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Reinforcement Learning Driven Garment Material Intelligent Design and Sustainability Optimization Strategy

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SUMMARY: *The core of intelligent design of clothing materials is to form a collaborative optimization between wear performance, process adaptation and sustainable goals. Aiming at the problems of traditional material development relying on manual screening, long sample cycle, and lagging green index feedback, this paper proposes a reinforcement learning driven intelligent design and sustainability optimization strategy for clothing materials. The strategy integrates material performance state modeling, material combination decision-making, process parameter adjustment and sustainable reward feedback, and integrates fiber proportion, fabric structure, dyeing and finishing parameters, carbon emission, water consumption and recyclable proportion into a unified calculation framework. The experimental results show that the comprehensive performance score of the complete reinforcement learning scheme is improved from 77.1 to 84.6, the design adaptation accuracy is improved to 90.8%, the unit carbon emission is reduced from 4.82 kgCO₂e/kg to 3.91 kgCO₂e/kg, and the sustainability score is improved to 81.5. The results show that the proposed method can improve the efficiency of clothing material design and the level of green optimization, and provide technical support for the intelligent and low-carbon transformation of the clothing industry.*

KEYWORDS: *Reinforcement learning; Clothing material design; Sustainable optimization; Process parameter adjustment*

1 Introduction

Different from traditional garment material development methods that rely on designer's experience judgment, repeated comparison of material samples and manual correction of process parameters, reinforcement learning driven intelligent design of garment materials can transform factors such as fiber composition, organizational structure, dyeing and dyeing process, wear performance and environmental impact into a computable state space, and constantly find a better material combination scheme through strategy iteration. This method no longer regarded material selection as a single point screening process, but incorporated strength, air permeability, drapability, wear resistance, cost, carbon emission, recyclability and production suitability into a unified decision-making chain, so as to form a dynamic coordination between functional performance and sustainability goals in clothing material design.

Aiming at the problems of scattered performance evaluation, difficulty in quantifying green indicators, dependence on experience for process adjustment, and obvious conflict of multi-objective constraints in clothing material design, this paper proposes a reinforcement

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learning driven intelligent design and sustainability optimization strategy for clothing materials. The research is carried out from four aspects: clothing material performance state modeling, material combination and process parameter decision-making, sustainability reward function construction, and adaptation optimization under multi-objective constraints. The computer model is used to encode, learn and feedback modify the characteristics of material samples, which promotes the material scheme from static evaluation to intelligent generation and continuous optimization. Through this strategy, the efficiency of material design can be improved, the cost of repeated proofing can be reduced, and the method support for the green, precision and intelligent transformation of the garment industry can be provided.

The structure of this paper is as follows: the second part combs the related research of artificial intelligence material design, circular fashion and sustainability evaluation; The third part describes the reinforcement learning driven intelligent design and optimization scheme of clothing materials. The fourth part analyzes the effect of the model and the sustainable feedback results by combining the sample data. The fifth part discusses the application value and limitations of this method. Section 6 summarizes the research conclusions and puts forward the future improvement direction.

2 Related Research

The intelligent design of garment materials is not simply to complete the screening of fabric performance, but to establish a computable synergistic relationship between fiber composition, fabric structure, finishing process, wear comfort, cost control and environmental load. The development of existing clothing materials mostly relies on laboratory tests, designer experience and historical process data of enterprises. The material scheme is often adjusted repeatedly among proofing, trying, testing and rework, which is difficult to respond to the needs of small-batch, multi-category and green manufacturing in a timely manner. With the development of artificial intelligence, material computing and sustainable evaluation methods, clothing material design has begun to shift from empirical judgment to data-driven modeling. However, there is still room for further expansion in continuous decision-making, dynamic feedback and multi-objective optimization.

Papadimitriou et al. [1] systematically reviewed the application of artificial intelligence in material design, discovery and manufacturing, and pointed out that machine learning can extract the potential structural-property relationship from complex material data and provide a prediction basis for material design. Pyzer-Knapp et al. [2] further emphasize the synergy between artificial intelligence, high performance computing and automated experimental platforms, and believe that the material discovery process can form a closed loop through algorithmic search, computational simulation and experimental feedback. Tran et al. [3] focused on functional and sustainable polymer design, and proposed that artificial intelligence could be used for molecular structure screening, performance prediction and environmentally friendly material development, which provided a method for intelligent design of clothing fiber and polymer-based materials. The above studies demonstrate the computational potential of artificial intelligence in the field of materials, but their focus is more on material discovery and performance prediction, and there is insufficient discussion on wearing experience, process adaptation, and sustainable constraint integration in clothing material scenarios.

In terms of textile and garment material recognition, Seckin et al. [4] constructed the FabricNET fabric microscopic image dataset, and used machine learning to predict fabric texture and weaving parameters, which provided a data basis for the digitization of fabric structural features. Aydın and Altun[5] applied machine learning to early fabric quality prediction in an attempt to reduce rework and quality fluctuations in the manufacturing front-end. Such studies show that fabric images, production parameters, and inspection metrics can be transformed into model inputs for quality control. However, clothing material design does not only focus on single quality indicators, but also needs to take into account elasticity, air permeability, wear resistance, drapiness, skin affinity and life cycle impact. Without the reinforcement learning strategy update mechanism, the model usually can only complete the static prediction, and it is difficult to constantly revise the material combination and process parameters according to the reward feedback.

Sustainable fashion and circular clothing research offer another important path for material optimization. Dissanayake and Weerasinghe[6] analyzed the strategies, obstacles and promoting factors of the fashion industry from the perspective of circular economy, and pointed out that material recycling, recycling and supply chain collaboration are the key to the sustainable transformation of clothing. D 'Itria and Colombi[7] focus on the role of bio-based innovation in fashion and textile design, emphasizing that material provenance itself has become an important component of design decisions. Manshoven and Van Opstal[8] discussed the role of mandatory policies in promoting circular fashion systems, showing that sustainable material design is not only affected by technology, but also restricted by regulations, consumer acceptance and distribution of responsibility in the industry chain. Abbate et al. [9] analyzed the circular business model through the case of Italian clothing industry, and pointed out that the transformation from fast fashion to slow fashion requires the simultaneous improvement of material durability, product use cycle and recycling path. Seidu et al. [10] summarized the research on circular fashion and bio-based materials, and further indicated that environmental impact, functional performance and industrial feasibility should be put into the same evaluation framework for sustainable material selection.

In recent years, the coupling between digital technology and sustainable clothing has gradually increased. Casciani and D 'Itria [11] proposed the adoption direction of digital technology for sustainable and circular fashion, emphasizing that digital laboratories, data platforms and material information management can improve the transparency of clothing development process. Saha et al. [12] conducted a comprehensive review of the research on circular economy in the textile and garment industry, and pointed out that the existing research has rich achievements in resource efficiency, waste management and life cycle assessment, but it is still insufficient in intelligent decision-making model. Rehman et al. [13] analyzed waste flow and life cycle management in sustainable fashion, revealing obvious differences in resource consumption and environmental emissions in different production links. Barletta et al. [14] studied innovative business models such as clothing rental, indicating that material design needs to consider the frequency of use, maintenance cost and cycle service mode. Starting from the goal of sustainable leather production and consumption, D 'Adamo et al. [15] indicated that material evaluation should include social acceptance and production responsibility. Khatami et al. [16] analyzed the relationship between sustainability and textile, clothing, leather and footwear industries at the national level, providing a macro basis for regional industrial policies and material optimization strategies.

In terms of sustainability evaluation methods, Karadayi-Usta and Tirkolaee[17] used the Neutristica ORESTE method to evaluate the sustainability of fashion brands, indicating that the multi-index decision-making method can deal with uncertainty and preference differences in the clothing industry. Amicarelli et al. [18] used the life cycle assessment method to analyze the "acquire-manufacturing-waste" mode in textile production, revealing the environmental burden in the traditional production chain. Bianco et al. [19] measured the life-cycle environmental impact of textile products through the case of wool underwear, and proved that specific materials, processing routes and use stages would affect the final evaluation results. Bianco et al. [20] further carried out life cycle assessment of worsted and worsted wool processing, indicating that by-product utilization and process route selection would change environmental performance. Hammar et al. [21] studied the life cycle impact of fiber-to-fiber recycling, which provided a quantitative basis for fiber recycling technology to enter clothing material design. Related research provides the basis for the construction of sustainable reward functions in this paper, but most of them belong to evaluation research, which has not yet been fully transformed into an optimization mechanism that can be fed back in real time during the design process. In order to further present the differences of existing research in terms of method paths, application scenarios and shortcomings, this paper summarizes the relevant results of intelligent design and sustainable optimization of clothing materials, as shown in Table 1.

Table 1: Comparison of related studies on intelligent design and sustainable optimization of clothing materials

Research Direction	Representative References	Method or Technology	Implications for This Study	Limitations
AI-based material design	Papadimitriou et al. [1], Pyzer-Knapp et al. [2], Tran et al. [3]	Machine learning, high-performance computing, material structure prediction	Material properties can be transformed into computable features	Insufficient consideration of garment-wearing scenarios
Fabric quality and structure recognition	Seçkin et al. [4], Aydın and Altun [5]	Image datasets, quality prediction models	Supports digital modeling of fabric parameters	Weak capability in multi-objective decision-making
Circular fashion and bio-based materials	Dissanayake et al. [6], D'Itria et al. [7], Seidu et al. [10]	Circular strategies, bio-based material analysis	Provides a basis for green material selection	Lacks algorithmic optimization pathways
Digital technology and sustainable apparel	Casciani et al. [11], Saha et al. [12], Rehman et al. [13]	Digital platforms, waste-stream management, lifecycle management	Supports data-driven design feedback	Insufficient connection with material combination decisions
Business models and industrial sustainability	Abbate et al. [9], Barletta et al. [14], D'Adamo et al. [15], Khatami et al. [16]	Circular business models, industry-level analysis	Expands the industrial adaptation dimension of material design	Difficult to directly guide parameter adjustment
Lifecycle and multi-indicator evaluation	Karadayi-Usta et al. [17], Amicarelli et al. [18], Bianco et al. [19][20], Hammar et al. [21]	LCA, multi-indicator decision-making, recycling evaluation	Can serve as sources for reward functions and constraint terms	Mostly focuses on post-evaluation, with insufficient real-time optimization

Based on the above research, it can be found that the existing results have formed a good foundation in the intelligent prediction of materials, fabric quality recognition, circular fashion strategy and life cycle assessment respectively, but there are still gaps between different research directions: Material performance model focuses on prediction accuracy, sustainability research focuses on evaluation framework, and industrial research focuses on pattern analysis. There is a lack of a continuous decision-making mechanism that can connect "material state -- design action -- performance feedback -- sustainable reward". Reinforcement learning can deal with complex constraints in the process of multiple rounds of trial and error, feedback correction and long-term profit maximization, which is suitable for clothing material combination, process parameter adjustment and green index balance.

Therefore, this paper intends to focus on the following issues:

(1) How to represent the physical properties, appearance characteristics, processing parameters and sustainability indicators of clothing materials into a unified reinforcement learning state space;

(2) How to design material decision actions for fiber proportions, fabric organization, finishing parameters and application scenarios;

(3) How to incorporate strength, comfort, cost, carbon emission, recyclability and durability into the reward function, so as to avoid the lack of comprehensive adaptation caused by the single optimal performance of the model;

(4) How to realize the dynamic adjustment and sustainable optimization of intelligent design scheme of clothing materials under multi-objective constraints.

The main idea of this paper is to construct a reinforcement learning optimization framework for clothing material design, which combines the material sample database, performance feature extraction, action strategy update and sustainable feedback evaluation. The performance, production cost, environmental impact and recycling indicators are introduced into the reward function, so that the material design results are both functional and green. The influence of different features, reward weights and constraints on the optimization results is analyzed through ablation experiments, so as to provide an interpretable, iterative and landing calculation method for the intelligent design of clothing materials.

3 Reinforcement learning driven garment material intelligent design and optimization scheme

The intelligent design scheme of clothing materials constructed in this paper takes the main line of "material performance state modeling - reinforcement learning strategy decision - sustainable reward feedback - multi-objective parameter correction" as the main line, and transforms the clothing material development process into a computable, iterative, and evaluable intelligent optimization process. Traditional clothing material design usually relies on the designer's comprehensive judgment of fiber hand feel, fabric appearance, wearing scene and process experience. Although it can retain a certain degree of aesthetic flexibility, it is easy to have problems such as too many samples, lagging performance evaluation and difficult to synchronously control sustainability indicators when multi-material combination, multi-process parameters and green manufacturing constraints are combined. In response to this situation, we introduce reinforcement learning method to treat the material design process as a continuous decision-making task, so that the model can adjust the design strategy according to performance feedback and environmental constraints in multiple rounds of interaction.

In this scheme, the clothing material sample library provides basic data, including fiber proportion, yarn specification, fabric structure, gram weight, thickness, breaking strength, wear resistance times, air permeability, moisture absorption, drenching coefficient, dyeing and finishing process parameters, unit cost, carbon emission estimation value and recyclable proportion. The system converts the data from different sources into a unified vector through the feature encoding module, and then inputs it into the reinforcement learning agent. The agent outputs design actions based on the current material state, such as adjusting the ratio of natural fibers to recycled fibers, changing fabric tightness, selecting a low-temperature dyeing and finishing scheme, reducing the amount of finishing AIDS, or adjusting the applicable clothing category. The environment module generates new material schemes according to actions and feeds back comprehensive performance scores and sustainability evaluation results. The overall process is shown in Figure 1.

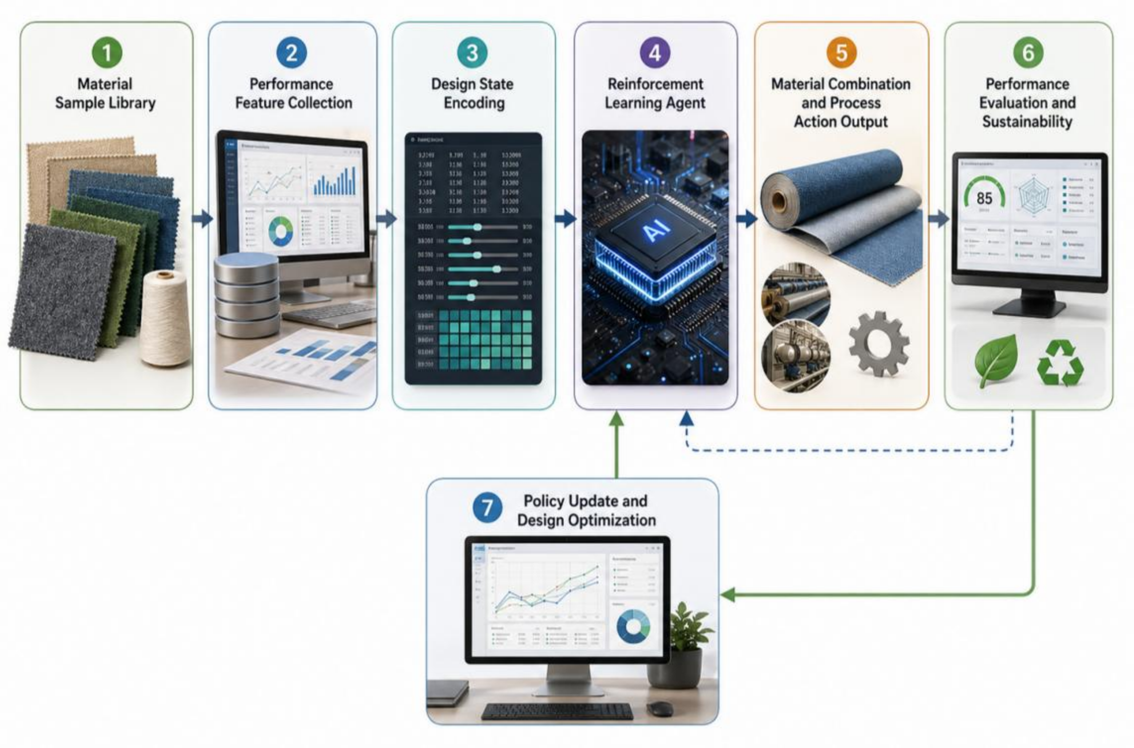

Figure 1: General framework of intelligent design of clothing materials driven by reinforcement learning

3.1 Modeling of design state based on performance characteristics of clothing materials

Design state modeling is the basic link of reinforcement learning optimization, and its core task is to transform the multi-dimensional attributes of clothing materials into a state representation that can be recognized and learned by the agent. The performance of clothing materials has obvious heterogeneous characteristics: mechanical indicators reflect the durability of materials, heat and humidity indicators affect wearing comfort, appearance indicators are related to the expression of clothing style, process indicators determine the production stability, and sustainable indicators reflect the performance of materials in resource consumption, carbon emission and recycling. If the original detection data is directly input into the model, the dimension difference between different indicators is large, and the numerical range is inconsistent, which is easy to make the high numerical features occupy unreasonable weight in the learning process. Therefore, this paper introduces standardized processing, feature grouping and state fusion mechanism in the state modeling stage. Let the original feature set of the ith clothing material sample at time step t be represented as follows.

$$X_i^t = \{x_{i1}^t, x_{i2}^t, \ldots, x_{in}^t\} \tag{1}$$

where X_i^t represents the original performance vector of the material sample, x_{ij}^t represents the JTH material index, and n represents the number of indicators involved in the modeling. Considering that the indicators of fracture strength, air permeability, gram weight, carbon emission and cost have different measurement units, this paper uses the standardization method to unify the scale of the original data:

$$\hat{x}_{ij}^{t} = \frac{x_{ij}^{t} - \mu_j}{\sigma_j + \varepsilon} \tag{2}$$

where, $\hat{x}_{ij}^{t}$ represents the normalized eigenvalue, μ_j and σ_j represent the mean and standard deviation of the JTH index in the sample library, and ε is a minimal constant to prevent the denominator from being zero. Through this processing, different types of material performance indicators can enter the same computational space, providing stable input for subsequent state coding.

In terms of feature organization, this paper divides the garment material state into four sub-states: material composition state, wear performance state, process adaptation state and sustainable state. Material composition mainly includes fiber type, blending ratio, yarn density and fabric structure. The wear performance status includes strength, elasticity, air permeability, moisture absorption, drape, wrinkle resistance and wear resistance; The process adaptation state includes dyeing and finishing temperature, bath ratio, processing time, additive dosage and production stability. The sustainable status includes unit carbon emissions, water consumption, renewable content, recyclable proportion, and difficulty in disposal of waste. The four categories of sub-states together constitute the complete state description of the material design, as shown in Figure 2.

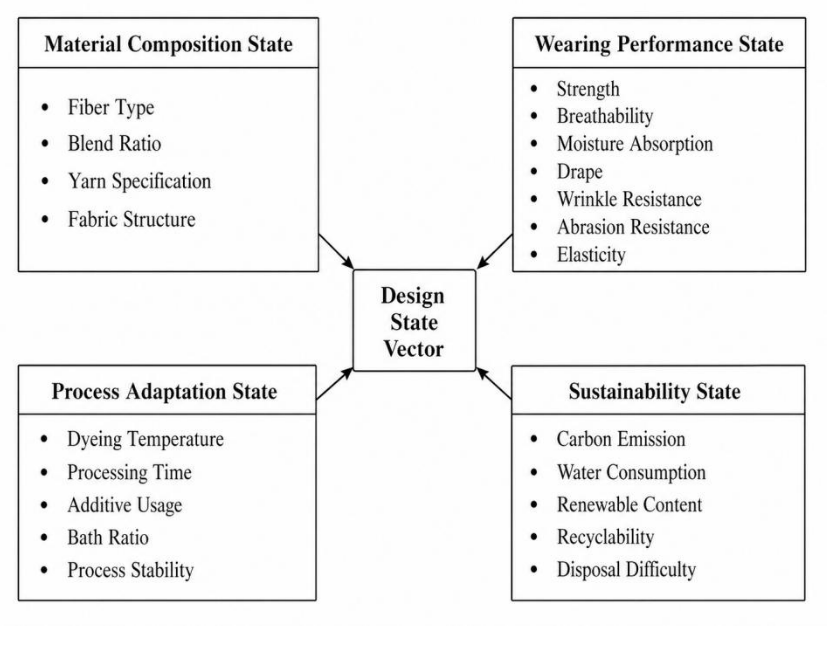

Figure 2: Garment material design state feature composition

It can be seen from Figure 2 that the garment material design status is not a simple arrangement of single performance indicators, but a combinatorial expression established around material structure, wearing experience, production conditions and green goals. In order to avoid the strong interference of a certain type of features on the design strategy, this paper sets adjustable weights for different sub-states, and forms the final state vector through the fusion function:

$$S_t = \alpha C_t + \beta P_t + \gamma G_t + \delta E_t \tag{3}$$

where, S_t represents the material design state at time step t, C_t, P_t, G_t, E_t represent the material composition, wear performance, process adaptation and sustainable sub-states respectively, and α, β, γ and δ are the corresponding weight coefficients. The weight can be adjusted according to the clothing category. For example, sportswear can increase the weight of air permeability, elasticity and wear resistance, business clothing can increase the weight of drabability, wrinkle resistance and appearance stability, and environmental protection theme clothing can increase the weight of renewable content, low carbon emissions and recyclable proportion.

3.2 Reinforcement learning decision mechanism for material combination and process parameters

After the state modeling of garment material performance characteristics is completed, the system needs to further transform the state vector into an executable material combination and process parameter adjustment scheme. The decision object in garment material design is not a single variable. Fiber proportion, yarn size, fabric structure, dyeing and finishing temperature, finishing agent dosage and processing time will all affect the final performance. If the artificial sample and single factor parameter adjustment method are still used, the model is difficult to form a stable balance among strength, air permeability, overhang, cost and environmental load. Therefore, this paper constructs a reinforcement learning decision mechanism for hybrid action space, so that the agent can output material selection and process adjustment actions according to the current design state.

In this paper, material design action is defined as the joint form of discrete action and continuous action. Discrete actions mainly include fiber type selection, fabric organization selection, dyeing and finishing process selection. Continuous action mainly includes blending ratio, fabric tightness, dyeing and finishing temperature, processing time and additive concentration adjustment. Let the design action at time step t be as follows.

$$A_t = \{A_t^d, A_t^c\} \tag{4}$$

where, A_t^d represents discrete material and process category action and A_t^c represents continuous parameter adjustment action. In order to adapt to the coexistence of category selection and numerical adjustment in clothing material design, this paper uses the Actor-Critic structure to construct a decision network. The policy network generates the action distribution according to the state St, and the value network evaluates the long-term optimization potential of the current design solution, which is expressed as follows.

$$A_t \sim \pi_\theta(A|S_t), \quad V_t = V_\phi(S_t) \tag{5}$$

where, π_θ denotes the policy network with parameter θ, and V_ϕ denotes the value network with parameter ϕ. The strategy network is responsible for giving suggestions on material combination and process parameters, and the value network is used to judge whether the scheme has the value of continuous optimization. The material design decision flow is shown in Figure 3.

Figure 3: Reinforcement learning material combination and process parameter decision process

As shown in Figure 3, the agent does not directly output the unique material result, but is updated cyclically between candidate plan generation, performance feedback, and policy correction. After each round of action execution, the environment module will generate new candidates according to the material database, process experience constraints and performance prediction model, and return the change of strength, change of permeability, change of cost and change of sustainability index. The policy update uses the advantage function to reduce the fluctuation caused by random exploration, and its parameter adjustment process is expressed as follows.

$$\theta \leftarrow \theta + \eta \nabla_\theta \log \pi_\theta \left(A_t | S_t\right)\left(G_t - V_\phi(S_t)\right) \tag{6}$$

where η represents the learning rate, G_t represents the cumulative feedback obtained since the current step, and $G_t - V_\phi(S_t)$ represents the degree of advantage of the action with respect to the baseline value of the current state. When a material combination can improve the wearing performance and reduce the environmental load at the same time, its advantage value will increase, and the policy network is more inclined to choose similar actions in subsequent iterations. When an action results in excessive cost, decreased comfort, or reduced recyclable ratio, the probability corresponding to that action is depressed.

3.3 Sustainability evaluation of clothing materials and reward function construction

The intelligent design of clothing materials can not only be optimized based on strength, feel, air permeability and appearance stability, but also need to incorporate resource consumption, carbon emission, water consumption, chemical additives risk, renewable content, recyclable proportion and service life into the same evaluation system. If the reinforcement learning model lacks sustainable feedback, it is easy to generate material schemes with high performance but large environmental burden. Therefore, this paper constructs a sustainability evaluation module in addition to the material performance evaluation, and converts the evaluation results into reward signals, so that the agent can perceive green constraints synchronously in the process of material combination and process parameter adjustment.

In this paper, the sustainability evaluation of clothing materials is divided into three categories: environmental load, recycling potential and service durability. Environmental load mainly includes carbon emission per unit material, water consumption and the amount of chemical additives. The recycling potential includes the proportion of recycled fibers, the proportion of bio-based materials and the difficulty of recycling. The durability was characterized by the number of wear resistance, dimensional stability after washing, color fastness and the expected service life of the garment. Let the comprehensive sustainability score of the material plan at time step t be:

$$\mathrm{Z_t} = \omega_1(1-\hat{\mathrm{C}}_\mathrm{t}) + \omega_2(1-\widehat{\mathrm{W}}_\mathrm{t}) + \omega_3\mathrm{R_t} + \omega_4\mathrm{B_t} + \omega_5\mathrm{D_t} \tag{7}$$

where, $\mathrm{Z_t}$ represents the comprehensive sustainability score, $\hat{\mathrm{C}}_\mathrm{t}$ and $\widehat{\mathrm{W}}_\mathrm{t}$ represent the normalized carbon emissions and water consumption respectively, Rt represents the recyclable proportion, $\mathrm{B_t}$ represents the proportion of bio-based or recycled materials, $\mathrm{D_t}$ represents the durability score, and ω_1 to ω_5 are the weight coefficients. The formula takes "low consumption" and "high circulation" into the evaluation at the same time to avoid the deviation of reducing the consumption performance caused by increasing the proportion of recycled materials alone. The sustainable evaluation results do not exist independently, but directly enter the reinforcement learning reward function. In this paper, the reward function is designed as a combination of performance gain, sustainable gain and constraint penalty.

$$\mathrm{R_t} = \lambda_1\mathrm{P_t} + \lambda_2\mathrm{Z_t} - \lambda_3\mathrm{K_t} - \lambda_4\mathrm{Q_t} \tag{8}$$

where, $\mathrm{R_t}$ represents the reward value of the agent after the current action, $\mathrm{P_t}$ represents the comprehensive score of taking performance, $\mathrm{Z_t}$ represents the comprehensive score of sustainability, $\mathrm{K_t}$ represents the production cost penalty, $\mathrm{Q_t}$ represents the penalty term generated by violating the process boundary or environmental protection threshold, and λ_1 to λ_4 are the reward weights. If a solution reduces carbon emissions and improves recyclability while ensuring strength, air permeability and drape, its reward value will be increased. Schemes that rely on energy-efficient processes or high additive usage for local performance gains are penalized. The computation path of the sustainable reward function is shown in Figure 4.

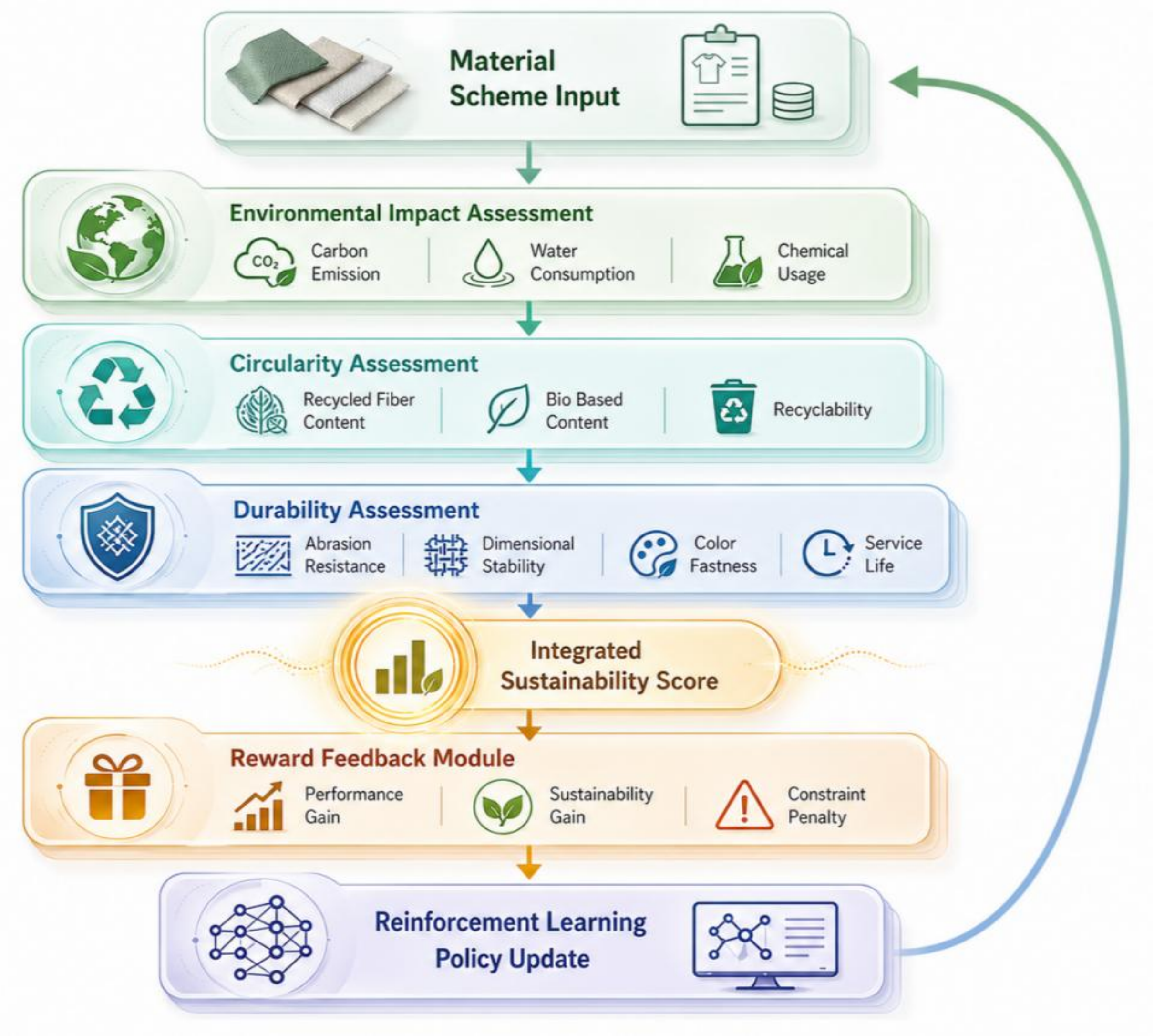

Figure 4: Sustainability evaluation of clothing materials and reward feedback path

As can be seen from Figure 4, the sustainability evaluation is embedded in the feedback link of material design in this paper, so that the model can simultaneously compare performance improvement, environmental benefits and production costs in each round of strategy update. In order to improve the stability of the reward function, the piecewise constraint processing method was used in the training phase. When the material scheme did not reach the basic consumption performance threshold, the system did not continue to enlarge the sustainable score. When the environmental index exceeds the set boundary, the penalty term is directly raised, thus restricting the model to generate solutions that are not produceable or generalizable. In the experimental implementation, the carbon emission and water consumption data are obtained from the material life cycle estimation, the durability index is obtained from the fabric inspection results, and the recycling proportion is calculated according to the fiber composition and the post-finishing process. This design can make the reinforcement learning model form the optimization direction of "available performance, feasible process, and controllable environment" in the intelligent design of clothing materials.

3.4 Garment material adaptation and sustainable optimization parameter adjustment under multi-objective constraints

In the process of intelligent design of clothing materials, material adaptation is not to improve a single performance index alone, but to perform collaborative adjustment among wearing function, production stability, material cost and environmental load. Different clothing categories have different emphasis on material properties. Sports clothing pays more attention to elastic recovery, moisture absorption, quick drying and wear resistance, professional clothing pays more attention to crisp, wrinkle-resistance and appearance maintenance, and children's clothing needs to take into account skin-friendliness, safety and easy care. If the reinforcement learning model updates the strategy only according to the comprehensive score, it is easy to improve the local performance and decrease the overall adaptation. Therefore, this paper further sets multi-objective constraints on the basis of reward feedback, so that the material scheme can maintain a stable balance between producibility, wearability and sustainability.

In this paper, the garment material optimization parameters are denoted as Θ_t, which includes variables such as fiber blending ratio, fabric tightness, yarn density, dyeing and finishing temperature, processing time, and additive concentration. The comprehensive optimization objective can be expressed as follows.

$$\max_{\Theta_t} J\left(\Theta_t\right) = \rho_1 F_t + \rho_2 S_t + \rho_3 Z_t - \rho_4 C_t - \rho_5 E_t \tag{9}$$

where, $J(\Theta t)$ represents the comprehensive adaptation benefit of the current material scheme, F_t represents the consumption function score, S_t represents the production stability score, Z_t represents the sustainability score, C_t represents the unit material cost, E_t represents the environmental load penalty, and ρ_1 to ρ_5 are the target weights. The objective function takes the benefit of material performance, cost and environmental cost into account at the same time, which can avoid the generation of "high performance but high consumption" design scheme.

In the parameter adjustment stage, this paper sets the base performance constraint, process boundary constraint and sustainable threshold constraint. Basic performance constraints are used to ensure that the material meets the requirements of clothing use, such as breaking strength, wear resistance, air permeability and color fastness must not be lower than the category standard; The process boundary constraint is used to limit the dyeing and finishing temperature, processing time and additive concentration within the executable range of the enterprise. Sustainability threshold constraints are used to control unit carbon emissions, water consumption, and the proportion of non-recyclable components. In order to illustrate the regulatory focus of different material schemes, the main parameters and their constraint effects are summarized in Table 2.

Table 2: Parameter Settings for garment material optimization under multi-objective constraints

Parameter Category	Adjustment Variable	Main Affected Object	Constraint Direction	Optimization Significance
Material composition parameters	Proportions of natural fibers, regenerated fibers, and bio-based fibers	Comfort, recyclability, material cost	Control the proportion range to avoid strength reduction	Improve green attributes while maintaining basic performance
Structural parameters	Fabric tightness, yarn linear density, weave structure	Air permeability, drapability, abrasion resistance	Avoid overly dense or overly loose structures	Balance wearing comfort and appearance stability
Dyeing and finishing parameters	Temperature, time, liquor ratio	Color fastness, energy consumption, water consumption	Reduce high-temperature and long-duration processing	Reduce resource consumption and processing fluctuations
Auxiliary parameters	Dosage of softeners, fixing agents, and functional finishing agents	Hand feel, functionality, emission risk	Set environmental protection limits	Control chemical load and production safety
Application adaptation parameters	Garment category, usage scenario, maintenance frequency	Service life, maintenance cost	Match the requirements of target product categories	Improve the practical applicability of material schemes

It can be seen from Table 2 that parameter optimization is not a single path adjustment, but a linkage control is formed around material composition, structure design, dyeing and finishing process and application scenarios. In each iteration, the agent screens out infeasible solutions according to the constraints, and then selects the action with higher comprehensive revenue from the feasible region. For sportswear materials, the model will give priority to increasing the weight of elastic recovery and moisture absorption and sweat elimination, and limit the weight of excessive weight. For commuting clothing materials, the system will enhance the weight of anti-wrinkle, draping and washing resistance indicators. For environmentally friendly themed clothing, the model will increase the proportion of recycled fibers, the proportion of recyclable fibers and the weight of low-carbon processing, while preventing the lack of material durability through strong constraints.

4 Empirical results and optimization effect analysis

4.1 Research data source and clothing material sample construction

The experimental data in this paper focus on the intelligent design task of clothing materials, and the data sources include four categories: material basic information, laboratory performance testing data, process processing records and sustainable evaluation data. Material basic information is mainly used to describe structural properties such as fiber composition, yarn specification, fabric structure and weight. The performance test data are used to reflect the performance of the material in terms of strength, wear resistance, air permeability, moisture absorption, draping and stability after washing. Process records cover dyeing and finishing temperature, processing time, bath ratio, dosage of additives and finishing mode. Sustainability evaluation data include unit carbon emission estimation, water consumption, proportion of recycled materials, proportion of recyclable materials and difficulty of waste disposal. The above data together constitute the training environment of the reinforcement learning model, which enables the linkage evaluation of the material scheme among performance, process and green indicators.

In terms of sample construction, this paper selected five types of clothing materials, including cotton fabric, recycled cellulose fabric, polyester fabric, wool blend fabric and bio-based composite fabric, and collected 72 groups of samples for each type, forming a total of 360 groups of effective material samples. Each group of samples was cut according to uniform specifications and pretreated under constant temperature and humidity conditions. The test environment was set as temperature 23±2℃ and relative humidity 50%±5%, and the samples were left for 24 h before the test to reduce the influence of the difference in moisture state on the experimental results. Each performance measure was repeated three times and averaged into model training. In this paper, each material sample is represented as a comprehensive data unit containing structure, performance, process and sustainability information:

$$\mathcal{D} = \{(\mathrm{U_i}, \mathrm{V_i}, \mathrm{G_i}, \mathrm{E_i}, \mathrm{Y_i})\}_{\mathrm{i}=1}^{\mathrm{N}} \tag{10}$$

where, D represents the clothing material sample data set, $\mathrm{U_i}$ represents the material composition and structural characteristics of the ith sample, $\mathrm{V_i}$ represents the wearing performance characteristics, $\mathrm{G_i}$ represents the process parameter characteristics, $\mathrm{E_i}$ represents the sustainable evaluation characteristics, $\mathrm{Y_i}$ represents the corresponding clothing application scene label, and N is the total number of samples. This representation can incorporate data from different sources into a unified computing structure, which provides the input basis for subsequent state modeling, reward feedback and policy update. In order to illustrate the sample composition and data usage, this paper sorts out the material sample types, main indicators and modeling functions, as shown in Table 3.

Table 3: Sample composition and data usage of clothing materials

Material Type	Main Testing Indicators	Main Process Records	Modeling Purpose
Cotton fabric	Air permeability, moisture absorption rate, breaking strength, shrinkage rate	Dyeing and finishing temperature, soft finishing	Comfort analysis and basic material comparison
Regenerated cellulose fabric	Drapability, moisture absorption, abrasion resistance, color fastness	Low-temperature dyeing and finishing, liquor ratio control	Green material substitution analysis
Polyester fabric	Abrasion resistance, dimensional stability, elastic recovery rate	Heat setting, functional finishing	Adaptation evaluation for high-durability materials
Wool blended fabric	Thermal insulation, wrinkle resistance, drapability, pilling resistance	Shrink-proof finishing, setting treatment	Modeling for mid- to high-end garment scenarios
Bio-based composite fabric	Strength, softness, recyclable proportion, degradation potential	Eco-friendly auxiliaries, low-energy treatment	Training of the sustainability reward function

It can be seen from Table 3 that the sample in this paper is not limited to a single fiber material, but covers natural fibers, recycled materials, synthetic fibers and bio-based materials, so as to ensure that the reinforcement learning model can learn the performance differences and sustainable characteristics between different materials. The experimental data were divided into training set, validation set and test set according to the proportion of 70%, 15% and 15%, that is, 252 groups of training set, 54 groups of validation set and 54 groups of test set. The proportion of each material category was kept close to the same by stratified sampling, so as to reduce the influence of class distribution deviation on model training results.

4.2 Material performance data processing and design feature extraction methods

In order to ensure the stability and comparability of different clothing material samples in reinforcement learning training, this paper conducts multi-level processing on the original material data, and combines the input requirements of the intelligent design model to complete the feature extraction. The raw data includes structural indicators, continuous performance indicators, process parameters and sustainability evaluation indicators. Among them, fiber type, fabric organization and application scenario are categorical variables, while breaking strength, air permeability, moisture absorption, wear resistance times, draption coefficient, unit carbon emission and water consumption are continuous variables. If different types of data are directly input into the model, it is easy to cause inconsistent numerical scale and insufficient expression of category information. Therefore, it is necessary to complete data cleaning, scale unification and feature coding before model training.

In terms of performance data processing, three repeated measurements were carried out for each group of material samples, and the average value was used as the input value of this index to reduce the influence of single detection error on model judgment. Let the RTH test result of the ith material sample on the JTH performance index be $\mathrm{x_{ijr}}$, then the stable input value of this index is expressed as follows.

$$\bar{\mathrm{x}}_{\mathrm{ij}} = \frac{1}{3}\sum\nolimits_{\mathrm{r}=1}^{3} \mathrm{x_{ijr}} \tag{11}$$

where, xij represents the mean feature after repeated detection. Experimental statistics show that the proportion of original missing values in 360 groups of samples is 2.1%, mainly concentrated in the recyclable proportion and process energy consumption records of some bio-based composite fabrics. The proportion of outliers was 1.7%, which mostly appeared in the permeability and overhang coefficient detection results. For missing data, the median of similar materials and similar gram weight samples were used to complete the missing data. For the data that significantly deviates from the detection range, the experimental records are combined for verification, and the sample values whose source cannot be confirmed do not enter the training set.

In terms of category data processing, the fiber type, fabric organization and clothing application scene are represented by one-hot encoding to avoid the model misclassifying disordered categories as continuous values. The continuous performance index is treated in a unified direction, in which fracture strength, wear resistance times, air permeability, recyclable proportion and proportion of recycled materials are set as the forward index, and unit carbon emission, water consumption, auxiliary dosage and proportion of non-recyclable components are set as the reverse index. After processing, each material sample forms 42 dimensions of design features, including 12 dimensions of material structure features, 14 dimensions of wear performance features, 8 dimensions of process parameters features, and 8 dimensions of sustainability evaluation features.

In the feature extraction stage, the material suitability characteristics are further calculated, including strength-gram/weight ratio, breathability/tightness relationship, wear-resistance /fiber ratio relationship and low carbon processing suitability coefficient. Taking the cotton fabric sample as an example, the average air permeability is 286.4mm/s, and the average moisture absorption rate is 7.8%. The average drapability of regenerated cellulose fabric is 0.63, and the average recyclable ratio of bio-based composite fabric is 68.5%, but the breaking strength of bio-based composite fabric is 12.4% lower than that of polyester fabric. These differences provide a clear basis for the reinforcement learning model to distinguish between states, so that the agent can choose different combinations and process actions according to the material performance characteristics.

The processed data were divided according to the training set, validation set and test set, and the proportions of the five classes of materials were kept consistent. The training set is used for the policy network to learn the material design law, the validation set is used to adjust the reward weight and constraint threshold, and the test set is used to test the generalization ability of the model on the samples not participating in the training. The experimental running environment is Ubuntu 22.04, Python 3.11, PyTorch 2.2, and the hardware configuration is Intel Core i7-12700, 32 GB RAM, and NVIDIA RTX 4080 16 GB GPU. The model training batch size is set to 64, the initial learning rate is 2×10^{-4}, the maximum training round is 80, and the training is stopped when there is no improvement in the validation benefit for 8 consecutive rounds.

4.3 Evaluation of intelligent design results and sustainability feedback analysis of clothing materials

In the experimental evaluation stage, this paper verifies the intelligent design results of 360 groups of clothing material samples. The evaluation system consists of three parts: material wear performance, design adaptation effect and sustainable feedback. The wear performance mainly examined the breaking strength, wear resistance times, air permeability, moisture absorption, drapability and dimensional stability after washing; The design adaptation effect mainly evaluates the matching degree between the material scheme and the application scenarios such as sports clothing, commuting clothing, and environmental protection theme clothing. Sustainable feedback focuses on unit carbon emissions, water consumption, proportion of recycled materials, recyclable proportion and comprehensive reward value changes. This evaluation method is not only used to test the optimization effect of the reinforcement learning model, but also to judge whether the model generation scheme has the actual production and promotion value.

In terms of objective indicators, this paper selects comprehensive performance score, sustainability score and design adaptation accuracy as the main evaluation indicators. The experimental results show that the comprehensive performance scores of five types of materials are improved after reinforcement learning optimization, among which bio-based composite fabrics are improved from 72.6 to 81.8, recycled cellulose fabrics are improved from 75.4 to 84.1, and polyester fabrics are improved from 80.2 to 86.7. Cotton fabric and wool blend fabric have relatively stable improvement, reaching 84.9 and 85.6 respectively. The performance changes before and after optimization for different materials are shown in Figure 5.

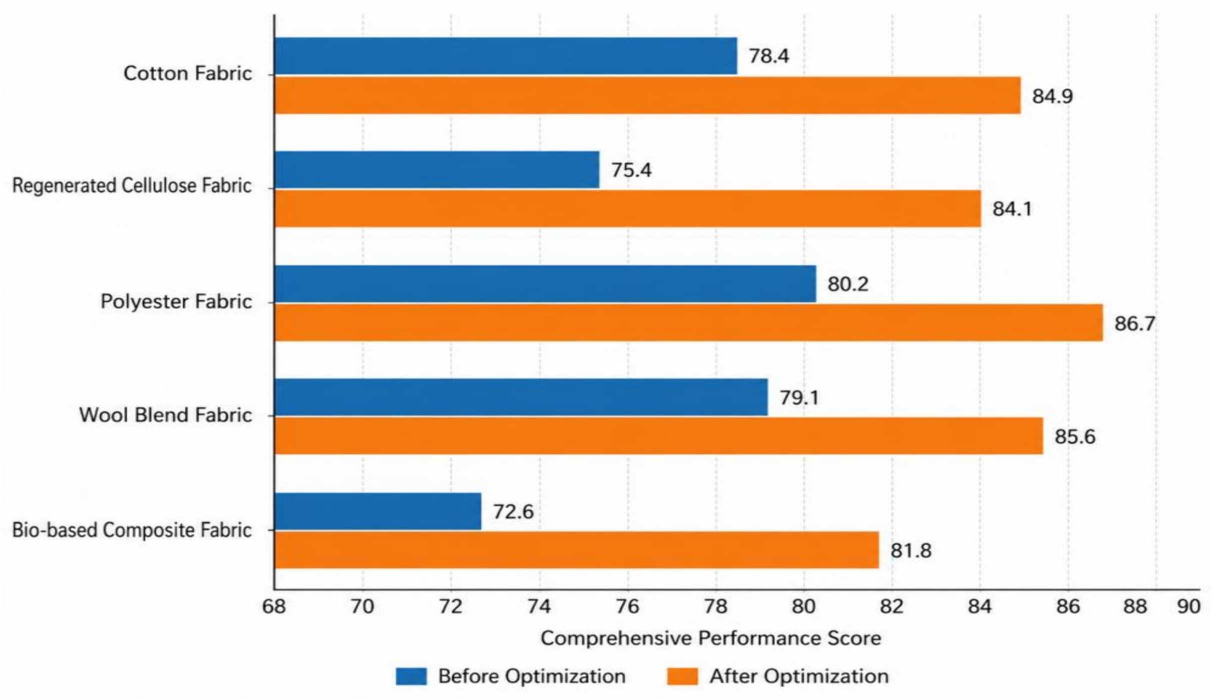

Figure 5: Changes in comprehensive performance scores before and after optimization of different clothing materials

It can be seen from Figure 5 that the model has a more obvious optimization effect on materials with low initial performance but high green potential. The bio-based composite fabric is compensated in fracture strength and wear resistance after parameter adjustment, and the regenerated cellulose fabric has a better balance between drapability, moisture absorption and recyclable proportion. Compared with the artificial experience scheme, the average comprehensive performance score of the reinforcement learning scheme is improved from 77.1 to 84.6, with an increase of 9.7%. The design adaptation accuracy is improved from 81.3% to 90.8%, indicating that the model can match the material features to the target clothing scene more accurately.

In terms of sustainability feedback, the experiment focuses on comparing the changes in carbon emissions per unit, water consumption and recyclable proportion before and after optimization. The results show that the reinforcement learning model can reduce the average carbon emission per unit from 4.82 $kgCO_2e/kg$ to 3.91 $kgCO_2e/kg$, and the average water consumption from 58.4 L/kg to 47.6 L/kg by adjusting the fiber combination, reducing the weight of high temperature dyeing and finishing, and reducing the amount of auxiliary. The proportion of recyclables increased from 51.2% to 63.8%. See Figure 6 for the change of sustainability indicators.

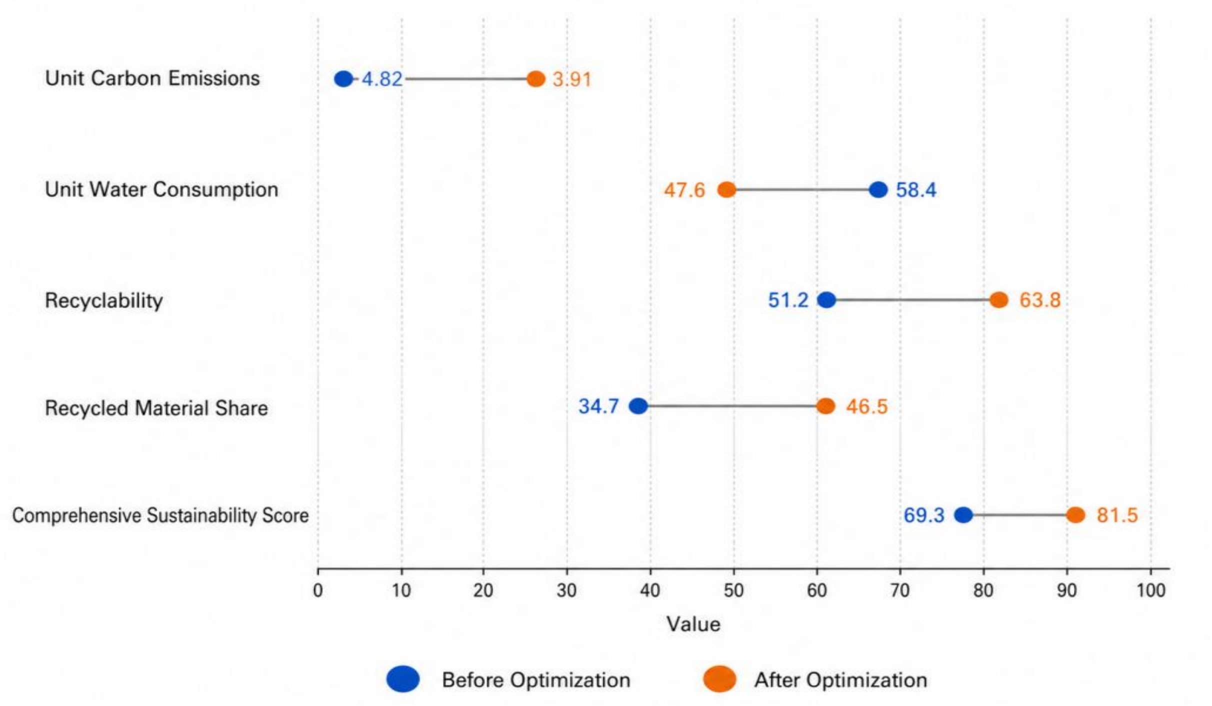

Figure 6: Changes in sustainability indicators of clothing materials before and after optimization

It can be seen from Figure 6 that the optimization scheme does not rely on the sacrifice of wear performance in exchange for the improvement of green indicators, but performs collaborative adjustment between material composition and process parameters. When the proportion of recycled fiber was increased, the model adjusted the fabric tightness and finishing process synchronously to control the risk of strength decline. After reducing the dyeing and finishing temperature, the system maintained the color fastness by extending the reasonable processing interval and optimizing the combination of additives. The comprehensive sustainability score increases from 69.3 to 81.5, indicating that the reward function can effectively guide the model to converge to the direction of low carbon, low water consumption and high recycling.

From the feedback results, there is a good consistency between objective performance improvement and sustainable improvement. Among the 54 groups of samples in the test set, there were 28 groups with comprehensive performance scores higher than 84, of which 22 groups (78.6%) simultaneously met the recyclable proportion higher than 60% and the unit carbon emission lower than 4.2 kgCO_2e/kg. The designer evaluation results also show that the optimized materials have higher scores in hand stability, clothing category matching and green material acceptance, and the average score is increased from 3.72 to 4.28. It can be seen that the design method of clothing materials driven by reinforcement learning can not only improve the evaluation results of material properties, but also embed the sustainable goal into the design decision-making process, which provides effective support for the green and intelligent development of clothing materials.

4.4 Ablation experiment and analysis of key influencing factors

In order to further test the independent contribution of each module in the reinforcement learning driven intelligent design framework of clothing materials to the overall optimization effect, this paper designs an ablation experiment and compares it with manual experience parameter adjustment, a single performance prediction model and a complete reinforcement learning scheme. The ablation experiment was carried out around four key steps: removing the material state group modeling, removing the sustainable reward term, removing the process constraint boundary, and removing the dynamic weight adjustment mechanism, and the complete model was used as a control scheme. The evaluation metrics include comprehensive performance score, sustainability score, design adaptation accuracy, and proportion of invalid alternatives. The experimental samples still use 360 groups of clothing material data constructed in the previous section, and all models are run under the same partition conditions of training set, validation set and test set.

Experimental results show that the complete model performs best in terms of comprehensive performance, green index and design adaptation. The comprehensive performance score of the manual experience parameter adjustment scheme is 77.1, the sustainability score is 69.3, and the design adaptation accuracy is 81.3%. A single performance prediction model can improve the consumption performance, but the improvement of carbon emissions, water consumption and recycling proportion is limited, and its sustainability score is only 73.6. The comprehensive performance score of the complete reinforcement learning scheme reaches 84.6, the sustainability score reaches 81.5, and the design adaptation accuracy is improved to 90.8%. The comparison of the main indicators of different schemes is shown in Figure 7.

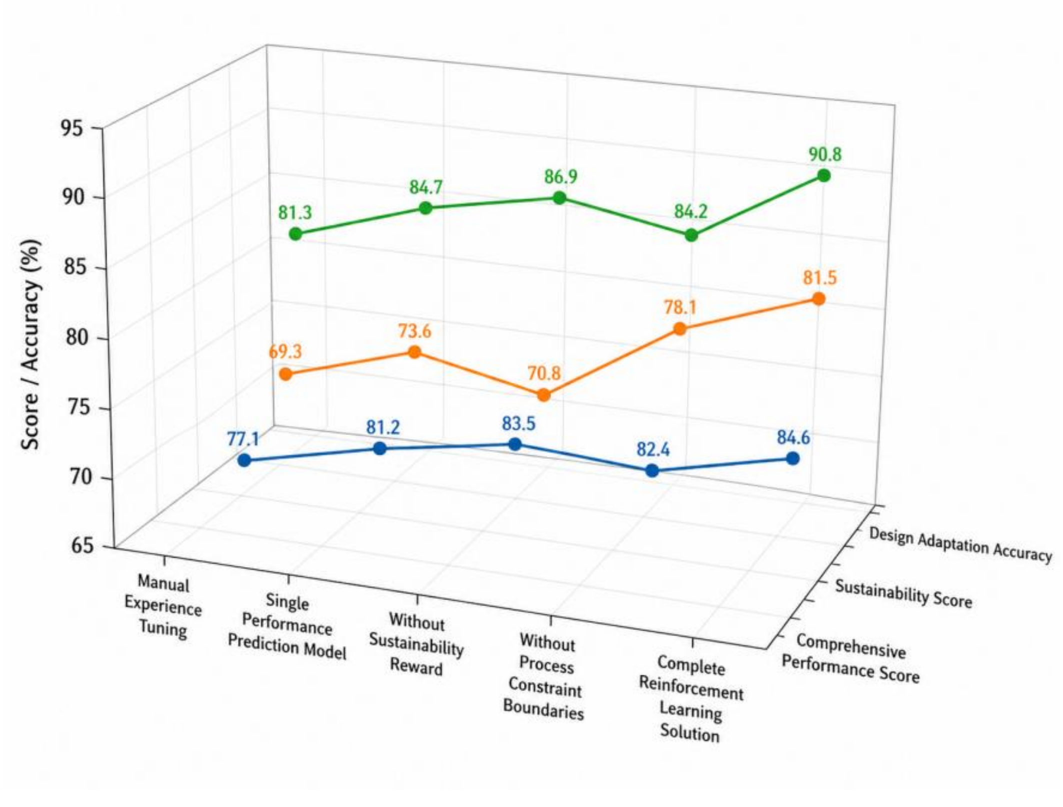

Figure 7: Comparison of optimization effects of different model schemes

It can be seen from Figure 7 that after removing the sustainable reward item, the model can still maintain a high consumption performance score, but the green index decreases significantly, indicating that the low carbon, water consumption and recycling factors in the reward function play a key role in guiding the direction of the material plan. After removing the process constraint boundary, although some schemes have higher theoretical performance, the proportion of invalid schemes increases due to the high dyeing and finishing temperature, excessive dosage of auxiliary and excessive increase in the proportion of recycled fiber. This result illustrates that intelligent design of clothing materials cannot rely only on model search capabilities, but must also embed production executable conditions.

To further analyze the key factor contributions, this paper compares the proportion of invalid schemes and the average iteration convergence rounds when different modules are missing. The results are shown in Figure 8.

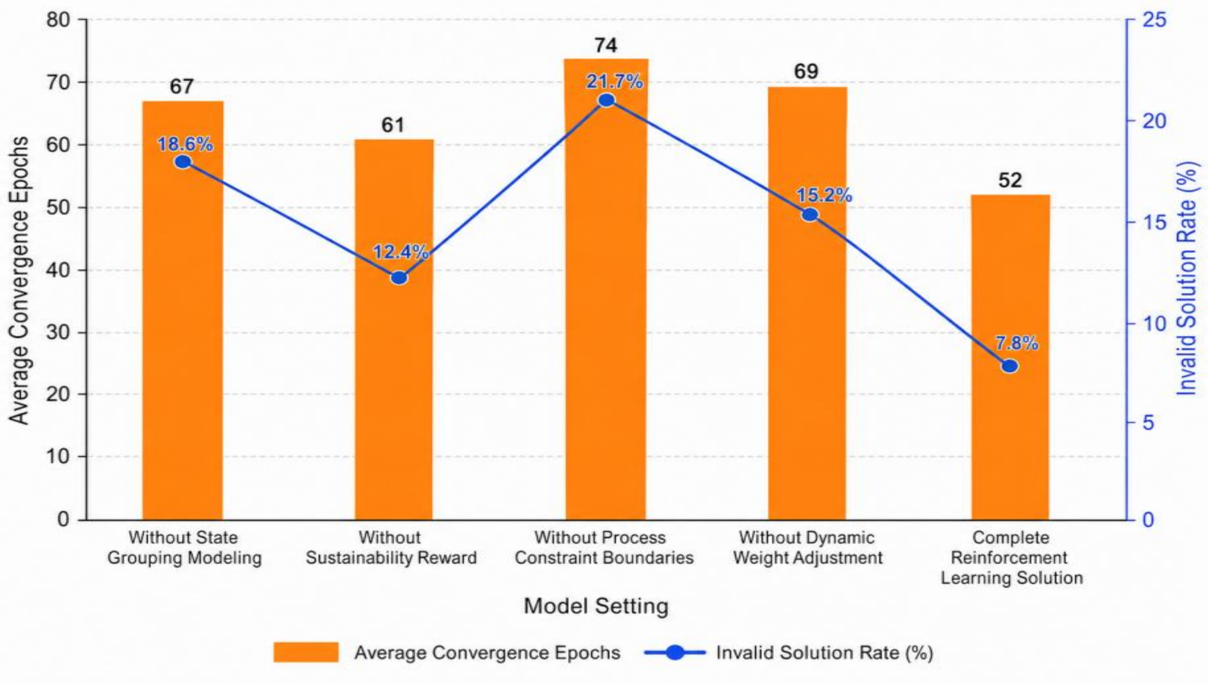

Figure 8: Changes in training stability with different missing modules

Figure 8 shows that the process constraint boundary has the greatest impact on reducing the proportion of invalid schemes, and the proportion of invalid schemes increases to 21.7% after missing this module. State grouping modeling directly affects the ability of the model to distinguish material structure, wear performance and sustainability indicators, and the average convergence rounds increased to 67 rounds after removal. The dynamic weight adjustment mechanism mainly acts on multi-objective conflict processing. When the proportion of recycled materials increases, resulting in the decline of wear resistance, the mechanism can guide the model to compensate through the fabric structure and post-finishing parameters, so as to reduce the strategy fluctuation.

In terms of material types, bio-based composite fabric was the most sensitive to the sustainable reward item, and the increase of recyclable proportion decreased from 14.9 percentage points to 5.6 percentage points after removing this item. Polyester fabric is more sensitive to process constraints. Without boundary constraints, the model is easy to rely on high-strength finishing process to improve wear resistance, resulting in increased environmental load. In summary, the grouping modeling of material state determines whether the model can accurately understand the input, the sustainable reward function determines the optimization direction, the feasibility of process constraint control scheme, and the dynamic weight adjustment improves the multi-objective balance ability. There is an obvious synergistic relationship between the four modules, which jointly supports the stability and generalization of the intelligent design results of clothing materials.

5 Discussion

From the extension of the experimental results to the clothing material development scenario, it can be seen that the value of reinforcement learning method is not limited to improving single performance indicators, but to transforming material screening, process modification and green constraints into sustainable iterative calculation processes. Compared with the manual experience parameter adjustment, the complete reinforcement learning scheme can automatically identify the association between material composition, process parameters and sustainability indicators in multiple rounds of feedback, so that the material design no longer depends on a single test result or local experience judgment. The experimental results show that the comprehensive performance score of manual experience parameter adjustment is 77.1, the sustainability score is 69.3, and the design adaptation accuracy is 81.3%. The full reinforcement learning scheme improves to 84.6, 81.5 and 90.8%, respectively. This shows that the model can not only improve the wearing performance, but also reduce the environmental load and enhance the matching degree between the material scheme and the target clothing category.

In order to further present the differences in optimization effects of different methods, this paper compares the manual experience parameter tuning, the single performance prediction model and the complete reinforcement learning scheme, as shown in Table 4.

Table 4: Comprehensive comparison of different clothing material design methods

Method Type	Comprehensive Performance Score	Sustainability Score	Design Adaptation Accuracy	Proportion of Invalid Schemes	Average Convergence Iterations
Manual experience-based parameter tuning	77.1	69.3	81.3%	18.9%	—
Single performance prediction model	81.2	73.6	84.7%	14.6%	68
Reinforcement learning without sustainability reward term	83.5	70.8	86.9%	12.4%	61
Complete reinforcement learning scheme	84.6	81.5	90.8%	7.8%	52

It can be seen from Table 4 that although the single performance prediction model can improve the consumption indicators such as fracture strength, wear resistance and air permeability, it has a weak ability to regulate carbon emissions, water consumption and recycling. After removing the sustainable reward item, the model can still obtain a high comprehensive performance score, but the sustainability score drops to 70.8, indicating that if the green index does not enter the reward feedback, the agent is easy to give priority to the material scheme with high performance but high consumption. The proportion of invalid schemes of the complete reinforcement learning scheme is controlled at 7.8%, and the convergence is completed in 52 rounds on average, which indicates that a stable cooperative relationship is formed between state grouping, reward function, process constraint and dynamic weight adjustment.

From the perspective of industrial application, this method can shorten the sample and rework cycle in garment material development. Traditional material development usually requires multiple rounds of proofing, testing and process modification, which is easy to cause material consumption and time cost increase. Through material state coding and strategy update, the proposed model screens out the alternatives that do not meet the strong, environmental threshold or process boundary in advance, so that the proportion of effective candidates is significantly increased. After optimization, the average carbon emission per unit of the sample decreased from 4.82 $kgCO_2e/kg$ to 3.91 $kgCO_2e/kg$, the average water consumption decreased from 58.4 L/kg to 47.6 L/kg, and the recycling ratio increased from 51.2% to 63.8%, indicating that the method has practical support for low carbon and recycling design.

The study still has some limitations. The samples mainly cover cotton fabrics, recycled cellulose fabrics, polyester fabrics, wool blended fabrics and bio-based composite fabrics, and the coverage of intelligent temperature regulating fibers, functional film materials and composite coating materials is insufficient. Some sustainable data depend on life cycle estimation and are affected by the integrity of supply chain records. The generalization ability of reinforcement learning models in cross-enterprise, cross-device and cross-region production environments still needs to be further verified. The follow-up research on the scalable material database, the introduction of real production line feedback data, and the lightweight deployment method make the model form a more stable collaborative application in the design end, process end and supply chain management end of clothing enterprises.

6 Conclusions

The core of clothing material design is to achieve the coordination between material performance, process feasibility and sustainability goals. With the development of the garment industry in the direction of digitalization, green and flexibility, the material screening method relying on manual experience has been difficult to meet the needs of multi-category, small-batch and low-carbon production. In this paper, a reinforcement learning driven intelligent design and sustainability optimization strategy for clothing materials is constructed. The material composition, wear performance, process parameters and environmental indicators are incorporated into a unified state space, and the reward function and multi-objective constraints guide the model to continuously revise the design plan. Experimental results show that the proposed method can improve the comprehensive performance score of materials and the accuracy of design adaptation, reduce unit carbon emissions and water consumption, and enhance the recycling potential of material schemes. Subsequent research can further expand the sample of new functional materials, introduce real production line feedback, and optimize the lightweight deployment ability of the model, so as to improve its application value in intelligent design and green manufacturing of garment enterprises.

Author's Profile

Yu Miao, female, holds a Doctorate in Design, is an associate professor, and is recognized as a Shanghai School Curriculum Ideological and Political Teaching Expert. She serves as the director of the Visual Communication Design Department at the School of Art and Design of Shanghai Business School. Previously, she was an Assistant Professor at Dongmyung University in South Korea, a master's supervisor in Design at Dalian Polytechnic University, and a council member of the Dalian Fashion Designers Association. Currently, she is a member of the Shanghai Aesthetics Association and a researcher at the Tongmyong Institute of Sino-Korean Cultural and Artistic Exchange in South Korea. She has published over ten academic papers in Chinese, English, and Korean in core academic journals both domestically and internationally.

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References

[1] Papadimitriou I, Gialampoukidis I, Vrochidis S, et al. AI methods in materials design, discovery and manufacturing: A review[J]. Computational Materials Science, 2024, 235: 112793.

[2] Pyzer-Knapp E O, Pitera J W, Staar P W J, et al. Accelerating materials discovery using artificial intelligence, high performance computing and robotics[J]. npj Computational Materials, 2022, 8(1): 84.

[3] Tran H, Gurnani R, Kim C, et al. Design of functional and sustainable polymers assisted by artificial intelligence[J]. Nature Reviews Materials, 2024, 9(12): 866-886.

[4] Seçkin M, Seçkin A Ç, Demircioglu P, et al. FabricNET: A microscopic image dataset of woven fabrics for predicting texture and weaving parameters through machine learning[J]. Sustainability, 2023, 15(21): 15197.

[5] Aydın S, Altun K. Early prediction of fabric quality using machine learning to reduce rework in manufacturing processes[J]. International Journal of Optimization & Control: Theories & Applications, 2024, 14(4).

[6] Dissanayake D G K, Weerasinghe D. Towards circular economy in fashion: Review of strategies, barriers and enablers[J]. Circular Economy and Sustainability, 2022, 2(1): 25-45.

[7] D’Itria E, Colombi C. Biobased innovation as a fashion and textile design must: A European perspective[J]. Sustainability, 2022, 14(1): 570.

[8] Manshoven S, Van Opstal W. The carrot or the stick? Stakeholder support for mandatory regulations towards a circular fashion system[J]. Sustainability, 2022, 14(22): 14671.

[9] Abbate S, Centobelli P, Cerchione R. From fast to slow: An exploratory analysis of circular business models in the Italian apparel industry[J]. International Journal of Production Economics, 2023, 260: 108824.

[10] Seidu R K, Eghan B, Acquaye R. A review of circular fashion and bio-based materials

in the fashion industry[J]. Circular Economy and Sustainability, 2024, 4(1): 693-715.

[11] Casciani D, D’Itria E. Fostering directions for digital technology adoption in sustainable and circular fashion: toward the circular fashion-tech lab[J]. Systems, 2024, 12(6): 190.

[12] Saha K, Dey P K, Kumar V. A comprehensive review of circular economy research in the textile and clothing industry[J]. Journal of Cleaner Production, 2024, 444: 141252.

[13] Rehman M, Petrillo A, Ortíz-Barrios M, et al. Sustainable fashion: Mapping waste streams and life cycle management[J]. Journal of Cleaner Production, 2024, 444: 141279.

[14] Barletta M, D'Adamo I, Garza-Reyes J A, et al. Business strategy and innovative models in the fashion industry: Clothing leasing as a driver of sustainability[J]. Business Strategy and the Environment, 2024, 33(5): 4730-4743.

[15] D’Adamo I, Gagliarducci M, Iannilli M, et al. Fashion wears sustainable leather: A social and strategic analysis toward sustainable production and consumption goals[J]. Sustainability, 2024, 16(22): 9971.

[16] Khatami F, Rinaldi F R, Salvato C, et al. Country-level analysis of the relationships between sustainability and the textile–clothing–leather–footwear industries[J]. Business Strategy and the Environment, 2024, 33(8): 8668-8678.

[17] Karadayi-Usta S, Tirkolaee E B. Evaluating the sustainability of fashion brands using a Neutrosophical ORESTE approach[J]. Sustainability, 2023, 15(19): 14406.

[18] Amicarelli V, Bux C, Spinelli M P, et al. Life cycle assessment to tackle the take-make-waste paradigm in the textiles production[J]. Waste Management, 2022, 151: 10-27.

[19] Bianco I, De Bona A, Zanetti M, et al. Environmental impacts in the textile sector: A life cycle assessment case study of a woolen undershirt[J]. Sustainability, 2023, 15(15): 11666.

[20] Bianco I, Picerno G, Blengini G A. Life Cycle Assessment (LCA) of Worsted and Woollen processing in wool production: ReviWool® noils and other wool co-products[J]. Journal of Cleaner Production, 2023, 415: 137877.

[21] Hammar T, Penaloza D, Hanning A C, et al. Life cycle assessment of textile fibre-to-fibre recycling by cellulose carbamate technology[J]. Journal of Cleaner Production, 2023, 426: 139189.