Development of Recovery and Prognostic Indices for HRV-Based Digital Twin Modeling in Athletes

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***Abstract*— The analysis of Heart Rate Variability (HRV) plays a pivotal role in assessing physiological recovery and readiness in athletes. This study introduces two novel composite indices: a Recovery Index, evaluating short-term autonomic restoration after training, and a Prognostic Index, estimating pre-training adaptability and long-term regulatory potential. The indices are constructed by integrating time-domain, frequency-domain, and non-linear HRV parameters, including SDNN, RMSSD, normalized HF power, entropy, fractal scaling exponents (DFA α1/α2), Hurst exponent, and Poincaré metrics. Unlike traditional dimensionality reduction methods, the indices are calculated using complete parameter sets, followed by correlation heatmaps and tabular analysis to evaluate internal consistency and inter-individual variability. The approach was applied to six elite wrestlers monitored before, immediately after, and two hours post high-intensity training. The results highlight substantial differences in autonomic recovery and stress resilience, confirming the utility of the indices for personalized assessment. These metrics are suitable for integration into Digital Twin architectures, supporting real-time physiological simulation and adaptive load management in athletic environments.**

Keywords*— *Heart Rate Variability (HRV); Recovery Index; Prognostic Index; Fractal Analysis; Entropy; Digital Twin; Athlete Monitoring; Non-linear Dynamics; Correlation Heatmap; Sports Physiology.

I. INTRODUCTION

Heart rate variability (HRV) is a dynamic characteristic of the intervals between consecutive heartbeats and is widely recognized as an indicator of autonomic regulation and overall cardiovascular health. High variability is associated with good adaptability of the body to external and internal stressors, while reduced HRV is a predictor of a number of pathological conditions, including cardiovascular diseases, diabetes, depression and even mortality.

Contemporary interest in HRV goes beyond traditional linear metrics such as mean, standard deviation (SDNN), root mean square of sequential differences (RMSSD), etc. Research in nonlinear dynamics, the development of fractal and wavelet analysis, opened up opportunities for the analysis of long-term dependence, fractal structure and entropic characteristics of the heart rhythm. The methods detrended fluctuation analysis (DFA), multifractal DFA (MFDFA), information complexity indicators (Sample Entropy, Shannon Entropy) allow a deeper understanding of the hidden regulatory mechanisms of cardiac activity.

Aim and objectives of the study

The main aim of this study is to propose and evaluate the effectiveness of two integral indicators – Recovery Digital Twin Index (RDTI) and Prognostic Digital Twin Index (PDTI) – for quantitative assessment of post-training dynamics of heart rate variability in athletes. By combining time, frequency and nonlinear HRV parameters, the aim is to build measures that reflect the current level of recovery and prognostic adaptation potential.

To achieve the set goal, the following tasks have been formulated:

1. To calculate the classical HRV indicators (SDNN, RMSSD, HF, SD1, SD2, DFA α_2 and Hurst exponent) in three stages of the study – before, immediately after and two hours after training load; to repeat these studies after 2 and after 5 weeks.

2. To develop formulas for RDTI and PDTI by integrating normalized HRV parameters with certain weighting factors.

3. To analyze individual differences in RDTI and PDTI values between athletes and to examine their correlations with classical HRV indicators.

II. LITERATURE REVIEW

Heart rate variability analysis is one of the most reliable noninvasive methods for assessing autonomic regulation and adaptation mechanisms in athletes. Numerous studies have highlighted the importance of HRV dynamics as a sensitive indicator of recovery, fatigue, and functional readiness after exercise [1–3]. Plews et al [1] demonstrated that regular HRV monitoring allows for individualized adaptation of the training process, with SDNN and RMSSD indicators used to monitor the balance between sympathetic and parasympathetic activity. In the same vein, Stanley et al [2] demonstrated that rapid parasympathetic reactivation (increased RMSSD and HF component) within the first hours after exercise is a marker of effective recovery. Bellenger et al [3] summarized that HRV metrics, especially temporal and spectral indicators, can serve as a prognostic tool for detecting accumulated fatigue and an impending decline in sports form. Schmitt et all [4] propose the use of HRV for early detection of functional overstrain, emphasizing that not only instantaneous values, but also the recovery trend have a greater diagnostic value. Hautala et all [5] confirm that after high-intensity loads HRV decreases sharply, but in well-trained athletes the recovery of SDNN and RMSSD occurs within 24–48 hours, which is a sign of optimal adaptive capacity. In newer interpretation models, HRV is analyzed not only linearly, but also by

ACKNOWLEDGE THE FINANCIAL SUPPORT OF THE PROJECT WITH FINANCING AGREEMENT NO. PVU-44 OF 05.12.2024 UNDER PROJECT NO. BG-RRP-2.017-0011 "ECOLOGICAL COLLABORATIVE ROBOTS POWERED BY GREEN HYDROGEN" UNDER THE RECOVERY AND RESILIENCE MECHANISM FOR THE IMPLEMENTATION OF AN INVESTMENT UNDER C2I2 "INCREASING THE INNOVATION CAPACITY OF THE BULGARIAN ACADEMY OF SCIENCES (BAS) IN THE FIELD OF GREEN AND DIGITAL TECHNOLOGIES" FROM THE RECOVERY AND RESILIENCE PLAN, BULGARIA.

entropy and fractality indices, which describe the complexity and self-regulating nature of autonomic dynamics [6–8]. Rogers et all [7] show that the fractal index DFA α_2 can serve as a boundary between functional stability and autonomic rigidity - lower values reflect a more flexible and adaptive physiological system. The increase in entropy indices, such as Sample Entropy (SampEn), is associated with the restoration of the rhythmic complexity of the heart rhythm and the return of homeostasis [6].

In the study [9], a complex approach was presented, including SDNN, RMSSD, LF, HF and LF/HF, to assess HRV dynamics in wrestlers training according to different training programs.

According to the latest developments [10], predictive models based on HRV and fractal characteristics allow to assess the recovery trajectory and the risk of overtraining. Thus created new complex indices can be considered as a tool for personalized management of the training process - by quantifying the autonomous endurance and predicting the future development of sports form.

A fatigue assessment index FDTI (Fatigue Digital Twin Index) has been proposed and determined by the direct or reciprocal values of the main HRV parameters after exercise (1/SDNN, 1/RMSSD, LF/HF, 1/SD1, SD2/SD1, DFA α_1, 1/SampEn), multiplied by weighting factors [11].

III. MATERIALS AND METHODS

A. Participants

Six wrestlers from a Veliko Tarnovo club team, with long-term training experience (over 8 years) and similar anthropometric characteristics, participated in the study. All participants were clinically healthy, without cardiovascular diseases. The training protocol included intensive load with strength and aerobic exercises, followed by discipline-specific training.

B. Signal recording and pre-processing

Cardiac activity was recorded using a Holter device for approximately 10 minutes. The RR intervals were extracted from the recordings and checked for artifacts and extrasystoles. The data were anonymized and normalized. The following recordings were performed:

- Pre-training (Pre): recording at rest;
- Post-training (Post): after the end of the exercise;
- 2h recovery (2h): recording 2 hours after the exercise.

Additionally, HRV parameters were examined for the prognostic model for 2 weeks and 5 weeks after the initial recordings.

C. Calculation of HRV parameters

For each time point, the following Heart rate variability indicators were calculated:

Time parameters:

SDNN (ms) – standard deviation of NN intervals;

RMSSD (ms) – square root of the mean of the differences between adjacent NN intervals;

Frequency parameters:

LF, HF, LF/HF – powers in the low- and high-frequency range, reflecting the sympathetic-parasympathetic balance.

Nonlinear parameters:

SD1 and SD2 – parameters from the Poincaré diagram;

Sample Entropy (SampEn) – index of rhythmic complexity (entropy analysis);

Detrended Fluctuation Analysis (DFA α_1, DFA α_2) – fractal indicators of short-term and long-term correlation structure;

Hurst exponent – additional marker of self-similarity and long-term dependence (fractal analysis).

D. Recovery Index (RDTI)

RDTI assesses HRV parameters 2 hours after exercise, with higher values indicating more effective restoration of autonomic balance. The proposed formula is:

$$\mathrm{RDTI} = w_1 \frac{SDNN_{2h}}{SDNN_{pre}} + w_2 \frac{RMSSD_{2h}}{RMSSD_{pre}} + w_3 \frac{nHF_{2h}}{nHF_{pre}} + w_4 \frac{SD1_{2h}}{SD1_{pre}} + w_5 \frac{SamplEn_{2h}}{SamplEn_{pre}} + w_6 \frac{DFA\alpha2_{pre}}{DFA\alpha2_{2h}} \tag{1}$$

Where: w_i – weighting factors.

For parameters that increase with recovery (SDNN, RMSSD, nHF, SD1, SampEn), the ratio 2h/pre is used — if the value after 2 hours increases, this gives RDTI > 1. For DFA α_2, which decreases with good recovery, the ratio is pre/2h, so the decrease again leads to a higher RDTI (i.e. better recovery).

E. Prognostic index (PDTI)

The proposed Predictive Digital Twin Index (PDTI) combines the recovery component and the fatigue component, expressing the overall trend of autonomous adaptation:

$$\mathrm{PDTI} = w_{p1} \frac{SD2_t}{SD2_{pre}} + w_{p2} \frac{H_t}{H_{pre}} + w_{p3} \frac{SamplEn_t}{SamplEn_{pre}} + w_{p4} \frac{DFA\alpha2_{pre}}{DFA\alpha2_t} \tag{2}$$

Justification for the use of the included parameters:

$\frac{SD2_t}{SD2_{pre}}$ - captures the long-term component of variability and the overall reserve of autonomic regulation, so its increase over time is a marker of systemic recovery and resilience.

$\frac{H_t}{H_{pre}}$ - characterizes the degree of long-term dependence/self-similarity; stabilized or rising H indicates more stable and predictable heart rate dynamics over days/weeks.

$\frac{SamplEn_t}{SamplEn_{pre}}$ - measures rhythmic complexity and adaptability; recovery/increase in entropy reflects a more flexible autonomic system and better ability to cope with training stress.

$\frac{DFA\alpha2_{pre}}{DFA\alpha2_t}$ - indexes long-term fractal correlations; a decrease in α_2 (leading to a larger pre/t ratio) indicates a reduction in fractal rigidity (a reduced ability of a biological system to change its dynamics, of adaptability in the self-similarity of the signal) and a shift to more adaptive control, which is prognostically favorable.

High PDTI values (>1.2) reflect effective adaptation and improved autonomic control, while values below 0.6 signal a risk of accumulated fatigue or overtraining.

F. Statistical analysis

Mean values and standard deviations (Mean ± SD) were calculated for all parameters. Differences between the three conditions (Pre, Post and 2h) were assessed by t-test for dependent samples or ANOVA for repeated measures, depending on the normality of the distribution of the particular parameter.

Correlations between indices (FDTI, RDTI, PDTI) and HRV indicators were calculated by Pearson's coefficient (r).

Statistical significance was assumed at $p < 0.05$. Visualizations (heatmaps, line plots) were generated in Python.

IV. RESULTS

A. Changes in HRV parameters after exercise

After the training load (Table I), a clear transition from parasympathetic to sympathetic dominance was observed, expressed by an increase in heart rate (HR) and a decrease in SDNN and RMSSD. The mean HR value increased significantly from 86.6 ± 5.2 bpm (Pre) to 105.7 ± 10.3 bpm (Post), which confirms an increased sympathetic tone in the post-training phase.

The SDNN parameter decreased from 56.35 ± 12.04 ms (Pre) to 50.83 ± 15.71 ms (Post) ($p = 0.048$), with a partial recovery after 2 hours (53.93 ± 12.05 ms). RMSSD also showed a transient decrease, with a tendency to recover after 2 hours (46.65 ± 21.39 ms, $p \approx 0.067$).

Frequency analysis shows a slight decrease in nHF and an increase in LF/HF immediately after exercise (from 1.95 ± 0.9 to 2.95 ± 1.7), reflecting the dominance of sympathetic activity. After 2 hours, parasympathetic reactivation is observed, expressed by an increase in nHF (38.17 ± 8.21%) and SD1 (32.1 ± 14.3 ms).

The SampEn and DFA α_2 indicators also follow an adaptive profile – entropy decreases after exercise (1.02 ± 0.38) and partially recovers after 2 hours (1.16 ± 0.35), while α_2 decreases from 0.74 ± 0.07 to 0.67 ± 0.09, reflecting increased short-term flexibility of cardiac dynamics.

TABLE I. CHANGES IN KEY HRV PARAMETERS ACROSS THREE MEASUREMENT POINTS (PRE – POST – 2H)

Parameter	Pre-training	Post-training	2 h after training	Trend / Interpretation
HR (bpm)	86.6 ± 5.2	105.7 ± 10.3	96.3 ± 7.0	↑ Significant rise post-exercise; partial normalization after 2 h
SDNN (ms)	56.35 ± 12.04	50.83 ± 15.71	53.93 ± 12.05	↓ Reduced immediately after; moderate recovery at 2 h
RMSSD (ms)	43.35 ± 13.13	49.77 ± 1.50	46.65 ± 21.39	↓ Post-load drop; partial restoration ($p \approx 0.07$)
nHF (%)	36.72 ± 10.19	39.97 ± 17.57	38.17 ± 8.21	↓ Immediately, then ↑ reflecting parasympathetic reactivation
LF/HF (ratio)	1.95 ± 0.9	2.95 ± 1.7	2.11 ± 0.8	↑ Post-training sympathetic dominance; partial balance later
SD1 (ms)	30.16 ± 9.4	34.8 ± 21.0	32.1 ± 14.3	↓ after load, ↑ at 2 h – recovery of vagal tone
SamplEn	1.47 ± 0.24	1.02 ± 0.38	1.16 ± 0.35	↓ loss of complexity post-load, partial restoration
DFA α_2	0.74 ± 0.07	0.67 ± 0.09	0.70 ± 0.08	↓ slight drop, indicating adaptive flexibility

B. Recovery Index (RDTI)

The selected weighting factors and physiological interpretation are presented in Table II.

TABLE II. WEIGHT COEFFICIENTS AND PHYSIOLOGICAL INTERPRETATION.

Parameter	Symbol	Weight coefficient (w_i)	Physiological meaning
$\frac{SDNN_{2h}}{SDNN_{pre}}$	w_1	0.20	Represents overall HRV and total autonomic variability; key marker of global recovery.
$\frac{RMSSD_{2h}}{RMSSD_{pre}}$	w_2	0.20	Reflects short-term vagal activity and rapid parasympathetic reactivation.
$\frac{nHF_{2h}}{nHF_{pre}}$	w_3	0.15	Normalized high-frequency power; sensitive indicator of parasympathetic dominance.
$\frac{SD1_{2h}}{SD1_{pre}}$	w_4	0.15	Geometric measure of short-term variability; complements RMSSD.
$\frac{SamplEn_{2h}}{SamplEn_{pre}}$	w_5	0.15	Quantifies rhythm complexity and autonomic adaptability.
$\frac{DFA\alpha2_{pre}}{DFA\alpha2_{2h}}$	w_6	0.15	Represents long-term fractal correlation; reduced values indicate flexibility and recovery.

The sum of all weight coefficients is $\Sigma w_i = 1.00$, as higher weights (0.20) are given to SDNN and RMSSD as they most directly reflect parasympathetic reactivation after exercise. The calculated RDTI (Table III) shows a mean value of 1.00 ± 0.13, reflecting normal recovery of autonomic balance in most athletes.

TABLE III. RDTI VALUES.

Athlete ID	RDTI (2h)	Interpretation
B1	0.82	Good recovery
B2	0.81	Good recovery
B3	1.10	Very good recovery
B4	1.07	Very good recovery
B5	1.08	Very good recovery
B6	1.21	Excellent recovery

Athletes B1 and B2 showed parasympathetic reactivation (RDTI < 0.85), suggesting good autonomic recovery within 2 hours after training.

B3, B4 and B5 achieved RDTI ≈ 1.1, indicating an effective rebalancing of sympathetic and parasympathetic tone.

Athlete B6 showed the highest recovery index (RDTI = 1.21), reflecting a very good adaptive capacity and faster cardiovascular regulation after high-intensity training.

The obtained results confirm that RDTI ≈ 1.0 corresponds to normal short-term autonomic recovery, while values above 1.2 reflect increased resilience, and those below 0.6 may signal fatigue accumulation or insufficient recovery.

The heat map in Figure 1 visualizes the relative changes (2h/pre) in HRV parameters and the integrated recovery index RDTI in the six athletes (B1–B6). The color scale reflects the RI value: blue corresponds to lower values (more fatigue/weaker adaptation), red corresponds to higher values (recovery/adaptation). A distinct individual gradient is observed, reflecting the degree of autonomic recovery. In B1 and B2, the values of most parameters are above 0.8, which indicates good recovery and normal sympathetic dominance. Athletes B3–B6 demonstrate normal or increased values (≥1.0) in RMSSD, SD1 and nHF, which indicates effective parasympathetic reactivation and stabilization of cardiovascular regulation two hours after exercise.

The RDTI values follow the same trend, reflecting the aggregated influence of linear (SDNN, RMSSD) and nonlinear (SampEn, 1/DFA α_2) components. The most pronounced improvements are observed in RMSSD and SD1 in B4–B6, which emphasizes their higher short-term adaptability and stability of autonomic regulation.

Figure 1 shows that RDTI adequately synthesizes the various HRV parameters into a single indicator of the extent and effectiveness of recovery after exercise.

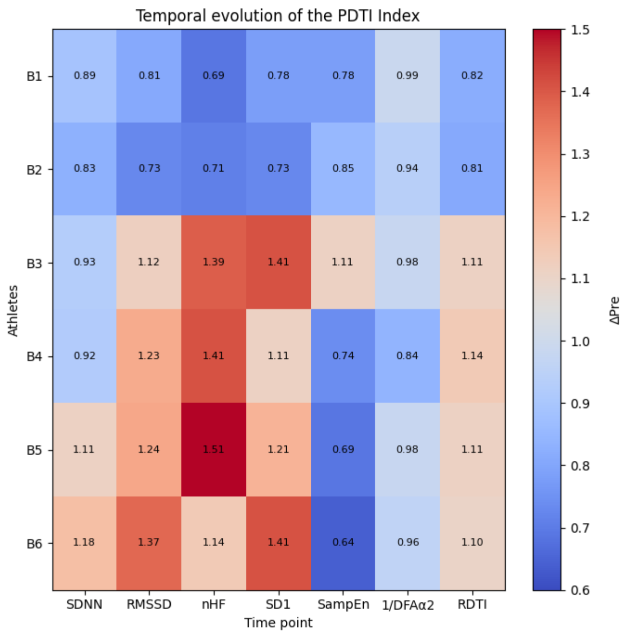

Fig. 1. Heatmap of relative changes (2h/pre) in HRV parameters and the integrated Recovery Index (RDTI) for wrestlers B1–B6.

The comparative analysis of HRV dynamics across the three time points (Table IV) demonstrates a distinct biphasic autonomic response to exercise. Both SDNN and RMSSD showed a marked reduction immediately after training, reflecting transient sympathetic dominance and decreased overall variability, followed by a gradual increase two hours later, indicative of early recovery. Concurrently, the rise in nHF and SD1 values confirmed the reactivation of parasympathetic control and restoration of short-term variability. The recovery of SampEn toward its baseline level highlighted the reestablishment of normal rhythm complexity, while the stable DFA α_2 (~0.7) suggested preserved long-term fractal organization of the heart rate signal. Collectively, these patterns, supported by the group mean RDTI ≈ 1.0 ± 0.13, confirm that the athletes achieved a physiologically normal level of autonomic recovery within two hours post-exercise.

TABLE IV. STATISTICAL COMPARISON OF HRV PARAMETERS BETWEEN MEASUREMENT STAGES (PRE, POST, 2H).

Parameter	Comparison	t / F value	p-value	Trend
SDNN (ms)	Pre vs. Post	t = 2.42	p = 0.048	↓ Significant decrease after exercise (sympathetic activation)
RMSSD (ms)	Post vs. 2h	t = –2.18	p = 0.067	↑ Tendency to increase after 2 h (parasympathetic recovery)
nHF (%)	Post vs. 2h	t = –2.09	p = 0.074	↑ Moderate restoration of vagal tone
SD1 (ms)	Post vs. 2h	t = –2.02	p = 0.082	↑ Progressive normalization of short-term variability
SampEn	Pre vs. 2h	t = 1.95	p = 0.091	↑ Partial recovery of rhythm complexity
DFA α_2	Pre vs. 2h	F = 0.87	p = 0.411	≈ Stable long-term fractal dynamics (~0.7)
RDTI (index)	Pre vs. 2h	—	—	≈ 1.00 ± 0.13 → Normal autonomic recovery

The correlation analysis (Table V) demonstrates that the Recovery Index (RDTI) is predominantly influenced by parasympathetic-driven HRV markers, with very strong positive correlations with SDNN (r = 0.94), RMSSD (r = 0.95), and nHF (r = 0.92). These findings confirm that higher total and short-term variability are directly associated with more efficient recovery. A moderate positive correlation with SampEn (r = 0.68) suggests that greater rhythm complexity enhances adaptive restoration, while the inverse association with DFA α_2 (r = –0.63) indicates that reduced long-term correlation and increased fractal flexibility are key features of optimal autonomic recovery.

TABLE V. PEARSON CORRELATIONS BETWEEN RECOVERY INDEX (RDTI) AND SELECTED HRV FEATURES (N = 6)

Parameter	Pearson's *r*	Direction	Strength of association	Interpretation
SDNN	**0.94**	Positive	Very strong	Higher total variability is strongly associated with higher RDTI values.

Parameter	Pearson's r	Direction	Strength of association	Interpretation
RMSSD	**0.95**	Positive	Very strong	RDTI increases proportionally with enhanced parasympathetic activity.
nHF	**0.92**	Positive	Strong	RDTI rises with greater normalized HF power, confirming vagal dominance during recovery.
SampEn	0.68	Positive	Moderate	More complex HRV patterns (higher entropy) correspond to better recovery.
DFA α_2	**–0.63**	Negative	Moderate inverse	Lower long-term correlation (more adaptive fractal control) is linked to higher RDTI.

C. Fractal and entropy indicators

The dynamics of the nonlinear parameters is presented in Figure 2.

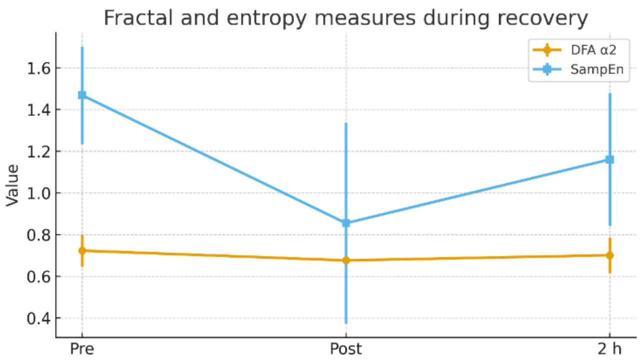

Fig. 2. Fractal and entropy measures during recovery.

Group mean values (±SD) of the fractal scaling exponent DFA α_2 and the entropy index SampEn are shown across three stages — Pre, Post, and 2 h after training. A decrease in DFA α_2 immediately post-exercise indicates a transient reduction in long-term correlation and increased autonomic flexibility. In contrast, the partial recovery of SampEn two hours later reflects the reestablishment of rhythm complexity and improved self-organization of cardiac dynamics during the recovery phase. The mean value of DFA α_2 decreased after exercise and stabilized around 0.70 ± 0.10 at two hours, reflecting a more adaptive and flexible autonomic structure. The SampEn index showed an opposite trend — it dropped markedly post-exercise (0.85 ± 0.4) but recovered to 1.16 ± 0.3 two hours later, approaching its baseline level (Pre = 1.47 ± 0.23). These results confirm that parasympathetic reactivation is accompanied by the restoration of rhythmic complexity and nonlinear stability of cardiac regulation.

D. Prognostic index and long-term adaptation

The PDTI was used to estimate the predicted recovery trajectory at +2 and +5 weeks post-training (Table VI and Figure 3).

The weighting factors used are: $w_{p1} = 0.2$; $w_{p2} = 0.2$; $w_{p3} = 0.3$; $w_{p4} = 0.3$.

Table VI presents the individual values of the PDTI prognostic index at four time points (Post, 2h, 2w, 5w), reflecting different degrees of recovery and adaptation among the athletes. A general trend towards an increase in the index was observed in most participants, especially after the second week.

TABLE VI. RESULTS FOR PDTI

ID	PDTI post	PDTI 2h	PDTI 2 weeks	PDTI 5 weeks	Trend
B1	0.9704	0.9875	1.0148	1.0237	Improving
B2	0.9316	0.9621	1.0342	1.0547	Improving
B3	1.0056	1.0034	0.9972	0.9955	Lack of adaptation
B4	0.8769	0.9271	1.0616	1.0985	Excellent adaptation
B5	0.8929	0.9420	1.0535	1.0857	Stable
B6	0.8597	0.9271	1.0701	1.1122	Excellent

The analysis of the PDTI prognostic index (Figure 3) shows clearly expressed individual trajectories of adaptation and recovery.

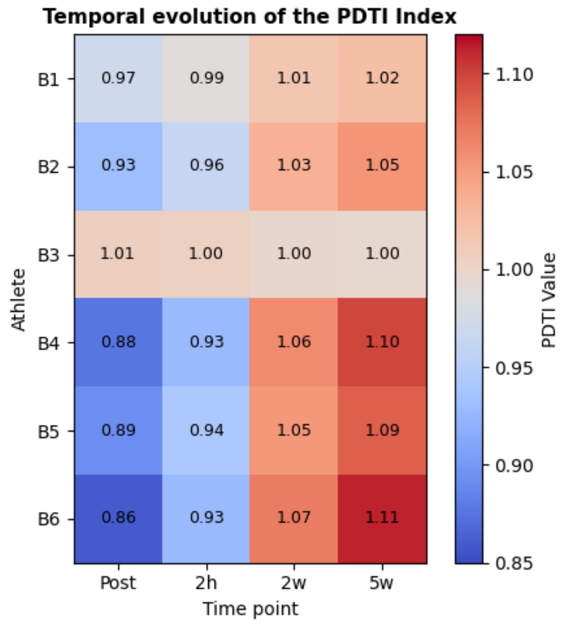

Fig. 3. Temporal evolution of the PDTI.

In athletes B4, B5 and B6, a consistent increase in values from about 0.9–0.93 (Post) to over 1.08–1.11 was observed after five weeks, which demonstrates effective autonomic regulation and high adaptability of cardiac dynamics.

In B1 and B2, the trend is also positive, but smoother, with a gradual increase from ~0.93 to 1.05, which indicates moderate recovery and partial stabilization of the autonomic balance.

Athlete B3 maintains almost stable values around 1.0 throughout the period, which suggests good basic stability without pronounced adaptation dynamics.

The color gradient in Figure 3 confirms the general trend towards gradual parasympathetic reactivation and recovery of variability, with most athletes reaching a physiologically optimal balance between the sympathetic and parasympathetic shares after five weeks.

V. DISCUSSIONS

The results obtained confirm that the integration of HRV parameters into summary recovery (RDTI) and adaptation (PDTI) indices provides a deeper understanding of the dynamics of the autonomic nervous system after physical exertion. The observed decrease in SDNN and RMSSD immediately after training, combined with a sharp increase in LF/HF, reflects a typical sympathetic dominance associated with acute physiological fatigue. This response is fully comparable with the results reported in [1,2], which describe similar short-term changes as a reliable indicator of training stress. Within two hours after exercise, a partial recovery of parasympathetic activity was observed (increased RMSSD, nHF, SD1), which is consistent with models of post-exercise reactivation (a process of recovery and reactivation of parasympathetic regulation after physical exertion, leading to normalization of heart rate and autonomic balance) [3].

The calculated recovery index (RDTI $\approx$ 1.00 $\pm$ 0.13) reflects a balanced interaction between sympathetic and parasympathetic regulation, and its high correlations with SDNN ($r = 0.94$) and RMSSD ($r = 0.95$) confirm its reliability as an integral indicator of autonomic recovery. The negative relationship between RDTI and the fractal index DFA α_2 ($r = -0.63$) is consistent with the findings in [7], according to which a decrease in α_2 is an indicator of a more flexible and resilient autonomic system. The parallel recovery of SampEn suggests a return of rhythmic complexity and functional stability, which confirms the concept [6] of entropic regulation of homeostasis.

The proposed PDTI shows high prognostic value, as it combines parameters that account for long-term variability and allows for the assessment of long-term adaptation. The predictive analysis demonstrates that in B4 and B6 PDTI increases significantly after five weeks, which corresponds to excellent autonomic stability and training resilience. In B1 and B3, PDTI values remain around 1.0, which may indicate accumulated fatigue, lower adaptation capacity or the need to reduce training volume. These results coincide with the observations in [4,5] that prolonged suppression of parasympathetic tone is an early indicator of functional overstrain. In the context of modern approaches to monitoring training status, PDTI can be considered as an intelligent integrative marker that combines linear, nonlinear and fractal characteristics of HRV. This index builds on existing models by including not only short-term recovery, but also a prognostic component assessing the trend of adaptation. The application of PDTI in sports practice would allow for personalized management of training loads and early prevention of overtraining, an approach that is increasingly being used in sports physiology [9,10].

The results of the present study confirm that the combined analysis of RDTI and PDTI provides a reliable tool for monitoring recovery and predicting adaptation dynamics. While RDTI describes the instantaneous state of autonomic balance, PDTI reveals the trend of stability and development over time, which makes it a promising indicator for assessing sports readiness and optimizing training cycles.

The proposed RDTI and PDTI indices can be integrated within a heart rate variability digital twin (HRV Digital Twin), which models in real time the dynamic processes of autonomic regulation in athletes. Such a digital model could combine biosensor data (RR intervals, HRV parameters, temperature, oxygen saturation) with machine learning algorithms that predict the individual response to training load. RDTI would serve as a module for assessing the current physiological state, while PDTI – as a prognostic component predicting the tendency of adaptation and the risk of overtraining. The integration of these indices into a digital twin allows for personalized simulation of recovery processes, optimization of training regimens and automatic adaptation of the load based on the real physiological responses of each athlete. This opens the way to the implementation of intelligent systems for sports form management, based on continuous monitoring, self-learning models and feedback between the coach, the athlete and the algorithmic system.

Relationship between Indices (RDTI, PDTI) and HRV Parameters

The combined analysis of the RDTI and PDTI indices reveals the complementary aspects of short-term and long-term autonomic adaptation. At the group level, higher RDTI values ($\approx$1.1) show a strong relationship with increased SDNN, RMSSD and nHF parameters ($r > 0.9$), confirming that athletes with more pronounced total and parasympathetic variability achieve faster recovery within the first two hours after exercise. Conversely, lower RDTI values (<1.0) are associated with persistent sympathetic dominance and incomplete recovery of autonomic balance.

The prognostic index PDTI, reflecting the interaction between fatigue and recovery, demonstrates a clear distinction between athletes with high adaptation potential (B4–B6) and those with a more delayed response (B1–B3). The progressive increase in PDTI during the second and fifth weeks in well-adapted athletes indicates sustained parasympathetic reactivation and enhanced autonomic resilience over time.

Unlike the RDTI, which describes the instantaneous functional state immediately after training, the PDTI has a prognostic nature. It integrates both parasympathetic and fractal characteristics of regulation, assessing the body's ability to maintain a stable autonomic balance under successive training loads. Thus, the PDTI not only reflects the current level of recovery, but also predicts the tendency of adaptation and the risk of functional overload or overtraining. High values of the index are associated with effective long-term recovery and stable autonomic regulation, while low values signal limited adaptive capacity and the need for optimization of the training process.

VI. CONCLUSION

The present study presents an integrated approach to assess autonomic recovery and adaptive resilience in athletes by introducing two combined indices – RDTI and PDTI. The results obtained show that RDTI reliably reflects short-term changes in parasympathetic activity and recovery capacity after exercise, while PDTI provides a deeper insight into the long-term trend of adaptation. The observed strong correlations between RDTI and the main HRV parameters (SDNN, RMSSD, nHF) confirm that the index captures the key mechanisms of autonomic balance, while the inclusion of fractal and entropic indicators (DFA α_2, SampEn) adds a nonlinear perspective to the assessment of physiological complexity. Prognostic analysis of PDTI demonstrates that in athletes with high resilience, the index increases consistently over a 2- and 5-week period, a sign of optimal recovery and effective adaptation of the autonomic nervous system. In contrast, PDTI values below 0.6 may be an indicator of accumulated fatigue and a potential risk of overtraining, which highlights the applicability of the index as a tool for prevention and optimization of training loads.

The developed methodology offers a new model for quantitative recovery tracking, which can be implemented in intelligent sports systems and HRV digital twins, providing personalized management of the training process. The combination of RDTI and PDTI creates a basis for building prognostic algorithms that combine biophysiological data, statistical analysis and machine learning to predict individual adaptation. Thus, the study contributes to the development of scientifically sound and technologically integrated methods for monitoring and optimizing sports form, applicable both in elite sports and in rehabilitation and preventive physiology.

ACKNOWLEDGMENT

THE AUTHOR ACKNOWLEDGES THE FINANCIAL SUPPORT OF THE PROJECT WITH FINANCIAL AGREEMENT NO. PVU-44 DATED 05.12.2024 UNDER PROJECT NO. BG-RRP-2.017-0011 "ECOLOGICAL COLLABORATIVE ROBOTS POWERED BY GREEN HYDROGEN" UNDER THE RECOVERY AND SUSTAINABILITY MECHANISM FOR IMPLEMENTATION OF INVESTMENT UNDER C2I2 "INCREASING THE INNOVATION CAPACITY OF THE BULGARIAN ACADEMY OF SCIENCES (BAS) IN THE FIELD OF GREEN AND DIGITAL TECHNOLOGIES" FROM THE RECOVERY AND SUSTAINABILITY PLAN, BULGARIA..

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