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Research on the rehabilitation cycle comparison and optimization strategy of different sports injury repair schemes

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SUMMARY: *Whether the selection of sports injury repair program is reasonable directly affects the rehabilitation cycle, the quality of functional recovery and the effect of regression training. Aiming at the problems that it is difficult to compare the rehabilitation process under different repair paths and the cycle judgment depends on experience, this paper constructs an analysis model that integrates rehabilitation data preprocessing, multi-source feature representation, cycle prediction and strategy optimization. Based on 192 sports injury samples and 5696 stage observation records, the clinical indicators, functional tests, training load and dynamic monitoring information were uniformly coded, and the rehabilitation cycle prediction framework of different repair schemes was established. The results show that the mean absolute error (MAE) of the proposed model on the test set is 5.0 d, the root mean square error (RMSE) is 6.4 d, and the determination coefficient reaches 0.95. After optimization, the average rehabilitation period was reduced from 78.6 days to 68.9 days, and the function standard rate was increased from 81.4% to 88.7%. The results show that this method can effectively reveal the recovery differences of different sports injury repair schemes, and provide data support for rehabilitation path optimization.*

KEYWORDS: *sports injury repair; Rehabilitation cycle prediction; Multi-source feature fusion; Scheme optimization*

1 Introduction

Sports injury repair is not only a simple accumulation of tissue healing time, but also involves the dynamic balance of inflammatory control, functional recovery, load reconstruction, psychological preparation and re-injury risk management. For competitive athletes, too long rehabilitation cycle will compress the training and competition window; For the general sports population, the imbalance of recovery rhythm may lead to the delay of pain, the aggravation of motor compensation and the occurrence of secondary injury. Therefore, how to establish a comparable, quantifiable, and optimized rehabilitation cycle analysis framework among different injury types, different repair schemes, and different individual bases has become an important issue with both theoretical and practical value in sports rehabilitation research. Existing clinical studies have shown that common sports injuries such as hamstring strain, anterior cruciate ligament injury and ankle sprain have obvious differences in repair paths, stage goals and return exercise criteria, and the rehabilitation duration corresponding to

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different programs also shows strong individual volatility [1, 2]. This means that if the rehabilitation process is still only based on empirical judgment or a single time node, it is difficult to accurately describe the recovery law, and it is difficult to provide a stable basis for program selection.

Focusing on sports injury repair, many studies have explored the effectiveness of intervention, training content configuration, and regression exercise criteria. Afonso et al. conducted a systematic review of conservative interventions for acute hamstring injury and pointed out that different interventions had certain effects in pain relief and functional recovery, but the rehabilitation cycle was greatly affected by differences in training compliance, injury degree and evaluation criteria, and the results were inconsistent among studies [3]. Hu et al. conducted meta-analysis on the hamstring eccentric training program and believed that the dose design and action form of training prescription would affect the prevention and recovery performance of lower limb injury, but the description of the stage transition mechanism in the rehabilitation process was still insufficient [4]. In the field of knee anterior cruciate ligament injury, Jenkins et al. and Glattke et al. respectively summarized the current research progress from the perspective of rehabilitation process and postoperative recovery, and pointed out that although the traditional staged rehabilitation has strong clinical feasibility, it still does not fully consider the synchronization of individual differences, load adaptation speed and psychological function recovery [5, 6]. Such studies provide a basis for the clinical application of different rehabilitation programs, but also expose a common problem: most of the conclusions are more inclined to the empirical induction of "effective programs" or "reasonable stages", and the multivariate coupling mechanism behind the rehabilitation cycle is not deeply revealed.

Furthermore, with the gradual integration of wearable sensing devices, motion capture systems and electronic medical record data, sports injury rehabilitation is no longer limited to single outpatient observation and scale recording. Gait parameters, range of motion, muscle strength test, pain score, training log, neurocognitive response, psychological questionnaire and imaging review information can be continuously accumulated in the same rehabilitation process, forming a rehabilitation data stream with temporal, heterogeneous and high-dimensional. Grooms et al. proposed that the combination of neurocognitive test and functional test for ACL return to exercise decision was helpful to improve the comprehensiveness of assessment [7]. Welling reviewed the research on ACL return and pointed out that it was difficult to judge the recovery status solely based on the fixed time window to meet the actual needs of equal emphasis on risk control and functional reconstruction [8]. Walker et al. case study showed that the staged group rehabilitation model focusing on the synchronous intervention of physical function and psychological function could improve the quality of postoperative return exercise [9]. Hwang et al. further introduced the machine learning method into the prediction of return movement after ACL surgery, showing that the physical performance data in early rehabilitation had good prediction potential [10]. These studies show that the comparative study of sports injury repair schemes is shifting from static empirical judgment to data-driven analysis. However, existing work still focuses on a single injury or a single prediction task, and the systematic research on modeling, comparing and optimizing the rehabilitation cycle under different repair schemes is still insufficient. To facilitate the explanation of the basic characteristics of the existing repair paths, Table 1 briefly summarizes the common repair schemes for sports injuries.

Table 1: Traditional sports injury repair schemes and their rehabilitation cycle analysis characteristics

Injury Type	Conventional Repair Scheme	Main Rehabilitation Content	Criteria for Determining the Rehabilitation Cycle	Existing Limitations
Hamstring strain	Conservative rehabilitation	Pain control, flexibility recovery, eccentric training, and running reconstruction	Pain relief, muscle strength recovery, and return-to-sport testing	Large individual differences and non-uniform standards for stage transition
ACL injury	Post-reconstruction rehabilitation	Restoration of joint range of motion, strength training, neuromuscular control, and sport-specific training	Postoperative time, functional testing, and return-to-sport criteria	Excessive reliance on time nodes and insufficient integration of psychological factors
Ankle sprain	Functional rehabilitation	Swelling reduction, stability training, proprioceptive training, and gait adjustment	Pain score, stability testing, and movement performance	Insufficient re-injury risk assessment and limited long-term follow-up
Limb soft tissue injury	Functional rehabilitation or combined repair	Pain control, restoration of joint mobility, muscle strength reconstruction, and progressive movement loading	Pain relief, range of motion recovery, and functional testing	Large differences in individual recovery pace and insufficient long-term load tracking

At present, related research still faces several limitations. First, the data sources of different sports injury repair schemes are not uniform, and the dimension differences between manual records, sensor data and clinical scores are obvious, and direct comparison is easy to cause feature distortion. Secondly, the rehabilitation process has significant stages, and the core indicators concerned by early swelling and pain relief, mid-term functional reconstruction and later specific regression are not the same. If a single feature set is used to describe the whole recovery state, it is often difficult to accurately reflect the key turning points. Third, the evaluation of traditional rehabilitation programs pays more attention to the final outcome, and the balance analysis between recovery efficiency, resource investment and recurrence risk is still not detailed enough. Fourth, common statistical analysis mostly stays at the level of mean comparison or correlation recognition, which has limited support for complex nonlinear relationships, individual difference propagation paths and scheme dynamic optimization ability. It can be seen that in the comparative study of different sports injury repair schemes, the introduction of computer methods such as data preprocessing, feature coding, multi-source fusion, period prediction and strategy optimization has become a feasible direction to improve the accuracy and interpretation ability of research.

Based on the above analysis, this paper focuses on the comparison and optimization of rehabilitation cycle of different sports injury repair schemes. On the basis of retaining clinical rehabilitation logic, the idea of computer modeling is introduced to preprocess and feature code multi-source rehabilitation data, and the rehabilitation state representation model and rehabilitation cycle prediction model are constructed. On this basis, a scheme optimization strategy for improving recovery efficiency is designed. The focus of this paper is not to summarize a single injury plan repetitively, but to establish a unified analysis framework suitable for multiple types of sports injury repair scenarios, so that different repair paths can be compared, interpreted, and optimized in the same data space. Through this study, it can provide method support for the formulation of clinical rehabilitation plan, the arrangement of athletes' return training and the construction of digital rehabilitation management platform.

2 Modeling and optimization analysis of rehabilitation cycle for different sports injury repair schemes

In order to achieve a unified comparison of the rehabilitation cycle of different sports injury repair schemes, this paper divides the method process into four parts: rehabilitation data preprocessing, rehabilitation scheme feature coding, rehabilitation state representation modeling, rehabilitation cycle prediction and scheme optimization. The original data comes from medical records, scale assessments, joint range of motion tests, muscle strength results, training logs and wearable device monitoring information, and the data structure has problems such as inconsistent time scales, obvious differences in variable dimensions, and inconsistent recording frequency. If this kind of data is directly used for cycle analysis, it is easy to amplify the noise interference, and it is not conducive to the lateral comparison between different repair paths. Based on this, this paper first uniformly cleaned and structured the multi-source rehabilitation data, and then mapped the injury type, repair method, rehabilitation stage, training load and functional recovery results into computable features to form a standardized sample set for subsequent modeling. The overall processing flow is shown in Figure 1.

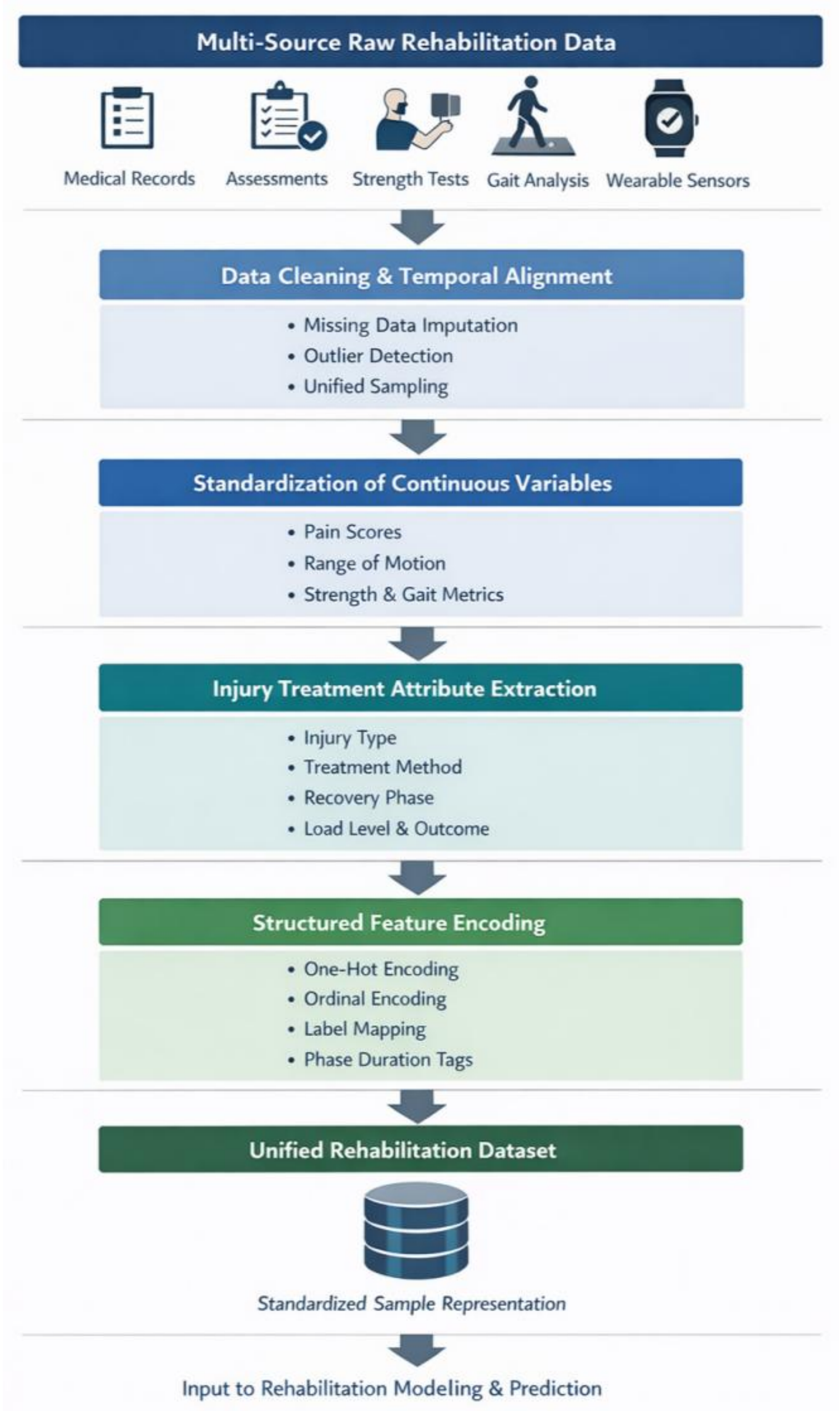

Figure 1: Rehabilitation data preprocessing and feature coding process of repair scheme

2.1 Rehabilitation data preprocessing and feature coding of rehabilitation scheme

Sports injury rehabilitation data have the characteristics of continuity, stage and heterogeneity at the same time. Variables such as pain score, joint range of motion, isokinetic muscle strength, and gait parameters are usually presented in numerical form, while repair mode, injury grade, stage goal, and whether regression criteria are met are mostly presented as discrete labels. In order to weaken the offset caused by the difference of the value range of different indicators, this paper standardized the continuous variables. Suppose the original value of the ith sample on the JTH index is x_{ij}, and the mean and standard deviation are μ_j and σ_j, respectively. Then the standardized result is expressed as follows.

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j + \varepsilon} \tag{1}$$

where, ε is a tiny constant set to prevent the denominator from being zero. After this process, different dimensional indicators are mapped to similar scales, which can reduce the dominance effect of high amplitude variables on the model training results, and make the indicators such as pain, range of motion, strength and load participate in the subsequent analysis in a unified numerical space.

Considering that there are often missing points, skip points and abnormal fluctuations in rehabilitation records, this paper corrects the data quality synchronously. The continuous variables were treated with the combination of "local time interpolation + median completion within the group", and the categorical variables were treated with the modal completion of samples with the same injury type and rehabilitation stage. Outlier identification does not rely on a single statistical threshold, but combines functional recovery logic for screening. For example, if the sample has a large muscle strength jump or activity mutation that does not conform to the physiological law in a short period of time, it will be judged as a suspected abnormal record, and combined with the change trend of the time point before and after correction or removal. After this process, all kinds of data are re-aligned to a unified timeline, which provides a basis for the comparison of different restoration schemes at the same stage.

After the completion of the foundation cleaning, it is necessary to structurally express the different repair options. In this paper, "injury type-repair method-rehabilitation stage-load level-recovery outcome" is defined as the core dimension of the program description, and the feature vector of the program is constructed:

$$s_i = [e_i^{(inj)}, e_i^{(rep)}, e_i^{(sta)}, e_i^{(load)}, e_i^{(out)}] \tag{2}$$

Here, $e_i^{(inj)}$ represents the injury type coding, $e_i^{(rep)}$ represents the repair mode coding, $e_i^{(sta)}$ represents the rehabilitation stage coding, $e_i^{(load)}$ represents the training load level, and $e_i^{(out)}$ represents the stage recovery outcome. This vector can transform protocol information originally scattered in text records, training prescriptions, and follow-up results into a unified representation. The specific coding rules for different repair paths are shown in Table 2. The contents listed in Table 2 show that this paper does not stop at the level of text description, but converts the repair plan into calculable structural variables through One-hot coding, sequential coding and label mapping, so that different paths such as conservative treatment, functional repair and postoperative reconstruction can enter the same modeling framework.

Table 2: Description of the feature encoding of the repair scheme

Feature Dimension	Original Information	Encoding Method	Example	Functional Role
Injury type	Hamstring strain, ACL injury, ankle sprain, etc.	One-hot encoding	ACL injury → [0,1,0,0]	Distinguishes different baseline rehabilitation pathways
Repair method	Conservative treatment, functional repair, postoperative reconstruction	Ordinal encoding	Conservative treatment = 1, postoperative reconstruction = 3	Represents differences in intervention intensity
Rehabilitation stage	Acute stage, recovery stage, sport-specific transition stage, return stage	Ordinal encoding	Return stage = 4	Characterizes the current rehabilitation position
Load level	Low, medium, moderately high, high	Hierarchical assignment	Moderately high = 3	Reflects the intensity of training stimulus
Recovery outcome	Target achieved, delayed recovery, elevated risk	Label encoding	Target achieved = 0	Serves as the basis for rehabilitation cycle prediction output

2.2 Rehabilitation state representation modeling based on multi-source feature fusion

Although the data of different sports injury repair schemes have been mapped into a unified expression space after preprocessing and feature coding, the coding results themselves are still difficult to directly reveal the potential state differences in the rehabilitation process. The reason is that although pain score, joint range of motion, muscle strength recovery, gait stability, training load and stage evaluation results jointly reflect the rehabilitation process, they correspond to different observation dimensions and change rhythms. If we only analyze each index in parallel, we can only get discrete local judgments, and it is difficult to form a continuous description of the overall rehabilitation state. Therefore, on the basis of feature coding in Section 2.1, this paper further constructs a rehabilitation state representation model based on multi-source feature fusion, and compresses rehabilitation information from different sources, different frequencies and different semantic levels into a unified state vector to provide stable input for subsequent rehabilitation cycle prediction.

At recovery time t, the observed feature from the m-th data source is $x_t^{(m)}$, where $m \in \{1,2,\cdots,M\}$ corresponds to the clinical scale, functional test, motion sensor, and training log, respectively. In order to reduce the interference caused by the inconsistent dimensions of different modes, the features of each mode are projected into the same latent space, which is expressed as follows.

$$p_t^{(m)} = \phi\left(W_m x_t^{(m)} + b_m\right) \tag{3}$$

Here, W_m and b_m represent the mapping parameters of the m-th mode, respectively, and $\phi(\cdot)$ is the nonlinear activation function. After this transformation, rehabilitation information from different sources is converted into intermediate representations with the same dimension, thus providing conditions for subsequent fusion calculations.

However, the contribution of different modalities to the rehabilitation state is not constant. During the acute phase, measures of pain and inflammation control are often more explanatory; After entering the functional recovery period, the importance of range of motion, muscle strength and motion control information increased significantly. When approaching the stage of return to exercise, the quality of special action completion and load tolerance are more worthy of attention. Based on this feature, this paper introduces the attention weight mechanism to adaptively calculate the contribution degree of each mode at the current time, and its expression is as follows.

$$\alpha_t^{(m)} = \frac{\exp\left(q^T \tanh\left(Up_t^{(m)}\right)\right)}{\sum_{k=1}^{M} \exp\left(q^T \tanh\left(Up_t^{(k)}\right)\right)} \tag{4}$$

Here, U is the transformation matrix, q is the attention parameter vector, and $\alpha_t^{(m)}$ represents the weight of the m-th mode at time t. The mechanism can automatically adjust the proportion of information according to the stage characteristics to avoid a single index dominating the judgment of rehabilitation status for a long time. After obtaining the modal weights, the multi-source features are weighted and fused to form the comprehensive rehabilitation representation at the current moment:

$$f_t = \sum_{m=1}^{M} \alpha_t^{(m)} p_t^{(m)} \tag{5}$$

where, f_t is the fused rehabilitation feature vector. This vector not only preserves information such as pain, function, load and action performance, but also compresses redundant features through weight allocation, making different repair schemes more comparable in the same representation space.

Considering that the rehabilitation process has obvious temporal evolution characteristics, this paper further inputs the fusion features and stage labels into the state update unit together to characterize the continuous changes of rehabilitation states over time. Let $e_t^{(sta)}$ be the embedding vector of the current rehabilitation stage and h_{t-1} be the hidden state at the previous time. Then the rehabilitation state at the current time can be expressed as follows.

$$h_t = \tanh\left(W_h[f_t\,;\, e_t^{(sta)}\,;\, h_{t-1}] + b_h\right) \tag{6}$$

where, $[\cdot\,;\,\cdot]$ represents vector concatenation, W_h and b_h are state update parameters. The resulting h_t is no longer a direct reflection of a single indicator, but a representation of the rehabilitation state after integrating multi-source observations, stage positions and historical recovery trajectories. Compared with the original features, the proposed state vector can better reflect the deep differences between different repair schemes in restoration rhythm, load adaptation and functional reconstruction.

Based on the above modeling process, this paper transforms multi-source heterogeneous rehabilitation data into continuous and learnable state sequences. Figure 2 shows the overall structure of this representation model. Figure 2 shows that, based on the multimodal input, the model generates the rehabilitation state vector after unified mapping, weight allocation and timing update, and outputs it to the subsequent rehabilitation cycle prediction module. In this way, different sports injury repair schemes no longer participate in the analysis in the form of static labels, but enter the model in the form of dynamic state trajectories, so that the comparison of rehabilitation cycles changes from "scheme name comparison" to "recovery process comparison", so as to enhance the interpretability of subsequent prediction and optimization analysis.

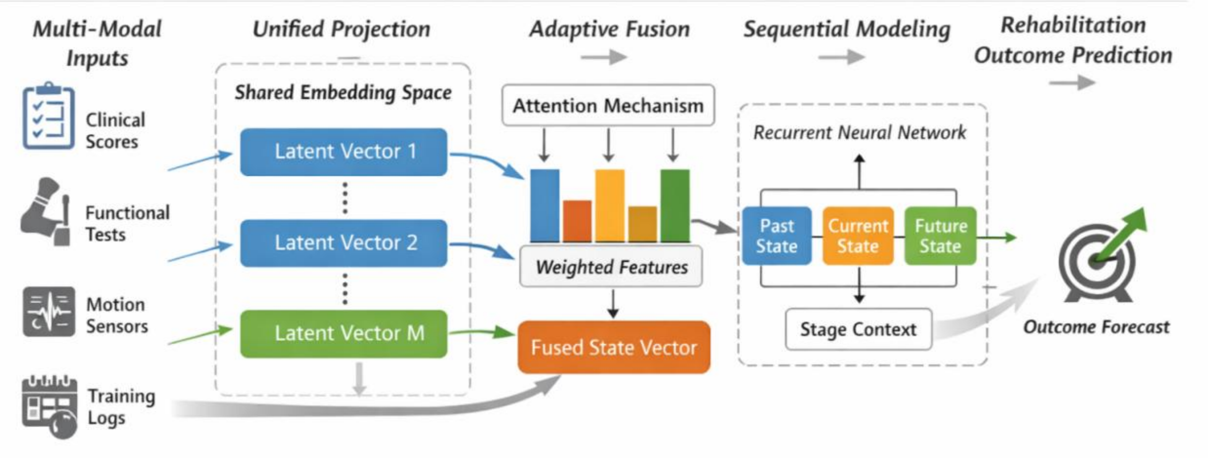

Figure 2: Rehabilitation state representation model based on multi-source feature fusion

2.3 Construction of rehabilitation cycle prediction models for different sports injury repair schemes

After multi-source feature fusion and rehabilitation state representation, although the model has been able to describe the recovery states of different injured individuals at various stages more stably, the state representation itself is still not equivalent to the prediction results of rehabilitation cycle. For different sports injury repair programs, the rehabilitation cycle is not directly determined by a single index at a certain time, but is a time result formed by the combined effect of the quality of tissue repair in the early stage, the level of functional reconstruction in the middle stage, the load tolerance capacity in the later stage, and the difference of program paths. In other words, even if the two samples show similar pain scores and activity levels at the current time point, the final time required to complete rehabilitation may still be significantly different due to different repair methods, stage advancement rhythms, and historical recovery trajectories. Based on this, based on the rehabilitation state vector in Section 2.2, this paper further constructs the rehabilitation cycle prediction model for different rehabilitation schemes, so as to realize the joint estimation of the total rehabilitation duration and the remaining recovery time.

Let the state sequence of sample i in the continuous rehabilitation observation window be $H_i = \{h_{i1}, h_{i2}, \cdots, h_{iT}\}$, where h_{it} is the rehabilitation state representation at time t. In order to preserve the temporal dependencies in state evolution, we encode the state sequence in a recursive manner, and obtain the hidden representation of stage advancement:

$$u_{it} = \Gamma(h_{it}, u_{i,t-1}) \tag{7}$$

where $\Gamma(\cdot)$ represents the temporal update unit, u_{it} is the temporal hidden state at time t, and $u_{i,t-1}$ is the historical information at the previous time. Through this process, the information of different stages, such as early inflammatory control, middle functional recovery and late specific regression, is concatenated into a unified time chain, so that the model not only focuses on the current state, but also recognizes the continuation characteristics of the recovery rhythm.

Considering that the rehabilitation cycle is often more affected by a number of key nodes, such as the point of obvious decline of pain, the point of reaching the target of range of motion, the point of symmetric near completion of strength, and the point of passing special tests, if all the moments are treated with equal weight, it is easy to weaken the decisive role of key stages on the cycle outcome. To this end, this paper introduces a stage attention allocation mechanism after temporal encoding to weight the importance of different time steps:

$$\beta_{it} = \frac{\exp(v^T \tanh(W_u u_{it} + W_s s_i))}{\sum_{k=1}^{T} \exp(v^T \tanh(W_u u_{ik} + W_s s_i))} \tag{8}$$

Here, s_i is the repair scheme coding vector for sample i, β_{it} represents the contribution weight to the cycle prediction at time t, and W_u, W_s and v are the learnable parameters. This design enables the model to automatically identify critical recovery nodes under different repair paths. For example, for postoperative reconstruction samples, the weight of the strength recovery versus motion control phase may be higher; For the conservatively treated sample, the effects of pain resolution and changes in load tolerance may be more prominent. After obtaining the time series weights, all hidden states are weighted and aggregated to form a global context vector for period determination:

$$c_i = \sum_{t=1}^{T} \beta_{it} u_{it} \tag{9}$$

The vector c_i synthetically reflects the recovery trajectory characteristics of the sample within the whole recovery window. Subsequently, the vector and the repair scheme coding are input into the output layer together to obtain the rehabilitation period prediction value $\hat{y}_i$:

$$\hat{y}_i = \mathrm{ReLU}(w_o^T [c_i; s_i] + b_o) \tag{10}$$

Here, $[c_i; s_i]$ represents the concatenation result of the context vector and the scheme vector, w_o and b_o are the output layer weight and bias, respectively, and $\hat{y}_i$ represents the predicted rehabilitation period. In order to ensure that the results have practical interpretation significance, this paper uniformly sets the prediction target as "the total number of days required to reach the regression training standard" or "the remaining number of days from the current time point to reach the standard", so that the prediction results of different damage types and different repair methods can be compared under the same caliber.

In the model training stage, the mean absolute error loss with regular constraints is used to maintain the stability of the prediction results while reducing the excessive deviation caused by abnormal samples. After model training, the rehabilitation cycles of different repair schemes can be compared and analyzed by the prediction mean, error distribution and key stage weights. In this way, the period prediction is no longer just output a single time value, but can simultaneously reveal more explanatory information such as "which kind of solutions recover faster", "which stages slow down the recovery progress" and "which path has more efficiency advantages in the same type of damage".

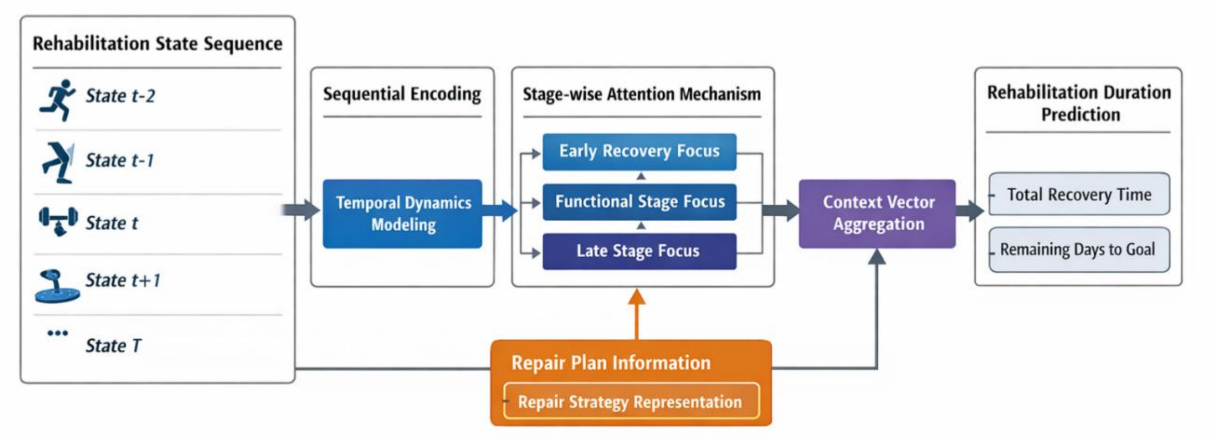

Figure 3: Structure of rehabilitation cycle prediction model for different sports injury repair schemes

Figure 3 illustrates the overall structure of the rehabilitation cycle prediction model for different sports injury repair schemes. The model takes the rehabilitation state sequence obtained in Section 2.2 as input and outputs the cycle prediction results after timing coding, stage weighting and scheme information injection. Through this modeling process, the basis of comparison between different sports injury repair schemes is changed from static scheme description to joint analysis of dynamic recovery trajectory and cycle results, which provides a direct basis for the design of scheme optimization strategy for recovery efficiency improvement in the next section.

2.4 Optimization strategy design for recovery efficiency improvement

After the rehabilitation state representation and rehabilitation cycle prediction, although the model has been able to estimate the recovery time of different sports injury repair schemes, the prediction results themselves still belong to the result layer information, and the key question of "how to adjust the current scheme to improve the recovery efficiency" cannot be answered directly. For sports injury repair, a shorter rehabilitation period does not necessarily mean a better program. If the training load is increased too quickly and the stage transition is too early, although the recovery days may decrease in the short term, it may also be accompanied by insufficient functional stability and increased risk of re-injury. Therefore, the optimization design for different restoration schemes should not only take the shortest cycle as the only objective, but also incorporate the restoration quality, risk control and load smoothness into the unified analysis framework. Based on the above cycle prediction model, this paper further constructs a scheme optimization strategy for improving recovery efficiency, which jointly adjusts the training load, intervention combination and stage promotion rhythm in different stages, so as to form a dynamic optimization mechanism considering cycle, quality and safety. Its overall structure is shown in Figure 4.

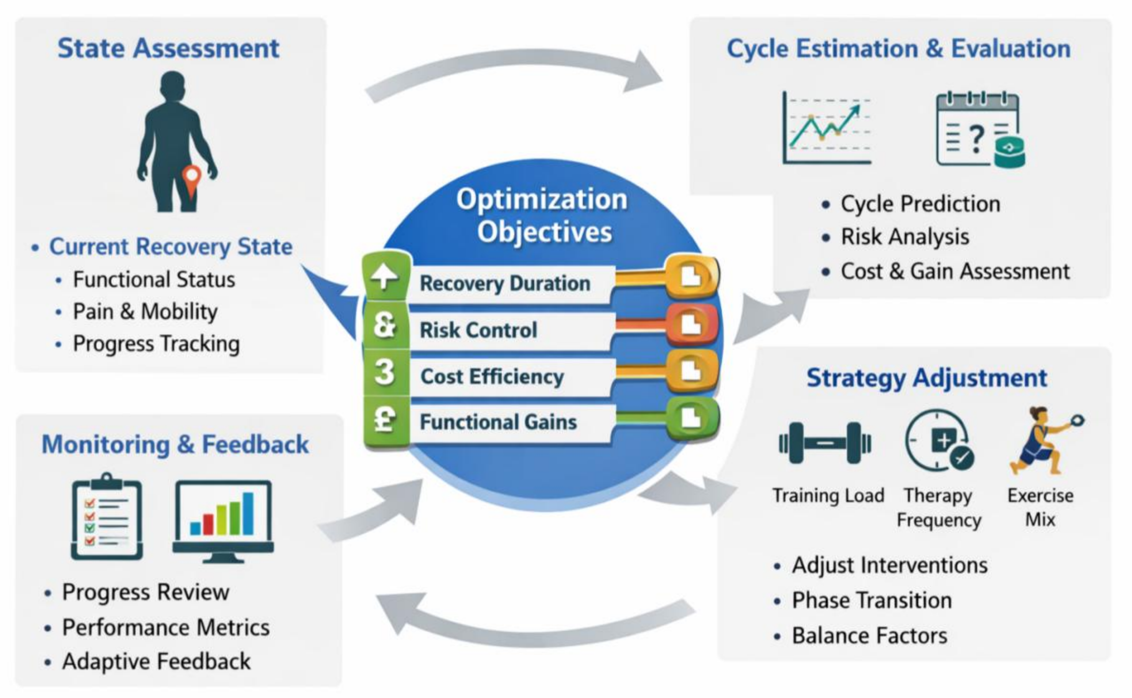

Figure 4: Design process of scheme optimization strategy for recovery efficiency improvement

Let the rehabilitation state of the sample at time t be denoted as h_t, and the corresponding candidate repair strategy as a_t, where a_t can be composed of the combination of training load, treatment frequency, action training proportion and recovery means. Aiming at the period change and risk change brought by different strategies, this paper constructs the objective function of recovery efficiency optimization:

$$J(a_t) = \lambda_1 \widehat{T}_t(a_t) + \lambda_2 \widehat{R}_t(a_t) + \lambda_3 C_t(a_t) - \lambda_4 \widehat{G}_t(a_t) \tag{11}$$

Here, $\widehat{T}_t(a_t)$ represents the residual rehabilitation period predicted under strategy a_t, $\widehat{R}_t(a_t)$ represents the risk of reinjury or recovery delay, $C_t(a_t)$ represents the cost of strategy implementation, $\widehat{G}_t(a_t)$ represents the expected functional gain, and $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are the weights of each objective term. By minimizing the recovery time, risk, and resource consumption, while increasing the functional improvement, the solution optimization is no longer limited to a single time compression, but to a comprehensive efficiency improvement.

Considering that the adjustment of rehabilitation program has the continuity requirement, and the excessive change of load is easy to destroy the existing recovery rhythm, this paper further sets the load stability constraint. Let l_t be the training load level in the current stage and l_{t-1} be the load in the previous stage, then the following should be satisfied.

$$|l_t - l_{t-1}| \leq \eta \tag{12}$$

Here, η is the maximum allowable load adjustment amplitude. This constraint can prevent unreasonable load transitions in pursuit of shorter cycles, and make the optimization results more in line with the progressive principle of exercise rehabilitation.

In the process of screening candidate strategies, we calculate the recovery efficiency score of each strategy based on the current state and the prediction result. Let the function improvement prediction value be $\widehat{F}_t(a_t)$ and the remaining period decline be $\Delta\widehat{T}_t(a_t)$, then the strategy efficiency index is defined as follows.

$$E_t(a_t) = \frac{\Delta \hat{F}_t(a_t)}{\Delta \hat{T}_t(a_t) + 1} \tag{13}$$

This index reflects the level of function improvement brought by unit cycle shortening. If a strategy can reduce the predicted recovery days, but the functional gain is limited, its efficiency score is not too high. On the contrary, if a strategy can effectively shorten the period while ensuring the recovery quality, it is more likely to be selected as the preferred scheme by the model. With this design, the optimization process is able to avoid a mechanical preference for "short recovery" and move towards the identification of "high quality recovery efficiency".

Based on the objective function and constraints, the optimization strategy is selected by adaptive updating method stage by stage. For the candidate set At A_t time t, the optimal policy is denoted as follows.

$$a_t^* = \arg\min_{a_t \in A_t} J(a_t), \quad s.t. |l_t - l_{t-1}| \le \eta \tag{14}$$

When the sample enters the next rehabilitation stage, the model will recalculation the candidate strategy score according to the new state representation, the updated cycle prediction results and the execution feedback, thus forming a closed-loop process of "state recognition-cycle estimation, strategy adjustment-feedback update". In this way, the scheme optimization is no longer a fixed plan given once, but a continuous decision-making mechanism that dynamically evolves with the recovery process.

From the perspective of method, the optimization strategy promotes the comparison of different sports injury repair schemes from static judgment to dynamic efficiency reconstruction level. For the scheme with slow recovery but low risk, the model can improve the cycle efficiency by fine-tuning the training load and phase switching conditions. For the scheme with fast recovery but large fluctuation, the load growth rate can be appropriately restrained to avoid damage to long-term stability due to short-term compression cycles. Therefore, the optimization output not only gives the judgment of "which scheme is better", but also further explains "which elements to adjust at which stage is more conducive to improving the recovery efficiency". This also provides a clear method basis for the subsequent experimental part to compare the optimization effects of different repair schemes.

3 Experimental Analysis

3.1 Experimental design and parameter setting

In order to verify the applicability of the rehabilitation cycle modeling and optimization method constructed in this paper in the comparison of different sports injury repair schemes, the experimental data were selected from the continuous follow-up records of a sports rehabilitation center and two high-level sports teams in two universities. The sample was included from January 2022 to December 2024, and individuals with complete records of the whole process from injury diagnosis, protocol development, stage intervention to achieving stage functional training standards were retained. After data screening, 192 effective rehabilitation samples were finally obtained, and a total of 5696 evaluation records were formed. The age of the samples was concentrated between 18 and 29 years old, with an average age of 22.8 years old, covering common sports injury types such as hamstring strain, anterior cruciate ligament injury, ankle sprain and upper limb soft tissue injury. The distribution of samples of various classes on the repair path is shown in Table 3. It can be seen from Table 3 that the experimental data are not a single injury scenario, but include a variety of schemes such as conservative repair, functional repair, staged postoperative rehabilitation and combined repair, which provides a data basis for testing the stability of the model in the cross-scheme comparison.

Table 3: Composition of experimental samples and distribution of repair schemes

Injury Category	Main Repair Scheme	Number of Samples/Cases	Number of Evaluation Records	Observation Period Range / d
Hamstring strain	Conservative repair + progressive eccentric training	48	1440	21–56
Anterior cruciate ligament injury	Postoperative staged rehabilitation + neuromuscular control training	42	1512	120–300
Ankle sprain	Functional repair + proprioceptive training	56	1456	14–70
Upper-limb soft tissue injury	Combined repair + progressive load training	46	1288	28–98
Total	—	192	5696	—

The original information used in the experiment included outpatient medical records, visual pain scores, joint range of motion, isokinetic muscle strength results, balance test results, training logs, and gait and action load data collected by wearable inertial sensors. In order to maintain the consistency of data from different sources on the time axis, this paper constructed the rehabilitation sequence based on the assessment records in the stage, and summarized it by week to obtain a unified time series input. Then, the training set, validation set and test set were divided according to the ratio of 8：1：1. The training set is used to learn the relationship between rehabilitation state representation and cycle prediction, the validation set is used for model tuning to participate in early stop control, and the test set is used to evaluate the generalization ability of the model on unseen samples. The evaluation indexes mainly include mean absolute error, root mean square error, coefficient of determination and cycle shortening rate after scheme optimization, so as to investigate the prediction accuracy and optimization effectiveness at the same time.

In terms of parameter Settings, the experimental environment and core model parameters in this paper are shown in Table 4. At the software level, Ubuntu 22.04 operating system, Python 3.11 programming environment and PyTorch 2.2 deep learning framework were used. At the hardware level, Intel Core i7-12700 processor, 32 GB memory and NVIDIA RTX 4080 16 GB graphics card are used. Based on the method design in Section 2.1-2.4, the length of time window was set to 6 in model training, indicating that each input was 6 consecutive rehabilitation observation units. The multi-source feature projection dimension was set to 64, and the state hidden layer dimension was set to 128, so as to balance the representation ability and computational overhead. The batch size is set to 32, the optimizer uses AdamW, and the initial learning rate is set to 2×10^{-4}. In the scheme optimization part, the weights of cycle loss, risk control, implementation cost and function gain were set to 0.45, 0.25, 0.10 and 0.20, respectively, in order to prevent the model from blindly pursuing cycle shortening and ignoring the quality of function recovery. Such weight configuration makes the model more emphasis on the balance between recovery efficiency and security, rather than one-sided compression of recovery time.

Table 4: Experimental environment and core parameter Settings

Parameter Category	Parameter Name	Setting Value
Runtime environment	Operating system	Ubuntu 22.04
Runtime environment	Programming language	Python 3.11
Runtime environment	Deep learning framework	PyTorch 2.2
Hardware environment	CPU	Intel Core i7-12700
Hardware environment	Memory	32 GB
Hardware environment	GPU	NVIDIA RTX 4080 16 GB
Data settings	Dataset split	8:1:1
Data settings	Time window length	6
Feature settings	Projection dimension	64
Model parameters	Hidden layer dimension	128
Model parameters	Attention dimension	64
Model parameters	Batch size	32
Training parameters	Optimizer	AdamW
Training parameters	Learning rate	2×10^{-4}
Training parameters	Maximum number of training epochs	80
Regularization settings	Dropout	0.2
Training control	Early stopping	Stop if no improvement is observed for 8 consecutive epochs
Optimization weights	Cycle term $\lambda 1$	0.45
Optimization weights	Risk term $\lambda 2$	0.25
Optimization weights	Cost term $\lambda 3$	0.10
Optimization weights	Functional gain term $\lambda 4$	0.20

The parameters in Table 4 are not set arbitrarily, but are matched around the structure of the proposed method. The length of the time window was set to 6, which was conducive to covering both early symptom fluctuations and mid-term functional changes. The hidden layer dimension was set to 128, which could retain the stage differences in the rehabilitation state sequence without excessive increase in model complexity. Dropout was set to 0.2 to reduce the over-fitting tendency under the condition of relatively limited sample size. Early Stopping, which is set to 8 consecutive rounds without boosting, helps to keep the model stable in the later stage of training. The setting of multi-objective optimization weights made the scheme recommendation results more in line with the decision logic of "recovery quality first and cycle efficiency" in the actual rehabilitation scenario.

After completing the above Settings, this paper conducts a preliminary stability check of the model training process. Figure 5 Results of the validation set mean absolute error varying with the number of training rounds. Figure 5 shows that the error of the model decreases rapidly in the first 30 rounds of iterations, indicating that an effective periodic mapping relationship has been gradually established between multi-source feature fusion and time series representation. After entering 50 rounds, the error decline slowed down significantly, and basically stabilized at a low level until about 60 rounds, indicating that the model has good convergence and operation stability under the current parameter setting.

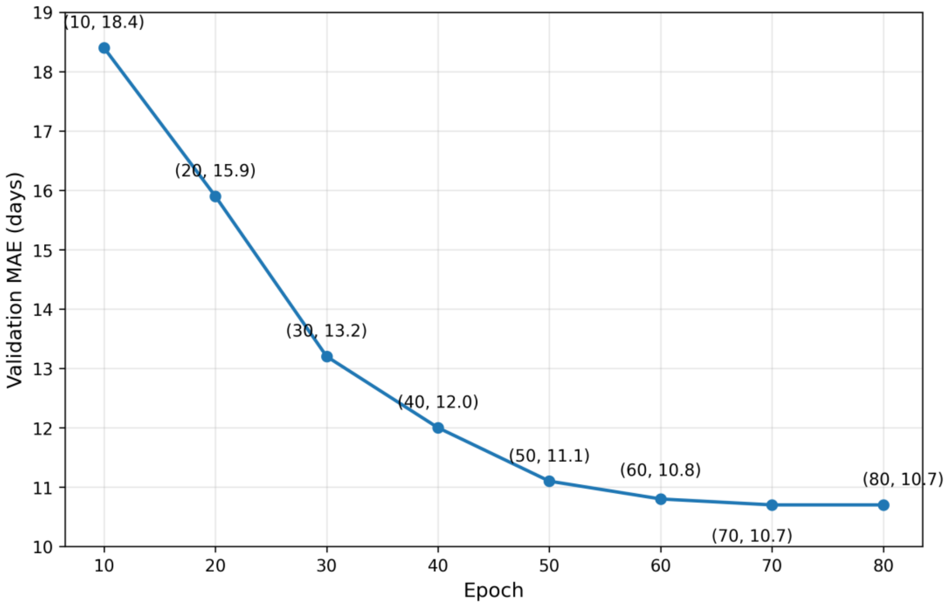

Figure 5: Results of the validation set mean absolute error as a function of the number of training rounds

3.2 Results comparison and optimization analysis

In order to test the effectiveness of the proposed model in the prediction of the rehabilitation period of different sports injury repair schemes, this paper carries out the result analysis from three levels: prediction error, fitting degree and program optimization benefit. The prediction accuracy was measured using mean absolute error, root mean square error and coefficient of determination, denoted as MAE, RMSE and R^2, respectively. It is calculated as follows.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{15}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2} \tag{16}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{17}$$

where $\hat{y}_i$ is the predicted recovery period, y_i is the true recovery period, $\bar{y}$ is the mean of the true period, and n is the number of test samples. Among the above indicators, the smaller MAE and RMSE are, the lower the model prediction error is. The closer R^2 is to 1, the better the ability of the model to explain the changing trend of the rehabilitation cycle is.

On the test set, the proposed method is compared with Random Forest, XGBoost and LSTM, and is uniformly evaluated by the same training set, validation set and test set division and the same evaluation index. The results show that the proposed model achieves low error in four main damage scenarios. Taking the hamstring strain as an example, the MAE of the proposed method is 4.8 d, which is significantly lower than that of Random Forest (7.1 d), XGBoost (6.4 d) and LSTM (5.6 d). In the ACL postoperative rehabilitation samples, the proposed method also maintains a low error level, and has different degrees of decline compared with the comparison methods. Figure 6 shows the MAE results of different methods on each damage category. As can be seen from Figure 6, with the increase of rehabilitation path complexity, the error of traditional machine learning methods on long-period samples increases more obviously, while the proposed method maintains a relatively stable error level in short-period scenarios such as ankle sprain and hamstring strain and long-period scenarios such as ACL surgery. This shows that the multi-source feature fusion and stage attention mechanism can more effectively capture the key node changes in the rehabilitation process, thereby improving the accuracy of period estimation under different repair schemes.

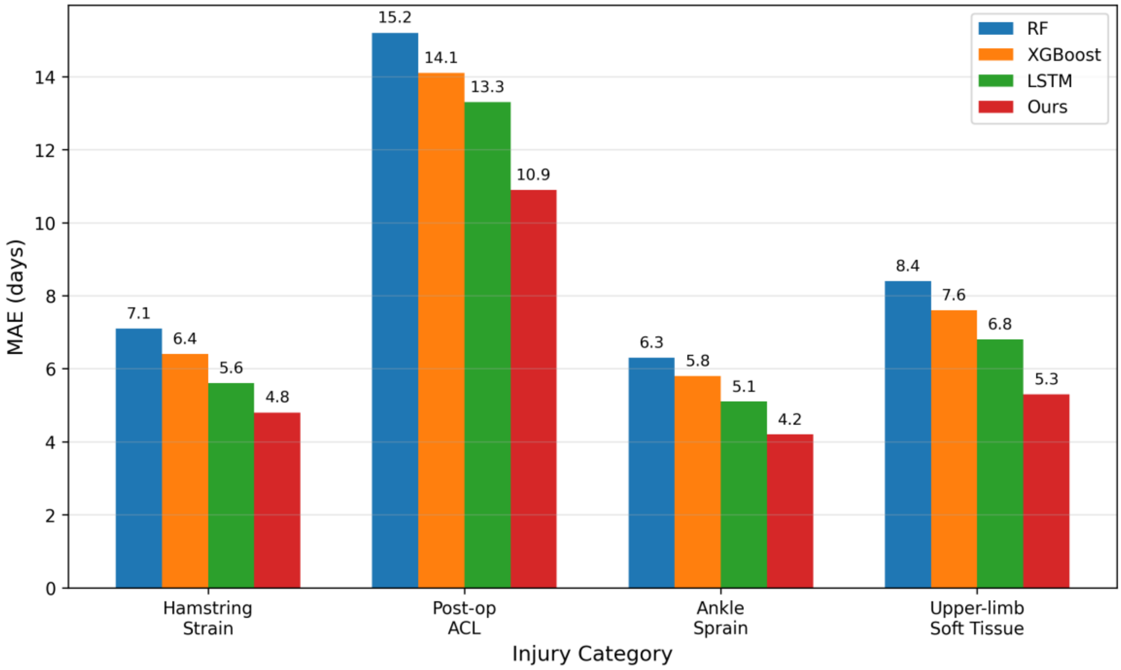

Figure 6: Comparison of MAE of different methods in various types of sports injuries

In order to further investigate the consistency between the model output and the real rehabilitation cycle, this paper grouped the test set samples according to the repair path, and compared the average of the real rehabilitation cycle and the predicted rehabilitation cycle under various schemes. Figure 7 shows the comparison results of four typical repair schemes, where the true average rehabilitation cycle of the conservative repair sample is 37.3 days, and the predicted average rehabilitation cycle is 35.6 days. The real average rehabilitation cycle of functional rehabilitation samples was 49.2 days, and the predicted average rehabilitation cycle was 47.9 days. The true average rehabilitation period of the combined repair sample was 64.7 days, and the predicted average rehabilitation period was 63.4 days. The true average rehabilitation period of the postoperative staged rehabilitation samples was 110.6 days, and the predicted average rehabilitation period was 111.7 days. It can be seen that the predicted value and the true value under each repair plan are generally close, and the change trend between groups is consistent, indicating that the model can better reflect the hierarchical difference of rehabilitation cycle under different repair paths. Further, the error index is calculated on all test samples, and MAE=5.0d, RMSE=6.4d, R^2=0.95. This indicates that the model not only has a good fitting effect at the group mean level, but also maintains a high prediction accuracy at the individual sample level. According to the results of the sub-scheme, the period of postoperative staged rehabilitation was the longest, but the prediction deviation was still controlled within a small range. The prediction results of conservative repair and functional repair samples are closer to the real observation values, indicating that the model has a stable ability to identify the short and medium cycle rehabilitation process. In general, the proposed method can accurately characterize the difference in rehabilitation cycle between different sports injury repair schemes, which provides a reliable data basis for subsequent scheme optimization analysis.

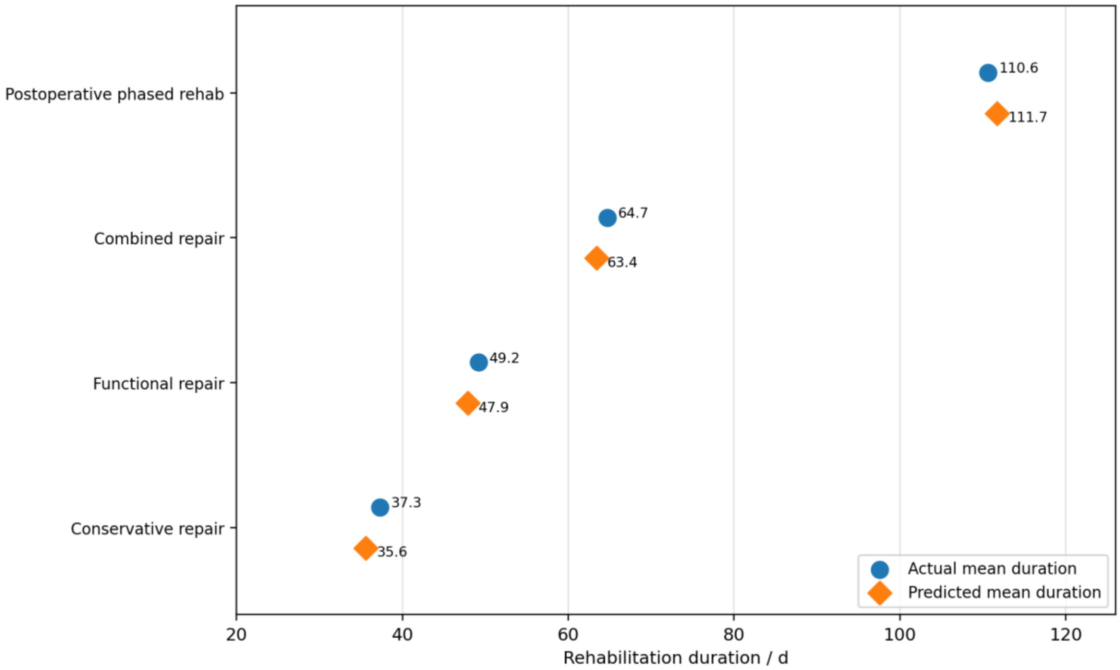

Figure 7: Comparison of true and predicted periods for different repair schemes

Based on the period prediction, this paper further tests the improvement effect of the optimization strategy on the recovery efficiency. The average rehabilitation cycle, function attainment rate and the proportion of high-risk samples were calculated before and after optimization. The results showed that the average rehabilitation period of the test sub-samples in the optimization module was reduced from 78.6 days to 68.9 days, a reduction of 12.3%. The function standard rate increased from 81.4% to 88.7%; The proportion of high-risk samples decreased from 16.8% to 11.2%. This result indicates that the optimization module in this paper does not simply compress the recovery time, but improves the repair efficiency under the premise of controlling the risk. Further analysis by injury category showed that the period of ACL samples was improved the most, with an average reduction of 15.1%. The sample of ankle sprain was the second, shortened by 11.6%. Hamstring strain and upper limb soft tissue injury samples were reduced by 9.8% and 10.4%, respectively. Figure 8 shows the changes of key indicators before and after optimization. It can be seen from Figure 8 that the change direction of the three indicators is consistent, indicating that the optimization strategy does not sacrifice the recovery quality while shortening the period, but improves the function recovery results.

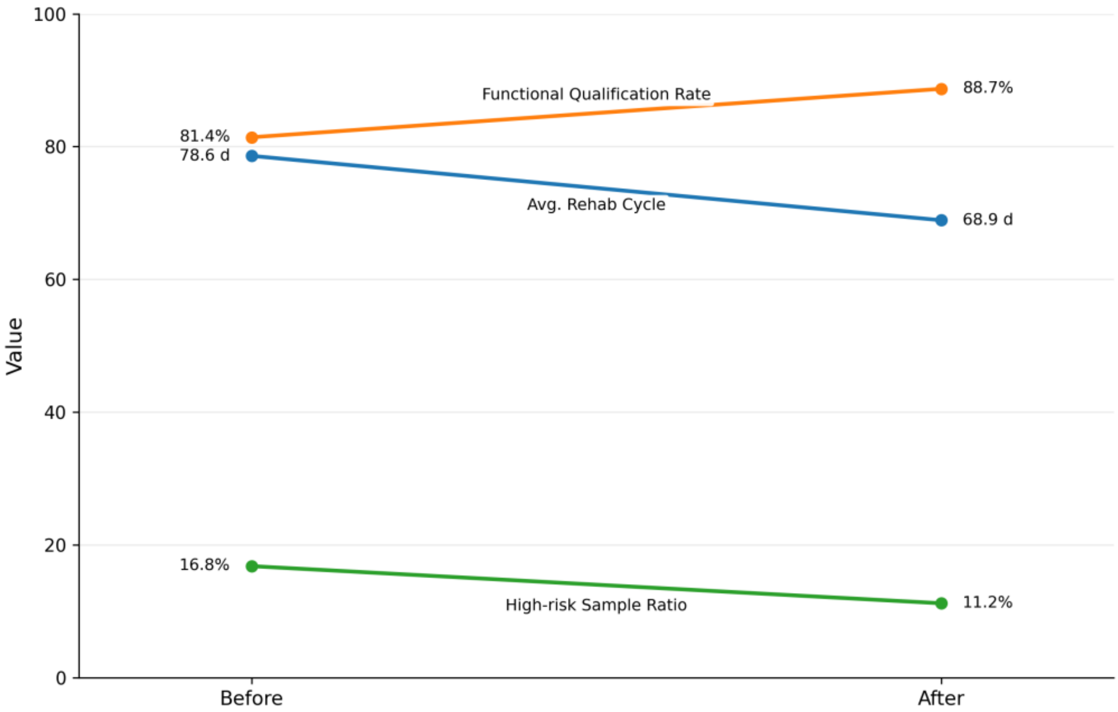

Figure 8: Change of recovery efficiency index before and after optimization

Taking the above results into account, it can be seen that the proposed method has good accuracy and stability in the prediction of rehabilitation period of different sports injury repair schemes. Compared with the comparison methods, the advantages of the proposed method are mainly reflected in two aspects. Firstly, through multi-source feature fusion and stage weight allocation, the dynamic information in the rehabilitation process is more fully retained, so that the model can still maintain a low error under complex repair paths. Secondly, by introducing the optimization module oriented to recovery efficiency, the cycle prediction results are further transformed into an executable basis for scheme adjustment, so that the research conclusion is not only limited to the level of "more accurate prediction", but also extended to the application level of "more effective optimization". This also shows that the method proposed in this paper can provide reliable data support for the cycle comparison and rehabilitation path optimization of different sports injury repair schemes.

4 Discussion

Compared with the comparison methods such as Random Forest, XGBoost and LSTM, the proposed method shows higher stability and better adaptability in the prediction and optimization analysis of the rehabilitation cycle of different sports injury repair schemes. This advantage mainly comes from the introduction of multi-source feature fusion and stage attention modeling. Traditional methods mostly rely on static features or single path data, which lack the description of the continuous association between pain change, functional recovery, training load adjustment and stage transition in the rehabilitation process, so they are prone to prediction bias in scenarios with long periods and strong individual differences. The proposed method integrates multi-source rehabilitation information into the state representation process, so that the recovery trajectories of different rehabilitation schemes can be compared under the same framework, which is an important reason why its prediction accuracy is better than that of the comparison methods. Looking further, this paper not only focuses on the prediction results of the rehabilitation cycle, but also incorporates the recovery quality, risk control and load stationarity into the optimization objective. Compared with the prediction model that only outputs time estimates, this processing method is closer to the actual rehabilitation decision-making process, and is more conducive to identifying the efficiency differences of different rehabilitation schemes in specific stages. The experimental results show that the optimized scheme can shorten the average rehabilitation period, improve the function standard rate, and reduce the proportion of high-risk samples, indicating that the method in this paper has achieved a good balance between recovery efficiency and safety. However, there are still some limitations in this paper. The sample sources mainly focused on common sports injury types, and the coverage of extreme cases and complex concurrent injuries was still insufficient. The acquisition frequency of some rehabilitation indicators is limited by the actual follow-up conditions, which may also affect the fine-grained description of the stage state. Subsequent studies can expand the sample scope, introduce more high-frequency dynamic monitoring data, and combine more refined individual differences modeling strategies to further improve the interpretation ability and promotion value of the model in complex rehabilitation scenarios.

5 Conclusion

Aiming at the comparison and optimization of rehabilitation period of different sports injury repair schemes, this paper constructs a unified analysis framework including state representation, period prediction and strategy optimization. Studies show that the proposed method can describe the recovery differences of different injury types and different repair paths in a unified modeling space, and provide clear data basis for the adjustment of rehabilitation programs. Its value is mainly reflected in two aspects: (1) through the fusion modeling of clinical indicators, functional tests, training load and dynamic monitoring information, the continuity and integrity of rehabilitation state recognition are enhanced; (2) By introducing the period prediction and multi-objective optimization mechanism, the scheme comparison is no longer limited to empirical judgment, but can take into account the recovery efficiency, functional standard and risk control.

The experimental results show that the proposed method has achieved good performance in the prediction accuracy of rehabilitation cycle and the effect of scheme optimization. It can reflect the difference in the recovery rhythm of different rehabilitation schemes more stably, and improve the pertinence of scheme adjustment to a certain extent. It should be noted that the sample type and data granularity still affect the generalization ability of the model. Subsequent studies can further expand the coverage of injury categories, introduce more high-frequency continuous monitoring data, and combine more refined individual differences modeling and lightweight deployment methods to improve the application depth and promotion value of the model in actual sports rehabilitation scenarios.

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