g., rolling estimates and smallest worthwhile change logic), suggesting that their practical value may lie more in managing unnecessary high-intensity exposure than in producing uniform performance gains, which often appear modest and context-dependent. Finally, we emphasize that the interpretability of HRV is contingent on measurement windows, posture/respiration control, and artifact processing, and we caution against mechanistic overreach of spectral ratios (notably LF/HF). We propose an implementation-oriented framework centered on standardized acquisition, individualized baseline modeling, and multimodal integration with external load and subjective recovery measures to enhance auditability and translational utility in training governance.

Keywords: Heart Rate Variability; Training Load; Recovery Monitoring; Autonomic Modulation.

1. Introduction

When training stimuli continue to accumulate under the combined pressure of dense competition schedules and periodized training cycles, while recovery windows are progressively compressed, an athlete's functional state may shift from short-term functional overreaching toward non-functional overreaching, with extreme cases ultimately developing into overtraining syndrome. In the joint ECSS/ACSM consensus statement, Meeusen et al. anchored the key diagnostic criteria of these functional states to the duration of performance decrement, the presence of accompanying psycho-physiological symptoms, and the time required for recovery, thereby underscoring that training prescription must be bounded by the sufficiency of recovery[1]. Consistent with this theoretical framework, epidemiological surveillance from large multi-sport events has repeatedly indicated that the health burden among athletes is not marginal. Data from the injury and illness surveillance report of the Tokyo Olympic Games revealed that a substantial proportion of athletes experienced injury or illness outcomes during the competition period[2]. Against this background, the objective of training monitoring should extend beyond the documentation of training volume and instead serve the dynamic calibration of individual dose–response relationships. Studies by Soligard and Bourdon et al. converge on the view that the central challenge of training monitoring lies in capturing inter-individual heterogeneity in dose–response relationships and translating such information into actionable load-adjustment strategies at the individual level [3, 4]. However, monitoring approaches that dominate current practice often exhibit an inherent tension between accessibility and physiological specificity: traditional indicators tend to be effective in describing what training has been performed, yet are frequently insufficient for delineating how the organism is regulated and when a recoverable and trainable window emerges. It is precisely within this gap that heart rate variability (HRV) has been brought to the forefront of discussions on training load and recovery monitoring. Accordingly, the present review situates HRV back within the load–recovery monitoring framework, focusing on its theoretical foundations, methodological constraints, and decision-making value in practice, while offering testable explanatory pathways for the sources of ongoing debate.

2. Theoretical Foundations of Heart Rate Variability

2.1. Autonomic Regulation During Exercise Stress and Recovery

During dynamic exercise, heart rate regulation does not operate as a simple binary switch of "sympathetic activation–

vagal withdrawal." Instead, with progressive increases in exercise intensity, vagal withdrawal, sympathetic drive, and the resetting of arterial baroreflex sensitivity jointly shape the temporal structure of sinoatrial node firing. By integrating evidence from pharmacological blockade and baroreflex manipulation, White et al. emphasized that parasympathetic influence remains functionally present throughout exercise, although its relative contribution diminishes as external load increases [5]. Fisher further identified the combination of central command and afferent input from skeletal muscle mechanoreceptors and metaboreceptors as critical pathways suppressing cardiac vagal outflow and elevating heart rate, thereby mechanistically linking autonomic modulation to the metabolic demands of the working musculature [6]. Following the cessation of exercise, the early phase of heart rate recovery is predominantly governed by vagal reactivation. Using post-exercise heart rate decay kinetics, Imai et al. demonstrated that training status and pathological conditions can be clearly differentiated by the rate of vagally mediated recovery[7].Michael et al. conceptualized this process as an autonomic rebalancing at the exercise–recovery transition, noting that both exercise intensity and duration systematically alter the trajectory of vagal reactivation[8]. Accordingly, autonomic regulation provides a traceable physiological entry point for understanding inter-individual differences in the sequence from stress exposure to recovery quality and adaptive outcome. However, this regulatory signal is inherently time-scale dependent and context sensitive, and therefore cannot be interpreted in isolation from the underlying load structure.

2.2. Heart Rate Variability as an Indirect Marker of Autonomic Regulation

Heart rate variability (HRV) is fundamentally a statistical and dynamical phenotype of the RR-interval time series. It reflects the final output of sinoatrial node modulation arising from the integrated influences of sympathetic activity, vagal activity, and baroreflex control, yet it is not equivalent to neural firing per se. In their standardization document, Malik et al. delineated the measurement domains, spectral partitioning, and physiological interpretive boundaries of HRV, while explicitly noting that variations in recording duration and analytical approaches alter the physiological time scales represented by specific indices [9]. Within the framework of cardiac vagal control, Laborde et al. proposed an operationalized pathway for the concept of vagally mediated HRV, more robustly positioning short-term RMSSD and HF power as indirect markers of parasympathetic modulation, and identifying posture, respiration, circadian timing, and artifact correction as prerequisite conditions for valid interpretation [10]. In contrast, Billman explicitly challenged the use of the LF/HF ratio as a quantitative surrogate of sympatho–vagal balance, arguing that frequency-domain indices, when treated as a unidimensional scale of sympathetic dominance, are prone to mechanistic misinterpretation [11]. Accordingly, within the context of training monitoring, HRV is better conceptualized as a low-invasive readout of cardiac autonomic modulation, whose utility depends on measurement standardization and longitudinal reference frameworks (e.g., individualized baselines and trends), rather than on isolated cross-sectional comparisons.

2.3. Physiological Meaning and Interpretive Frameworks of Different HRV Indices

Different transformations applied to the same RR-interval series yield distinct interpretive units: time-domain indices emphasize the magnitude of beat-to-beat variability, frequency-domain indices quantify the distribution of signal power across predefined bandwidths, whereas non-linear metrics aim to characterize scale invariance and system complexity within autonomic regulation. Shaffer et al. organized commonly used HRV metrics according to the correspondence between recording length, index families, and physiological interpretation, underscoring that short-term recordings and 24-h recordings do not share a common semantic framework for interpretation[12]. Building on developments that followed the 1996 standardization document, Sassi et al. further emphasized in a joint position statement that methodological comparability and algorithmic consistency of emerging approaches should take precedence over indiscriminate expansion of metric inventories[13]. Accordingly, the present review adopts a hierarchical approach to HRV interpretation: first, the recording duration and measurement context (e.g., resting, post-exercise, nocturnal) are explicitly defined; second, the index family most appropriate to the research question is selected; finally, observed changes are mapped back to plausible regulatory pathways while accounting for potential confounding sources.

2.3.1. Time-Domain Indices

Malik et al. classified RMSSD and pNN50 within the family of indices derived from successive RR differences. Under short-term resting conditions, these metrics tend to align more closely with the expression end of parasympathetic modulation[9]. Shaffer et al. further noted that RMSSD, owing to its heightened sensitivity to short-term high-frequency fluctuations, has become one of the most frequently adopted readouts of short-term, vagally mediated HRV in exercise and health research[12]. In contrast, SDNN carries a clearer interpretation of overall variability in 24-h recordings, whereas in short-term recordings it often aggregates variability arising from multiple time scales. Accordingly, when the research objective is daily recovery monitoring under training load, RMSSD (and its logarithmic transformation) is more consistent with a short-term, repeatable, and vagally related methodological positioning, whereas SDNN is better interpreted within long-duration recording frameworks.

2.3.2. Frequency-Domain Indices

Malik et al. linked high-frequency (HF; ~0.15–0.40 Hz) power more directly to respiratory sinus arrhythmia, such that HF is commonly used as a frequency-domain representation of parasympathetic modulation when breathing frequency remains relatively stable[9]. However, interpretive pitfalls are particularly pronounced in the frequency domain. Billman emphasized that the LF component cannot be reduced to a mirror of sympathetic outflow, nor should the LF/HF ratio be directly equated with an index of "sympatho–vagal balance[11].In response, Laborde et al. identified respiratory control and reporting standards as non-negotiable prerequisites for frequency-domain analyses, in order to exclude the possibility that shifts in breathing strategy—rather than changes in neural regulation—drive observed HF variations [10]. Consequently, frequency-domain indices are more appropriately positioned as complementary evidence in mechanistic discussions under tightly controlled methodological conditions. In ecologically valid training-monitoring settings, where respiratory and postural control are often lacking, conclusions drawn from frequency-domain metrics generally warrant more cautious interpretive language.

2.3.3. Non-linear Indices

Sassi et al. grouped detrended fluctuation analysis (DFA), entropy-based measures, and Poincaré plot descriptors within a toolkit that extends beyond linear statistics, with the central aim of capturing scale structure, unpredictability, and system complexity of autonomic regulation rather than mere changes in variability magnitude[13]. Non-linear indices are highly sensitive to data length, artifact correction, and algorithmic implementation, which increases the likelihood of "same-name, different-meaning" phenomena in cross-study comparisons. The Kubios HRV workflow described by Tarvainen et al. provides a more reproducible, engineering-oriented pathway for artifact identification, filtering, and multi-metric computation, thereby reducing avoidable variability along the analytical pipeline[14]. Accordingly, in training-monitoring applications, non-linear indices function more plausibly as supplementary dimensions when amplitude- or spectrum-based interpretations are constrained. Their added value typically depends on rigorous preprocessing and clearly specified physiological hypotheses, rather than on treating complexity metrics as universal probes of fatigue.

3. Applications of Heart Rate Variability in Training Load Monitoring

3.1. HRV Responses to Acute Training Load

Perturbations of HRV induced by acute training load are primarily manifested as alterations in the time course of vagal reactivation and in next-day resting vagal modulation. However, the sensitivity of these changes to "load dose" is jointly constrained by the exercise intensity domain and the measurement window. Existing evidence indicates that exercise performed within lower intensity domains is associated with relatively limited short-term autonomic disturbance, whereas high-intensity stimuli are more likely to delay recovery. This pattern suggests that intensity domain, rather than duration alone, functions as a more salient stratifying factor of acute autonomic stress[15]. From a complementary perspective, Stanley et al. interpreted cardiac vagal reactivation as an observable facet of a broader, multi-system recovery process, emphasizing that its temporal profile does not necessarily align with the recovery of energy substrates or neuromuscular function. In other words, directly equating post-session or post-competition reductions in HRV with a state of "global non-recovery" is not well supported by current evidence[16]. Accordingly, at the acute level, HRV is better positioned as a temporal gauge of autonomic recovery dynamics, whose interpretation should be explicitly bound to intensity domain and sampling window, rather than treated as a unidimensional diagnostic signal of fatigue.

3.2. Dynamic HRV Changes Under Accumulated Training Load

As training load evolves from isolated sessions into microcycle- and mesocycle-level accumulation, the actionable information contained in HRV more commonly resides in time-series structure rather than in single-point values. Such features include baseline drift, rolling averages, and structural changes in intra- and inter-day variability amplitude. In a case-comparison study of elite triathletes, Plews et al. shifted the analytical focus from the absolute level of lnRMSSD to the "variation of variability" (e.g., fluctuation magnitude), proposing that during training progression, the mean level of vagal modulation and its variability structure may convey distinct adaptive meanings[17]. Converging evidence comes from an 11-week longitudinal monitoring study in youth swimmers by Kamandulis et al., who observed that when training volume was persistently elevated across several days, resting HRV tended to exhibit a coherent downward shift, whereas day-to-day correlations with the immediate training load were not consistently tight. This pattern implies that HRV behaves more like a low-frequency integrator of accumulated stress rather than a high-resolution responder to daily load fluctuations [18]. Therefore, at the level of accumulated load, the primary utility of HRV lies not in tracking single-day rises or drops, but in identifying baseline migration and restructuring of variability on rolling time scales, interpreted within the context of periodized training design.

3.3. HRV in Fatigue Identification and Training Adaptation Assessment

The concept of "fatigue identification" is particularly prone to semantic conflation: functional overreaching, non-functional overreaching, sleep restriction, and travel-related stress may all cast similar signatures on HRV. A more defensible strategy is therefore to position HRV as an indicator of adaptation risk rather than as a categorical fatigue label. In a load–unload intervention involving collegiate sprint swimmers, Flatt et al. concurrently tracked HRV and psychometric responses, demonstrating that HRV exhibited systematic phase-dependent changes across training stages. Importantly, these changes frequently co-occurred with subjective fatigue and affective states, supporting the practical view that HRV is best integrated into a multi-source evidentiary framework[19]. Randomized evidence provides more direct support when HRV is elevated from monitoring to prescription-level decision-making. Kiviniemi et al. reported that using morning HRV to guide daily allocation of high- versus low-intensity sessions favored certain performance outcomes in the HRV-guided group[20]. Building on a threshold-based logic, Vesterinen et al. implemented HRV-triggered adjustments using the smallest worthwhile change criterion, observing that individualized strategies may reduce unnecessary high-intensity exposure under insufficient recovery while yielding modest performance advantages[21]. Across these two randomized controlled trials, conducted in different populations and training structures, morning HRV–informed intensity distribution appeared feasible; however, effect magnitude and external generalizability remained constrained by intervention duration and the specific measurement–threshold strategies employed. Consistent with this interpretation, a subsequent systematic review and meta-analysis likewise suggested a small advantage of HRV-guided endurance training over predefined programs, while emphasizing that the magnitude of benefit was limited and sensitive to methodological heterogeneity[22]. Taken together, the principal strength of HRV in fatigue and adaptation assessment does not lie in delivering definitive diagnoses, but in providing quantifiable trajectories of autonomic modulation to inform training prescription and recovery management—provided that HRV is embedded within a multi-indicator decision framework and its limited specificity is explicitly acknowledged. It should also be noted that, within the training-load context, HRV primarily serves as a monitor of the internal response to external load exposure. When the analytical focus shifts toward recovery processes, the central question correspondingly moves from whether deviation has occurred to how recovery unfolds: namely, the time constants of HRV deviation, the stability conditions of return trajectories, and whether these temporal characteristics can offer actionable reference points for the re-establishment of trainable windows.

4. Applications of Heart Rate Variability in Recovery Assessment

4.1. Temporal Characteristics of HRV During Post-exercise Recovery

Following the cessation of exercise, RR-interval fluctuations do not return to baseline through a linear process. Instead, recovery is better described as a time-dependent dynamic dominated by parasympathetic reactivation after vagal withdrawal, while being concurrently shaped by metaboreflex input, arterial baroreflex modulation, and humoral influences. Using intensity- and duration-manipulated protocols in highly trained endurance runners, Seiler et al. demonstrated that exercise intensity exerts a more pronounced delaying effect on autonomic rebalancing, and quantified delayed HRV recovery trajectories through continuous follow-up extending to four hours post-exercise[15]. In addition, Kaikkonen et al. employed short-time Fourier transformation to characterize frequency-domain recovery over the initial 5–30 min post-exercise, showing that higher-intensity or more continuous exposure was accompanied by lower HRV during recovery. These findings indirectly highlight that RR series in the early post-exercise phase are highly non-stationary; applying the stationarity assumptions of resting 5-min HRV analyses to this period substantially increases interpretive risk[23]. Accordingly, recovery-phase HRV is more appropriately interpreted as a set of time-dependent reactivation dynamics rather than being compressed into single time-point judgments. When recording window, posture, and signal stationarity are not tightly constrained, inferences about “good” or “poor” recovery are readily confounded by methodological noise.

4.2. Resting HRV and the Assessment of Recovery Status

When recovery monitoring is translated into daily practice, attention typically shifts toward short-term resting HRV recorded in the morning. The primary objective of this approach is not to pursue increasingly complex metrics, but to exploit the repeatability of vagally related components in order to establish individualized baselines. In discussions of training-status monitoring, Buchheit emphasized that vagally mediated indices derived from near-daily 5-min resting recordings offer greater practical utility, provided that their interpretation is embedded within frameworks accounting for measurement error and the smallest worthwhile change. Without such constraints, contextual variation inherent to training environments may be misinterpreted as physiological change[24]. In elite endurance populations, reductions in resting heart rate are not necessarily accompanied by increases in HRV. Thus, directly equating HRV elevations or depressions with “better adaptation” or “poorer recovery,” respectively, is not robust. Rolling averages and related smoothing approaches more closely align with the objectives of longitudinal monitoring[17, 25]. Systematic reviews and meta-analyses further indicate that vagally mediated HRV indices assessed at rest or during recovery do exhibit sensitivity, yet both the direction and magnitude of effects vary across studies. A substantial proportion of this inconsistency can be traced to heterogeneity in measurement protocols and interpretive strategies[26]. Therefore, for resting HRV to function as a meaningful recovery phenotype, it must be constrained by standardized measurement conditions and individualized thresholds; otherwise, it more likely reflects a composite response to sleep disruption, emotional load, dehydration, and training stress rather than a specific signal of training recovery.

4.3. Prospects for HRV in Individualized Recovery Monitoring

The central challenge of individualized recovery monitoring lies not in whether HRV can be measured, but in how HRV can be translated into auditable decision rules. Sampling quality, artifact correction, temporal windows, and condition control constitute the foundation of HRV’s physiological interpretability, and these measurement and interpretive standards continue to represent baseline consensus within the field [9]. In parallel, Laborde et al. systematized posture, respiration, temporal structure, and reporting conventions from the perspectives of experimental design and data processing, providing the methodological prerequisites for HRV to function as a comparable indicator across contexts[10]. Within the evidence chain supporting HRV-informed training and recovery decisions, a systematic review and meta-analysis by Düking et al. showed that HRV-guided endurance training programs tend to reduce the frequency of moderate-to-high-intensity training sessions. Their effects were more pronounced for submaximal physiological outcomes, whereas performance advantages were generally small and statistically unstable. This pattern favors an interpretation centered on reducing unnecessary exposure and improving responder proportion, rather than guaranteeing uniform performance gains [22]. From a sensor-validation perspective, Hernando et al. demonstrated the feasibility of HRV metrics derived from the Apple Watch under controlled resting and psychological stress conditions; however, such evidence does not automatically generalize to training environments characterized by high motion artifact and frequent postural transitions[27]. Taken together, individualized recovery monitoring based on HRV is more likely to converge toward a composite paradigm integrating standardized acquisition, error- and threshold-based decision frameworks, and multimodal evidence fusion (e.g., training logs, subjective scales, and simple performance tests). Within this paradigm, HRV can function as a central decision node, but it is unlikely to independently bear the full informational load required for recovery prescription.

5. Training Adjustment and Practical Implications Based on Heart Rate Variability

5.1. HRV-Informed Approaches to Training Load Adjustment

When training adjustments rely solely on external load metrics (e.g., distance, power output, pace) or on a single subjective scale, the same stimulus is often implicitly treated as imposing the same physiological cost across individuals. Under high-load microcycles, this assumption can amplify inter-individual differences and accelerate the accumulation of non-functional stress. Accordingly, the training-load consensus articulated by Bourdon et al. identified multimodal integration of internal load and recovery phenotypes as a necessary prerequisite for effective monitoring and adjustment [3]. Within HRV-mediated training adjustment, Flatt et al. demonstrated that evidence supporting the stabilization of ECG-derived lnRMSSD allows for abbreviated acquisition protocols, thereby reducing long-term compliance burden and providing a methodological foothold for field-based monitoring[28]. At the level of data interpretation, Vesterinen et al. embedded the concept of the smallest worthwhile change (SWC) into training prescription, emphasizing threshold-based logic to determine whether high-intensity sessions should proceed or be postponed, rather than reacting mechanically to single-day fluctuations [21]. A more robust strategy therefore typically involves characterizing slow-moving variables—such as adaptation and accumulated fatigue—via rolling means or coefficients of variation, integrating deviation magnitude with day-specific contextual factors (e.g., sleep, travel, inflammatory symptoms, psychological stress), and ultimately directing adjustments toward rebalancing intensity distribution and high-intensity exposure dose rather than indiscriminately reducing training volume. This approach resonates with Buchheit's observation that many apparent contradictions in heart-rate–based monitoring stem from insufficient statistical treatment and contextual control rather than from true physiological discordance [24].

5.2. Value of HRV in Individualized Training Monitoring

The value of HRV does not lie in reducing autonomic regulation to a single numerical score, but in translating individual recovery trajectories into trackable time series that provide an intra-individual reference frame for load–response relationships. Although HRV and vagally mediated indices are sensitive to both training adaptation and maladaptation, the direction and magnitude of their responses are highly heterogeneous across sports, load structures, and measurement paradigms—an observation that inherently favors individualized over group-level inference [26]. Within the evidence base for using HRV as a prescription signal, the randomized controlled trial by Kiviniemi et al. directly applied morning HRV to daily intensity allocation and showed advantages for the HRV-guided group in selected fitness and performance outcomes[21]. A subsequent meta-analysis by Düking et al. examining HRV-guided endurance training found that, compared with predefined programs, HRV-guided approaches were generally associated with fewer moderate- to high-intensity sessions. While the overall statistical evidence for performance enhancement was weak, more favorable signals emerged for submaximal physiological outcomes and reductions in the proportion of non-responders[22]. Collectively, these findings suggest that HRV is better positioned as a regulatory variable for individualized management of intensity exposure—aimed at mitigating unnecessary accumulation of high-intensity stress—rather than as a deterministic predictor of competitive performance.

5.3. Common Pitfalls and Practical Considerations in HRV Application

The most prevalent theoretical misapplication arises from overinterpretation of frequency-domain indices. Billman explicitly refuted the inferential chain that treats the LF/HF ratio as a proxy for sympatho–vagal balance, noting that continued use of LF/HF as a decision signal in training monitoring risks misattributing methodological noise to physiological mechanism shifts[11]. In field practice, another common issue is excessive sensitivity to single-day deviations, whereby any abnormal value is interpreted as a mandate to reduce training load. Plews et al. emphasized that both increases and decreases in HRV may occur under maladaptive conditions; without parallel information on load structure and subjective recovery, unidirectional interpretations substantially elevate the risk of misclassification[25]. Finally, although mobile and wearable technologies have lowered barriers to data acquisition, they have simultaneously introduced greater heterogeneity in signal quality. Hernando et al. validated the feasibility of Apple Watch–derived HRV under relaxed and psychologically stressful conditions in healthy individuals, providing evidence for usability, yet such findings do not automatically generalize to post-exercise contexts characterized by pronounced motion artifact or fluctuations in skin perfusion[27]. Accordingly, the practical boundary of HRV application can be delineated as follows: within strictly standardized resting windows, individualized thresholds and rolling statistics should be used to extract interpretable autonomic modulation drift, and training adjustments should be directed toward redistributing intensity exposure and recovery resources rather than toward indiscriminate load reduction.

6. Conclusion

Within the applied chain of training load and recovery monitoring, the interpretability of HRV is governed primarily by acquisition context and preprocessing procedures, rather than being inherently conferred by the label of a given metric. The same nominal index may correspond to distinct physiological time scales and regulatory sources when recording duration, posture, breathing pattern, or artifact-correction strategy varies. Only when the resting window is rigorously standardized, posture and respiratory conditions are tightly controlled, and consistent quality-control procedures are applied to missed beats, ectopic beats, and motion-related artifacts in the RR series does HRV attain validity for longitudinal comparison as an intra-individual trajectory of vagally related modulation.

Conversely, directly extrapolating spectral ratios to a putative index of sympatho–vagal "balance" risks compressing multi-determined spectral components into a unidimensional mechanistic interpretation, thereby amplifying conceptual error at the level of training decision-making. Accordingly, HRV is more appropriately positioned as a longitudinal monitoring signal obtained under standardized resting conditions, capable of characterizing baseline drift and meaningful deviation in autonomic modulation to inform the management of high-intensity training exposure and the allocation of recovery resources. Importantly, the scope of inference and the decision thresholds derived from HRV should be explicitly specified in advance within monitoring protocols.

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