

A MACHINE LEARNING-BASED READINESS FORECASTING MODEL FOR TRAINING LOAD DECISION SUPPORT

¹Medetbek A.^a, ²Berlibek D.

¹Astana IT University, Astana, Kazakhstan

²L.N. Gumilyov Eurasian National University, Astana, Kazakhstan

Corresponding author: Arailym Medetbek arailym.medetbek@astanaedu.kz

Abstract. This study proposes and evaluates a machine learning-based approach for forecasting athletes' readiness one week ahead to support coaching decisions on training-load management. A secondary analysis was conducted using an open dataset from a 12-week controlled study involving 48 competitive table tennis players. Weekly monitoring data included training load, session RPE, ACWR, training monotony and strain, heart-rate variability, resting heart rate, sleep, fatigue, stress, soreness, wellness, and current readiness.

Four forecasting models - Elastic Net, Random Forest, XGBoost, and a multilayer perceptron - were evaluated using athlete-grouped nested cross-validation. Raw monitoring indicators were compared with personalised temporal features incorporating week-to-week changes, three-week moving averages, and athlete-specific deviations. Model interpretation was performed using out-of-fold SHAP analysis, and temporal validation was used to assess generalisation to later phases of the training programme.

The best monitoring-based model was Random Forest with personalised temporal features, achieving MAE = 0.835, RMSE = 1.039, and $R^2 = 0.152$. Differences between algorithms were small, while personalised temporal features provided only modest improvement over raw indicators.

The results show that weekly monitoring data can provide a modest but interpretable forecast of next-week readiness. The proposed approach can support coaches by identifying athletes at risk of reduced readiness while preserving professional judgement in training-load decisions.

Keywords: decision support system, training load, machine learning, multilayer perceptron, athlete monitoring, training personalization.

Introduction. In modern high performance sports, the effectiveness of long-term and ongoing training is largely determined by the quality of training load management - the coach's ability to timely and reasonably adjust the volume, intensity and focus of training activities in accordance with the current functional state of the athlete. Errors in load dosing, both its insufficiency and redundancy, lead to a decrease in the effectiveness of training, the development of chronic fatigue and an increase in injuries [1, 2].

Since the mid-2010s, the so - called «training-injury prevention paradox», formulated by T. Gabbett, has been actively discussed in sports science: high training loads simultaneously increase the level of fitness and the risk of injury, while low loads reduce the risk of injury, but do not provide the necessary increase in physical fitness [2]. To quantify this balance, an indicator of the acute-chronic load ratio (Acute: Chronic Workload Ratio, ACWR) [3, 4], which has become widely used as one of the basic indicators in consensus recommendations for monitoring athletes [1, 9]. At the same time, subsequent systematic reviews and meta-analyses have shown a high methodological heterogeneity of ACWR studies and the ambiguity of its predictive value, which indicates the need for more comprehensive, multifactorial approaches to assessing an athlete's readiness [10, 11].

The development of wearable sensors, GPS tracking systems, and heart rate and heart rate variability (HRV) monitoring technologies has led to a dramatic increase in the volume and heterogeneity of data available to coaches and sports professionals [14, 17]. Traditional approaches

such as the construction of fixed thresholds (for example, the "green zone" ACWR 0.8—1.3) and visual analysis of time schedules do not always allow for taking into account the individual characteristics of an athlete, the mutual influence of multiple variables and the nonlinear nature of the relationship between exercise, recovery and outcome [1, 12]. This generates a request for intelligent decision support systems (DSS) capable of automatically analyzing multidimensional monitoring data flows and forming personalized, interpretable recommendations for the coach [13, 37, 38].

Literature Review. Monitoring of the training process is regarded in contemporary sports science as one of the key tools for managing athletes' preparation. Studies distinguish between external load, which characterizes the objectively measurable volume of physical work performed, and internal load, which reflects the physiological and subjective response of the body to training stimuli [1]. It has also been shown that athletes may respond differently to comparable training loads, which highlights the need for an individualized approach to assessing training status [6–8].

Considerable attention has been paid to the acute:chronic workload ratio (ACWR), which is used to assess the balance between current and accumulated training loads [2–5]. At the same time, research indicates that relying on a single indicator does not provide sufficient reliability for assessing functional status and the risk of adverse outcomes. Current recommendations therefore consider training load as a multifactorial process that also depends on physiological condition, recovery, and psychosocial factors [9–11].

Accordingly, recent studies increasingly focus on comprehensive monitoring that integrates training-load indicators, heart rate variability (HRV), heart rate, fatigue, recovery, and athletes' subjective well-being [14, 17, 35].

Research findings support the need to move from standardized training programs toward individualized load management. It has been shown that the use of HRV and indicators of current functional status makes it possible to adapt training intensity to an athlete's individual response and, in some cases, to achieve comparable or greater improvements with lower perceived exertion [32–35].

Another important research direction concerns the assessment of recovery, fatigue, and athletes' readiness for subsequent training loads. Studies have shown that predicting these states requires the simultaneous consideration of physiological, training-related, and subjective characteristics, since each individual indicator has limited informative value when considered separately [15–17]. Research also confirms the importance of analyzing temporal dynamics, as an athlete's current state is influenced by training load and recovery during previous periods [22, 27, 28].

Thus, the contemporary concept of athlete monitoring is gradually shifting from the assessment of isolated indicators toward the development of a comprehensive individual athlete profile that reflects the dynamics of training load and recovery.

The increasing volume of data generated by wearable devices and monitoring systems has led to the active use of artificial intelligence and machine learning in sports analytics. Existing studies address a wide range of tasks, including the prediction of injury risk, fatigue, recovery, functional status, and sports performance [12–17, 21–28].

Review studies indicate that intelligent data analysis is particularly valuable when working with multidimensional datasets that require the simultaneous consideration of training load, physiological parameters, recovery indicators, and individual athlete characteristics [12–14]. At the same time, the resulting predictions are generally regarded as complementary tools for specialists rather than as substitutes for professional coaching decisions.

A number of studies have demonstrated the possibility of identifying complex relationships between training load and subsequent athlete status that are difficult to detect using fixed threshold values or visual analysis of individual indicators [16, 21, 22, 24–28]. At the same time, researchers emphasize the need for interpretable predictions and for assessing the robustness of predictive models across different athletes and sports disciplines [12–14].

Therefore, an important direction of current research is not only the prediction of an athlete's condition, but also the transformation of analytical results into information that is understandable and practically useful for coaches in managing the training process.

Recent studies also demonstrate the development of decision support systems aimed at assessing athletes' condition, planning the training process, and generating personalized recommendations [20, 36–38]. Such systems make it possible to integrate monitoring data, assess an athlete's current state, and provide additional analytical information to support decisions related to training load and recovery.

At the same time, the analysis of existing publications reveals several persistent limitations. A substantial proportion of studies focus on predicting injury risk [21, 22, 24–28], whereas short-term prediction of athletes' functional readiness and the direct use of such predictions to support coaching decisions remain less extensively investigated. In addition, many studies examine individual load or recovery indicators separately, while the combined analysis of their temporal dynamics and athlete-specific deviations remains insufficiently explored [12–17, 32–35].

Personalization of athlete monitoring represents another important challenge. Despite the well-established inter-individual variability in physiological responses to training load [6–8], many studies rely primarily on absolute indicator values, whereas changes relative to an athlete's own baseline may provide additional information about their current functional state.

Therefore, there is a need to develop an approach that integrates training-load and recovery data, accounts for their temporal dynamics and individual athlete characteristics, and enables the prediction of readiness for the subsequent training period. Addressing this problem can provide a methodological basis for intelligent decision support in the management of athletes' training load [36–39].

Materials and methods. The study is a secondary analysis of the open dataset Individualized physical conditioning based on training monitoring in table tennis players (Zenodo record 21343993, CC-BY 4.0) [39]. The dataset originates from a 12-week randomized controlled trial involving 48 competitive table tennis players (EG $n = 24$; CG $n = 24$), each completing three training sessions per week. The experimental group followed an individualized conditioning programme guided by HRV and wellness monitoring, whereas the control group maintained standard training. The dataset contains 576 athlete-weeks and 1,728 individual training sessions.

Weekly monitoring included session RPE, weekly training load, training monotony, training strain, ACWR, HRV (rMSSD), resting heart rate, wellness score, sleep duration, fatigue, stress, readiness, and muscle soreness. Demographic, training-history, and pre/post performance variables are also available; however, only weekly monitoring data were used in the present forecasting task. No missing values were reported. Table 1 summarizes the variables included in the analysis.

Table 1. Weekly monitoring indicators (576 athlete-weeks; 48 athletes $\times$ 12 weeks).

Indicator	Unit	EG, mean (SD)	CG, mean (SD)	Range	ICC _{athlete}	r (all)	r (EG)	r (CG)
Load	AU	1269.10 (280.57)	1324.92 (87.25)	623.0–1758.0	0.03	+0.16	+0.24	-0.01
ACWR	ratio	1.00 (0.20)	1.00 (0.05)	0.5–1.3	0.00	+0.06	+0.05	+0.04
Monotony	a.u.	4.47 (3.47)	7.81 (7.47)	1.1–104.2	0.13	-0.10	-0.11	-0.05
Strain	AU	6033.86 (5072.31)	10323.14 (9791.03)	758.0–135517.0	0.13	-0.09	-0.09	-0.05
sRPE	CR-10	6.03 (1.06)	5.31 (0.30)	3.4–7.7	0.18	+0.21	+0.23	-0.01
HRV	ms	71.95 (7.25)	65.32 (7.00)	46.3–92.0	0.24	+0.04	-0.06	+0.05

RHR	bpm	57.08 (4.76)	58.07 (4.71)	44.0–72.0	0.08	-0.12	-0.09	-0.14
Wellness	0–28	20.07 (2.24)	18.58 (2.26)	12.7–25.0	0.15	+0.07	+0.02	+0.04
Sleep	h	7.53 (0.70)	7.12 (0.65)	5.2–9.4	0.15	+0.00	-0.10	+0.03
Fatigue	1–10	5.18 (1.49)	4.98 (1.50)	1.6–10.0	0.04	-0.20	-0.30	-0.11
Stress	1–10	4.62 (1.08)	4.44 (1.02)	1.3–7.6	0.08	-0.04	-0.10	+0.00
Soreness	1–5	2.28 (0.66)	2.82 (0.70)	1.0–4.8	0.19	-0.07	+0.04	-0.09
Readiness	1–10	6.94 (1.18)	6.63 (1.02)	3.3–10.0	0.07	+0.25	+0.35	+0.07
Programme week	1–12	—	—	—	—	+0.42	+0.48	+0.37

Let the state of athlete i in week t be described by the vector of the 13 weekly monitoring indicators

$$X_{i,t} = \{L, M, S, ACWR, sRPE, HRV, RHR, W, Sleep, Fatigue, Stress, Soreness, R\}_{i,t} \quad (1)$$

where L is the weekly training load, M the training monotony, S the training strain, W the composite wellness score and R the current readiness. The forecasting task is

$$R_{i,t+1} = F(X_{i,t}, X_{i,t-1}, \dots, X_{i,t-k}) \quad (2)$$

i.e. a one-step-ahead (one-week) forecast of readiness from the current and k preceding weekly state vectors.

To account for inter-individual variability, each indicator was additionally expressed relative to the athlete's individual historical profile.

$$D_{i,t,x} = (x_{i,t} - \mu_{i,\leq t}) / \sigma_{i,\leq t} \quad (3)$$

where $\mu_{i,\leq t}$ and $\sigma_{i,\leq t}$ are the mean and standard deviation of indicator x for athlete i over weeks $1 \dots t$. Thus, each indicator was represented by its current value, individual deviation, week-to-week change, and recent temporal average. For 13 monitoring indicators, this produced 52 features. The final modelling dataset contained 432 athlete-week observations. Because the three-week moving average requires three weeks of history, modelling started at week 3 and predicted weeks 4–12, resulting in nine forecasts per athlete ($48 \times 9 = 432$).

Table 2. Feature sets used in the ablation study.

Feature set	n	Features
A — Load only	5	Load, ACWR, Monotony, Strain, sRPE
B — Recovery only	7	HRV, RHR, Wellness, Sleep, Fatigue, Stress, Soreness
C — Multimodal (raw)	13	Load, ACWR, Monotony, Strain, sRPE, HRV, RHR, Wellness, Sleep, Fatigue, Stress, Soreness, Readiness
D — Personalised temporal	52	All 13 raw indicators of C plus $\Delta(\cdot)$, $MA3(\cdot)$ and individual $z(\cdot)$ of each

Four models were compared: Elastic Net as an interpretable linear baseline, Random Forest regression, XGBoost, and a multilayer perceptron (MLP). Random Forest and XGBoost used 300 trees/boosting rounds, while the MLP was trained with ReLU activations, Adam optimisation, and L2 regularisation. Because training monotony and strain were strongly right-skewed, they were $\log(1 + x)$ -transformed, and all features were standardised within the training fold.

To avoid leakage between repeated observations of the same athlete, evaluation used athlete-grouped cross-validation. The 48 athletes were divided into eight folds, with all observations from a given athlete assigned to the same fold. The procedure was repeated three times, producing 24 held-out folds. Hyper-parameters were selected using nested 3-fold grouped cross-validation within each training set.

A complementary temporal validation trained the models on target weeks 4–9 and evaluated them on weeks 10–12, providing a stricter test of generalisation to later phases of the training programme. Performance was compared with three naive baselines: persistence, the global training-fold mean, and the athlete-specific expanding mean of readiness.

Forecast quality is quantified with the mean absolute error, the root-mean-square error and the coefficient of determination:

$$MAE = (1/n) \sum |y_i - \hat{y}_i|, RMSE = \sqrt{[(1/n) \sum (y_i - \hat{y}_i)^2]}, R^2 = 1 - \sum (y_i - \hat{y}_i)^2 / \sum (y_i - \bar{y})^2 \quad (5)$$

MAE was used as the primary metric because it directly represents the average prediction error on the 10-point readiness scale. RMSE and R^2 were reported as complementary measures.

Model configurations were compared using paired per-athlete MAE values. For each comparison, the mean paired difference, 95% confidence interval, Cohen's d_z , and paired significance tests were reported.

To assess the contribution of different indicator groups, four feature configurations were compared (Table 2): load only, recovery only, multimodal raw, and personalised temporal. The latter includes raw indicators together with week-to-week changes, three-week moving averages, and individually normalised deviations. This comparison was used to determine whether personalised temporal features improve forecasting performance over raw indicators and to identify which indicator groups contribute most to the prediction.

For the best-performing non-linear model on feature set D, SHAP values were calculated on out-of-fold predictions to ensure that explanations were generated only for athletes not used during model training. Global feature importance was defined as the mean absolute SHAP value:

$$Importance(x_j) = (1/N) \sum_{i=1}^N |SHAP_{ij}| \quad (6)$$

SHAP analysis was used to identify the most influential predictors, determine the direction of their effects, and provide individual explanations of predicted readiness.

The experimental evaluation consisted of three stages. First, four forecasting models were compared to identify the most accurate approach for predicting next-week readiness. Second, several feature configurations were evaluated to determine whether personalised temporal information improves prediction quality compared with raw monitoring data. Finally, the best-performing non-linear model was interpreted using SHAP analysis to identify the main factors influencing the forecast and to provide individual-level explanations.

Results. Readiness averaged 6.78 ± 1.11 on the ten-point scale. Most variation in readiness and the monitoring indicators occurred within athletes across weeks rather than between athletes. Associations between individual week-t indicators and next-week readiness were generally weak

(absolute $r \leq 0.25$), while programme week showed the strongest association with subsequent readiness ($r = 0.42$).

Figure 1 illustrates the expected contrast in periodisation between the experimental (EG) and control (CG) groups. Readiness increased during the final weeks of the programme, while the EG showed larger planned changes in training load and ACWR.

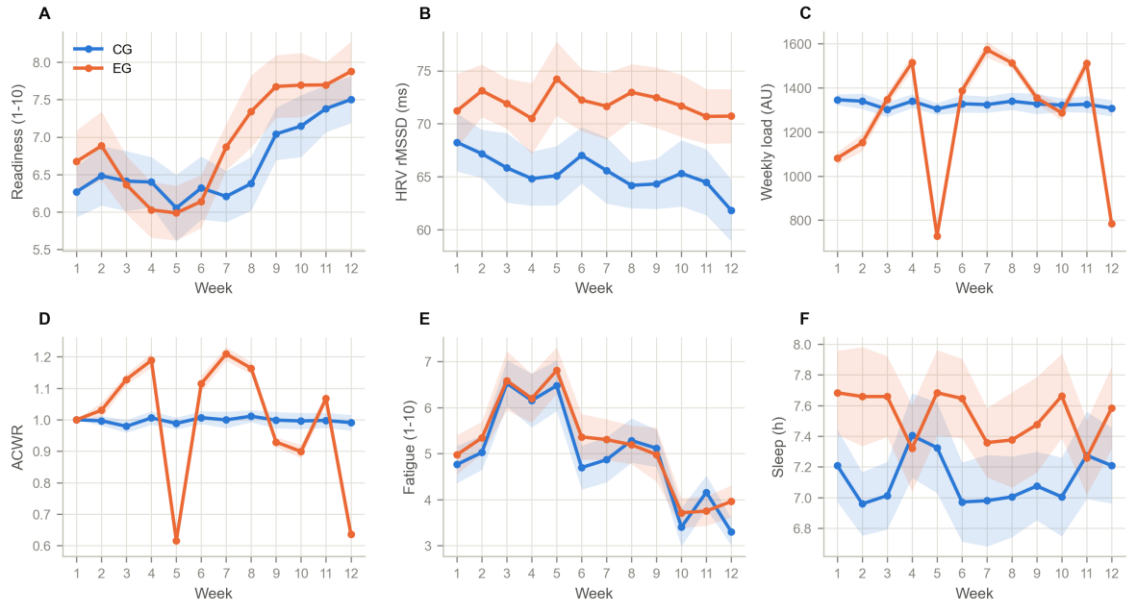


Figure 1. Group-mean weekly trajectories ($\pm 95\%$ CI) of readiness (A), HRV rMSSD (B), weekly training load (C), ACWR (D), fatigue (E) and sleep (F) over the 12-week programme in the experimental (EG) and control (CG) groups.

Table 3 and Figure 2 summarise the grouped cross-validation. The naive references set the scale of the problem: persistence gave $\text{MAE} = 1.093 \pm 0.142$, the athlete's expanding mean 1.004 ± 0.114 and the global training mean 0.917 ± 0.075 .

All learned models on the multimodal feature sets (C and D) improved on these references. Within the ablation sets the best configuration was RandomForest on feature set D ($\text{MAE} = 0.835 \pm 0.079$, $\text{RMSE} = 1.039$, pooled $R^2 = 0.152$). Against persistence its paired per-athlete advantage was 0.259 points (95% CI 0.191 to 0.326; $dz = 1.10$; better in 88% of athletes; $p < 0.001$), against the global mean 0.082 points (95% CI 0.034 to 0.130; $dz = 0.50$; better in 67% of athletes; $p = 0.001$) and against the personal mean 0.169 points ($p < 0.001$).

Table 3. One-week-ahead readiness forecasting on personalised temporal features (set D) and naive baselines.

Model	MAE	RMSE	R ²
Elastic Net	0.856 ± 0.072	1.059 ± 0.079	0.120
Random Forest	0.835 ± 0.079	1.039 ± 0.084	0.152
XGBoost	0.845 ± 0.085	1.056 ± 0.098	0.122
MLP	0.854 ± 0.069	1.058 ± 0.073	0.122
Persistence	1.093 ± 0.142	1.356 ± 0.159	-0.454
Personal expanding mean	1.004 ± 0.114	1.230 ± 0.118	-0.191
Global training mean	0.917 ± 0.075	1.131 ± 0.086	-0.004

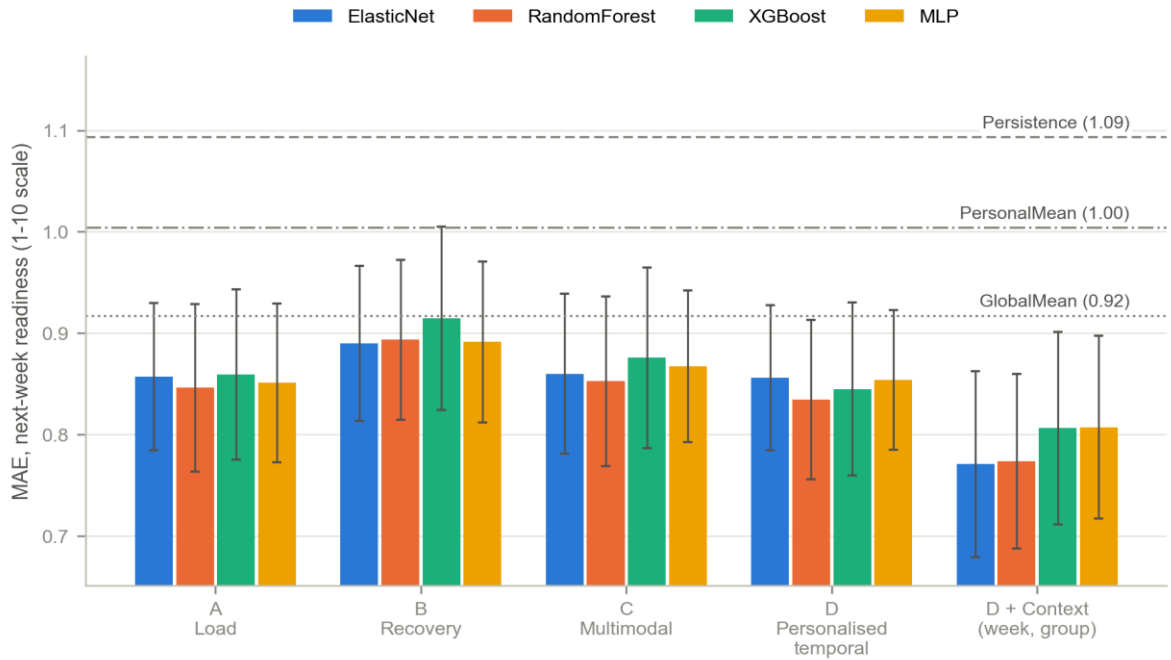


Figure 2. MAE across feature configurations and algorithms

Feature set D reduced MAE relative to the raw multimodal set C for 4 of the four algorithms, but the reductions were small — ElasticNet: -0.004 [-0.021, +0.013], $dz = -0.07$, D better in 48% of athletes, $p = 0.647$; RandomForest: -0.018 [-0.045, +0.009], $dz = -0.19$, D better in 60% of athletes, $p = 0.188$; XGBoost: -0.031 [-0.063, +0.002], $dz = -0.28$, D better in 58% of athletes, $p = 0.062$; MLP: -0.014 [-0.031, +0.004], $dz = -0.23$, D better in 58% of athletes, $p = 0.122$ — and no confidence interval excluded zero.

The supplementary configuration D + Context (Table 4; rightmost group in Figure 2) produced the largest improvement observed in the study. Temporal validation revealed a clear distribution shift. Models based only on monitoring variables systematically under-predicted readiness during weeks 10–12 and did not outperform the persistence baseline. Adding programme context reduced this bias; the context-aware Elastic Net achieved the lowest MAE (0.749). These results indicate that monitoring-only models did not fully generalise across a change in training phase.

Table 4. Compact ablation summary (best-performing algorithm within each feature set).

Feature set	Best model	MAE	R ²
A — Load only	Random Forest	0.846	0.110
B — Recovery only	Elastic Net	0.890	0.050
C — Multimodal raw	Random Forest	0.853	0.125
D — Personalised temporal	Random Forest	0.835	0.152
D + Context (supplementary)	Elastic Net	0.771	0.266

Table 5. Temporal hold-out summary for the most informative configurations.

Model	Features	MAE	R ²	Bias
XGBoost	C — multimodal raw	1.109	-1.075	+0.892
Elastic Net	D — personalised temporal	1.110	-1.007	+0.941

Elastic Net	D + Context	0.749	-0.004	+0.182
Persistence	—	1.086	-1.047	+0.110

The temporal hold-out (Figure 3) exposed the limit of the monitoring-only models. When trained on target weeks 4–9 and applied to weeks 10–12, every model without programme context was worse than persistence: MAE 1.109–1.203 for feature set C and 1.110–1.179 for feature set D, against 1.086 for persistence, 1.123 for the personal expanding mean and 1.164 for the global training mean. The failure was a systematic bias rather than added noise: the mean residual of the D-models was +0.84 to +1.03 points, i.e. the models under-predicted readiness by about one point throughout the taper, because the training weeks did not contain the higher readiness level of the taper weeks (mean 7.6). Persistence, which simply carries forward the athlete's latest value, tracked the shift (bias +0.11). All R² values were strongly negative because the variance of readiness within the three taper weeks is small relative to the squared bias.

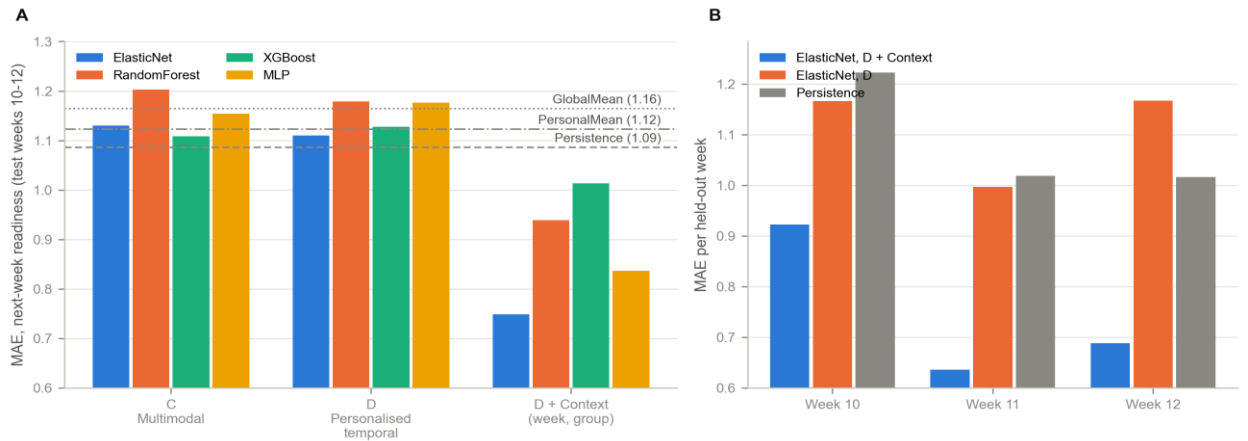


Figure 3. Temporal hold-out.

Out-of-fold SHAP analysis of the Random Forest model on feature set D showed that the forecast relied mainly on recent temporal trends. The most influential predictors were the three-week mean of sRPE (18.3% of total attribution), fatigue (10.4%), ACWR (5.3%), current readiness (5.2%) and training load (4.6%). Three-week moving averages accounted for 56.5% of total model attribution, compared with 18.3% for personalised deviations, 13.9% for raw values and 11.3% for week-to-week changes.

Load and recovery indicators contributed 45.9% and 42.3% of total attribution, respectively, while current readiness contributed 11.8%.

Table 6. Leading predictors of next-week readiness in the Random Forest model (feature set D).

Rank	Feature	Mean SHAP	Share
1	MA3(sRPE)	0.190	18.3%
2	MA3(Fatigue)	0.107	10.4%
3	MA3(ACWR)	0.055	5.3%
4	Readiness	0.054	5.2%
5	MA3(Load)	0.048	4.6%
6	z(Readiness)	0.042	4.0%
7	MA3(Monotony)	0.039	3.8%
8	MA3(RHR)	0.037	3.6%
9	z(Fatigue)	0.032	3.1%
10	MA3(Soreness)	0.024	2.4%

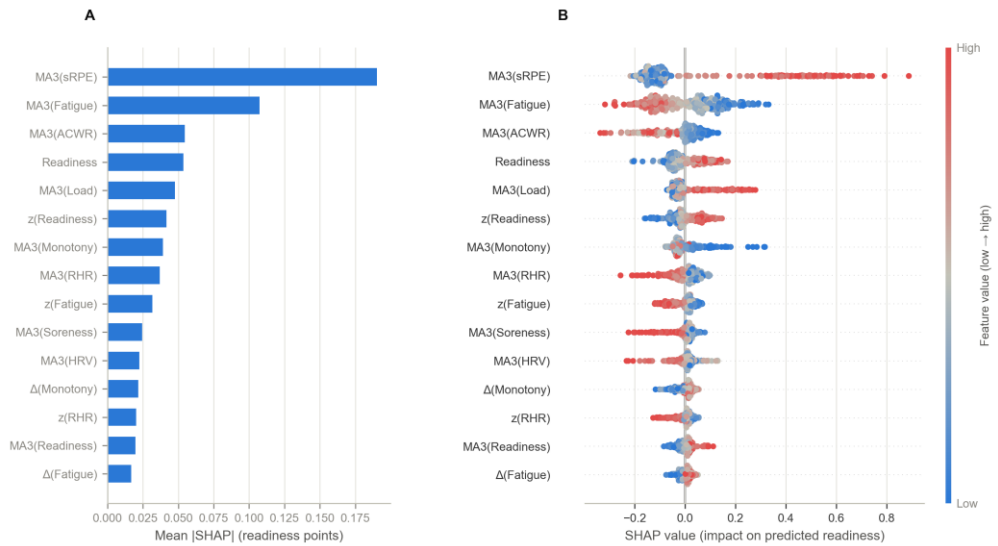


Figure 4. SHAP summary for the RandomForest model on feature set D.

The SHAP dependence plots in Figure 5 provide a more detailed view of how the leading predictors influenced the model output. Higher three-week mean fatigue and ACWR were generally associated with lower predicted readiness, whereas higher current readiness and its personalised deviation were associated with higher forecasts. The effects of sRPE and training load were more nonlinear, reflecting changes across different phases of the training programme. Overall, these patterns confirm that the model relied not only on the current values of the indicators but also on their recent temporal dynamics.

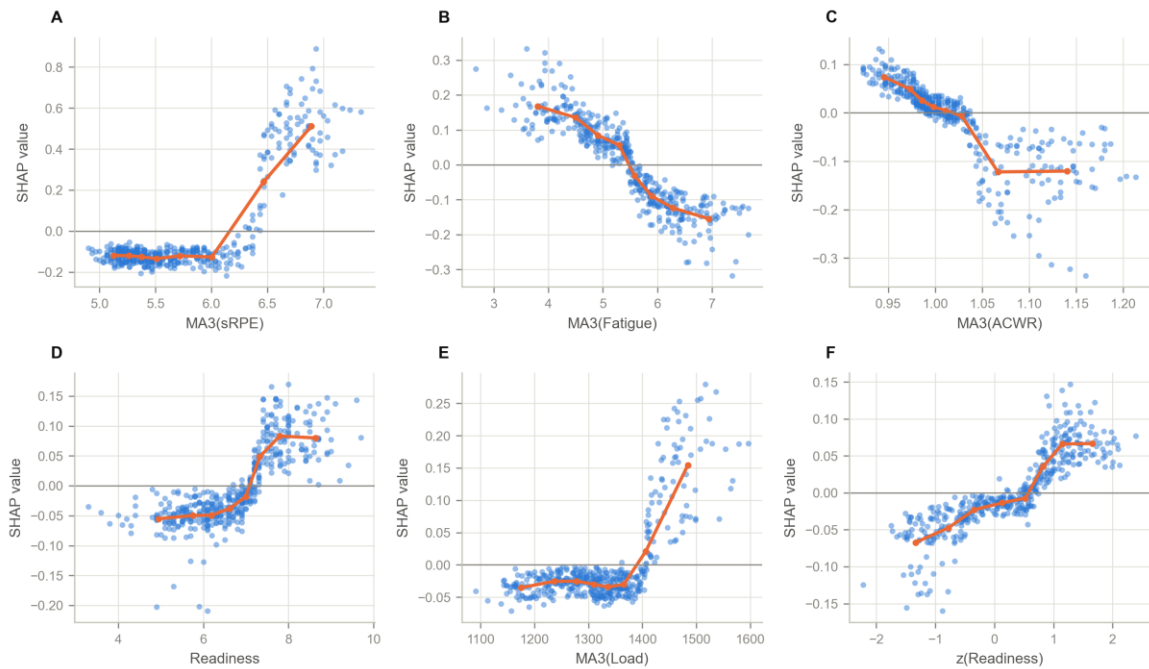


Figure 5. SHAP dependence plots for the six most important features. Points are athlete-weeks; the orange line connects the mean SHAP value within feature-value octiles.

Figure 6 illustrates how the importance of the leading predictors varied across individual athletes. Load-related features showed greater between-athlete variability, partly reflecting differences between the experimental and control training programmes. In contrast, recovery-related indicators, particularly fatigue and resting heart rate, showed more consistent contributions

across athletes. These findings suggest that the relative importance of training-load indicators is more dependent on the training context, whereas several recovery indicators provide a more stable signal across individuals.

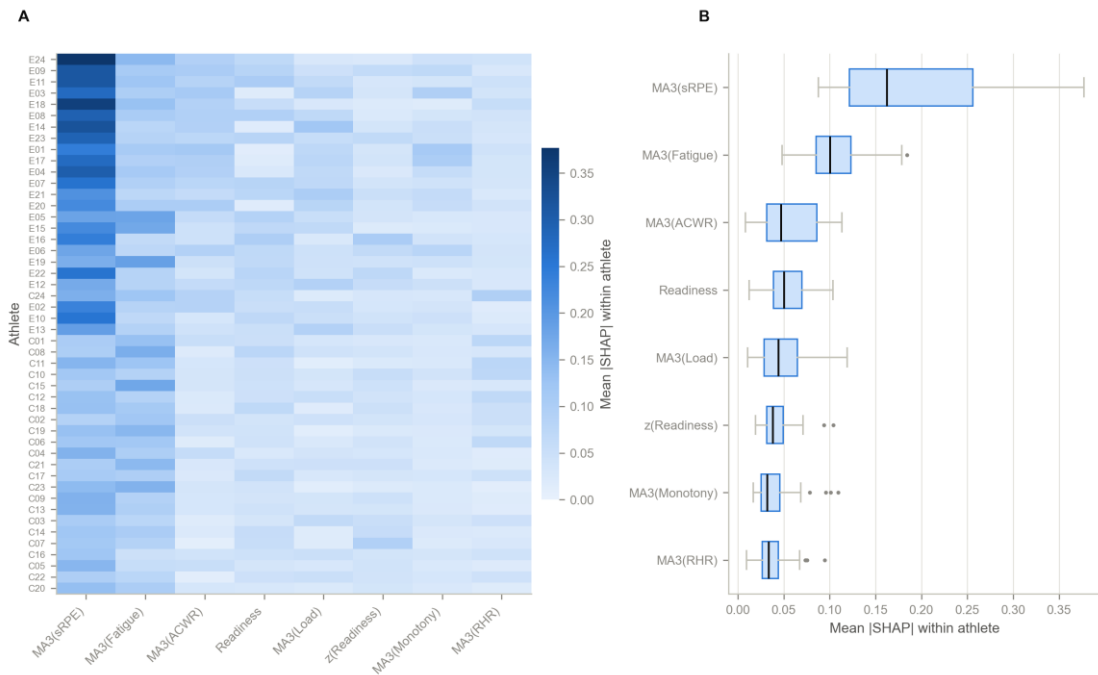


Figure 6. Between-athlete heterogeneity of the drivers of readiness.

Discussion. This study examined whether weekly training-load and recovery indicators can be used to forecast athletes' readiness for the following week and whether personalised temporal features improve prediction accuracy. The best model achieved an MAE of 0.83 points on the 10-point readiness scale and explained approximately 15% of the variance, indicating that next-week readiness is predictable, although only to a moderate extent.

Differences between the four learning algorithms were small, suggesting that model complexity was less important than the information contained in the input features. Personalised temporal features produced only modest improvements over raw multimodal indicators and did not clearly outperform load-only features. The main predictive signal was therefore associated with recent training-load dynamics rather than with athlete-specific normalisation alone.

The temporal validation revealed an important limitation. Models trained only on monitoring variables systematically under-predicted readiness during the taper phase, whereas the inclusion of programme context substantially improved performance. This indicates that readiness depends not only on physiological and subjective monitoring indicators, but also on the planned phase of the training programme. Consequently, training context should be considered explicitly when developing forecasting systems for practical use.

SHAP analysis supported this interpretation. The most influential predictors were recent trends in sRPE, fatigue, ACWR, current readiness and training load. Three-week moving averages contributed more to the predictions than raw values or week-to-week changes, indicating that short-term trends are more informative than isolated weekly measurements. These findings also emphasise that feature importance should not be interpreted as evidence of causal physiological effects.

The proposed approach can be integrated into athlete-monitoring systems as an additional decision-support layer. Weekly monitoring data can be transformed into a forecast of next-week readiness together with an explanation of the main factors influencing that forecast. Such

information may help coaches identify athletes who are likely to enter the next training period with reduced readiness and support decisions regarding training load and recovery.

The model should, however, complement rather than replace professional judgement. Programme phase and contextual information should be considered alongside physiological and subjective indicators when interpreting the forecast.

Several limitations should be acknowledged. First, the study included only 48 athletes from a single sport and a 12-week training programme, which limits generalisability. Second, readiness was measured using a subjective 10-point scale and may be influenced by factors not included in the monitoring data. Third, the analysis was based on weekly averages, which limits the ability to capture short-term fluctuations. Finally, SHAP values describe how the model uses a feature and should not be interpreted as evidence of a causal relationship with readiness.

Future research should validate the approach on independent datasets, longer training periods and other sports. Prospective studies are also needed to determine whether readiness forecasts improve actual coaching decisions and subsequent athlete outcomes. Further work may investigate daily-resolution data, longer forecasting horizons and objective performance indicators.

Conclusion. Using an open, richly documented monitoring dataset from a 12-week controlled trial in 48 competitive table tennis players, we showed that routinely collected load and recovery indicators support a modest one-week-ahead forecast of perceived readiness that outperforms persistence and mean-based references for unseen athletes under athlete-grouped nested cross-validation (best MAE ≈ 0.83 versus 1.09 for persistence; $R^2 \approx 0.15$). The choice of learner was immaterial, and personalised temporal features improved the forecast only marginally a consequence of the low between-athlete variance of the indicators in this dataset with smoothed recent trajectories proving more useful than athlete-relative deviations. The forecastable signal was carried by the load indicators of the periodised group and, above all, by the position in the programme: adding the week index improved every model substantially, and without it no model transferred across the transition into the taper, whereas a context-aware linear model did (MAE 0.75 versus 1.09 for persistence). Out-of-fold SHAP analysis yielded coach-readable individual explanations and, at the same time, revealed that the dominant driver was a marker of training phase rather than of physiology, while fatigue, resting heart rate, ACWR and soreness relative to the athlete's recent weeks acted as athlete-general, physiologically coherent drivers. For practice, the results recommend that readiness-forecasting models include the planned periodisation as an input, be re-validated across phase transitions rather than by resampling alone, and be delivered with explanations that let the coach distinguish calendar effects from the athlete's state.

МОДЕЛЬ ПРОГНОЗИРОВАНИЯ ГОТОВНОСТИ СПОРТСМЕНОВ НА ОСНОВЕ МАШИННОГО ОБУЧЕНИЯ ДЛЯ ПОДДЕРЖКИ РЕШЕНИЙ ПО УПРАВЛЕНИЮ ТРЕНИРОВОЧНОЙ НАГРУЗКОЙ

¹ Медетбек А., ² Берлибек Д.

¹Astana IT University, Астана, Казахстан

²Евразийский национальный университет имени Л.Н. Гумилева, Астана, Казахстан

Автор для корреспонденции: Arailym Medetbek, arailym.medetbek@astanaitedu.kz

Аннотация. В данном исследовании предлагается и оценивается подход на основе машинного обучения для прогнозирования готовности спортсменов на одну неделю вперед с целью поддержки тренерских решений по управлению тренировочной нагрузкой. Был проведен вторичный анализ открытого набора данных, полученного в рамках 12-недельного контролируемого исследования с участием 48 спортсменов, занимающихся настольным теннисом на соревновательном уровне. Еженедельный мониторинг включал тренировочную нагрузку, субъективную оценку воспринимаемой нагрузки после

тренировочной сессии (session RPE), соотношение острой и хронической нагрузки (ACWR), монотонность и напряженность тренировок, вариабельность сердечного ритма, частоту сердечных сокращений в покое, показатели сна, утомляемости, стресса, мышечной болезненности, общего самочувствия и текущей готовности.

Были оценены четыре модели прогнозирования: Elastic Net, Random Forest, XGBoost и многослойный перцептрон, с использованием вложенной перекрестной проверки с группировкой по спортсменам. Исходные показатели мониторинга сравнивались с персонализированными временными признаками, включавшими изменения от недели к неделе, трехнедельные скользящие средние и индивидуальные отклонения спортсмена от его собственных значений. Интерпретация моделей проводилась с использованием SHAP-анализа на прогнозах вне обучающих выборок, а временная валидация применялась для оценки способности моделей обобщать результаты на более поздние этапы тренировочной программы.

Лучшей моделью на основе данных мониторинга оказался Random Forest с персонализированными временными признаками, показавший MAE = 0,835, RMSE = 1,039 и $R^2 = 0,152$. Различия между алгоритмами были небольшими, а использование персонализированных временных признаков обеспечило лишь умеренное улучшение по сравнению с исходными показателями.

Результаты показывают, что данные еженедельного мониторинга могут обеспечивать умеренно точный и интерпретируемый прогноз готовности спортсменов на следующую неделю. Предлагаемый подход может использоваться для поддержки тренеров при выявлении спортсменов с риском снижения готовности, сохраняя при этом ключевую роль профессионального тренерского суждения при принятии решений по управлению тренировочной нагрузкой.

Ключевые слова: система поддержки принятия решений, тренировочная нагрузка, машинное обучение, многослойный перцептрон, мониторинг спортсменов, персонализация тренировок.

ЖАТТЫҒУ ЖҮКТЕМЕСІН БАСҚАРУ БОЙЫНША ШЕШІМ ҚАБЫЛДАУДЫ ҚОЛДАУҒА АРНАЛҒАН МАШИНАЛЫҚ ОҚЫТУ НЕГІЗІНДЕГІ СПОРТШЫЛАРДЫҢ ДАЯРЛЫҒЫН БОЛЖАУ МОДЕЛІ

¹ Медетбек А., ² Берлибек Д.

¹Astana IT University, Астана, Қазақстан

²Л.Н. Гумилев атындағы Еуразия ұлттық университеті, Астана, Қазақстан

Хат-хабарға жауапты автор: Arailym Medetbek, arailym.medetbek@astanaitedu.kz

Аңдатпа. Бұл зерттеуде жаттығу жүктемесін басқаруға қатысты жаттықтырушылық шешімдерді қолдау мақсатында спортшылардың алдағы бір аптадағы даярлығын болжауға арналған машиналық оқытуға негізделген тәсіл ұсынылып, бағаланады. Ашық деректер жиынтығы негізінде екінші реттік талдау жүргізілді. Деректер 48 жарыс деңгейіндегі үстел теннисі спортшысы қатысқан 12 апталық бақыланатын зерттеу барысында жиналған. Апталық мониторинг көрсеткіштеріне жаттығу жүктемесі, жаттығу сессиясынан кейінгі субъективті жүктемені бағалау (session RPE), жедел және созылмалы жүктеме арақатынасы (ACWR), жаттығу монотондылығы мен strain көрсеткіші, жүрек соғу жиілігінің вариабельдігі, тыныштық кезіндегі жүрек соғу жиілігі, ұйқы, шаршау, стресс, бұлшықет ауырсынуы, жалпы әл-ауқат және ағымдағы даярлық енгізілді.

Төрт болжау моделі Elastic Net, Random Forest, XGBoost және көпқабатты перцептрон спортшылар бойынша топтастырылған кірістірілген кросс-валидация арқылы бағаланды. Бастапқы мониторинг көрсеткіштері аптадан аптаға өзгерістерді, үш апталық жылжымалы орташа мәндерді және спортшының өзіне тән ауытқуларын қамтитын дербестендірілген

уақыттық белгілермен салыстырылды. Модельдерді түсіндіру үшін оқыту үлгілерінен тыс алынған болжамдарға негізделген SHAP-талдау қолданылды, ал уақыттық валидация модельдердің жаттығу бағдарламасының кейінгі кезеңдеріне жалпылау қабілетін бағалау үшін пайдаланылды.

Мониторинг деректеріне негізделген ең жақсы модель дербестендірілген уақыттық белгілері бар Random Forest болды: $MAE = 0,835$, $RMSE = 1,039$ және $R^2 = 0,152$. Алгоритмдер арасындағы айырмашылықтар аз болды, ал дербестендірілген уақыттық белгілер бастапқы көрсеткіштермен салыстырғанда тек шектеулі жақсару көрсетті.

Нәтижелер апталық мониторинг деректері келесі аптадағы спортшы даярлығына қатысты орташа деңгейдегі, бірақ интерпретациялауға болатын болжам бере алатынын көрсетеді. Ұсынылған тәсіл жаттықтырушыларға даярлығы төмендеу қаупі бар спортшыларды анықтауға көмектесе алады, сонымен бірге жаттығу жүктемесіне қатысты шешімдер қабылдауда кәсіби жаттықтырушылық пайымдаудың негізгі рөлін сақтайды.

Түйін сөздер: шешім қабылдауды қолдау жүйесі, жаттығу жүктемесі, машиналық оқыту, көпқабатты перцептрон, спортшылар мониторингі, жаттығуды дербестендіру.

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Авторлар туралы ақпарат // Информация об авторах // Information about the Authors

Медетбек Арайлым – Школа программной инженерии, Astana IT University, г. Астана, Казахстан

Медетбек Арайлым – Бағдарламалық инженерия мектебі, Astana IT University, Астана қ., Қазақстан

Arailym Medetbek – School of Software Engineering, Astana IT University, Astana, Kazakhstan

e-mail: arailym.medetbek@astanaitedu.kz

ORCID iD: 0009-0001-7192-0360

Берлибек Диас – магистрант образовательной программы «Системы информационной безопасности», Евразийский национальный университет имени Л.Н. Гумилева, г. Астана, Казахстан

Берлібек Диас – «Ақпараттық қауіпсіздік жүйелері» білім беру бағдарламасының магистранты, Л.Н. Гумилев атындағы Еуразия ұлттық университеті, Астана қ., Қазақстан

Dias Berlibek – Master’s student in Information Security Systems, L.N. Gumilyov Eurasian National University, Astana, Kazakhstan
e-mail: 021201550905@enu.kz
ORCID iD: 0009-0005-4570-3505