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Explainable Personalized Funding Recommendation by Fusing Decision Analysis and Reinforcement Learning

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ABSTRACT

The efficient matching of academic journals with research funds is a key issue in improving the efficiency of research resource allocation, shifting to personalized recommendation methods. This paper proposes a personalized fund recommendation method that integrates multi-source decision analysis and reinforcement learning within a trilateral feature fusion model of textile engineering journals, fiber science scholars, and research funds. By optimizing recommendation strategies through deep reinforcement learning and implementing an explainability framework, the system enhances transparency in identifying high-impact funding opportunities specifically tailored to the evolving technological landscape of textile manufacturing and material innovation. The study establishes a matching degree evaluation model based on multi-source data fusion, uses the proximal policy optimization algorithm for dynamic recommendation strategy learning, and constructs a multi-level explainability system including attention visualization, decision path tracing, and comparison cases. Experimental results show that this method significantly outperforms traditional recommendation algorithms in terms of recommendation accuracy, novelty, and user satisfaction. In the Top-5 recommendation scenario, the hit rate reaches 0.427, which is 12.3% higher than the best benchmark method, and the user score for explainability exceeds 4.0. This study provides strong support for intelligent matching of academic resources, an innovative approach that cannot be implemented by traditional methods.

KEYWORDS

fund recommendations, multi-source data fusion, reinforcement learning, explainable artificial intelligence, textile engineering

INTRODUCTION

Amidst increasingly fierce research competition, scholars must navigate the dual challenges of selecting from a vast array of funding opportunities and making strategic submission decisions within the rapidly evolving landscape of modern textile engineering and fiber science. To maximize the impact of their work, researchers must align their findings with high-level journal requirements while addressing the complex technical demands of textile manufacturing excellence and yarn spatial distribution. Traditional recommendation methods are mostly based on single-dimensional features or static matching models, which cannot adapt to the dynamic changes in scholars' research and the complex constraints of funding projects, resulting in insufficient recommendation accuracy and lack of decision-making transparency. Existing research has not effectively addressed the synergy between multi-source heterogeneous data fusion, long-term benefit optimization, and recommendation interpretability. There is an urgent need to construct a new framework that integrates dynamic decision analysis and interpretable recommendations, and shift towards intelligence. This paper proposes a dynamic decision analysis model integrating journal features, scholar profiles, and funding data to optimize long-term recommendation strategies through reinforcement learning, specifically tailored to the intricate technical parameters of fiber morphology and textile engineering. By incorporating attention mechanisms and case comparison techniques, the model enhances explainability within the complex decision-making frameworks of high-performance textile manufacturing. Specifically, the study starts from the mechanism of multi-source data fusion to construct a journal - fund matching degree evaluation model, and on this basis, designs a recommendation strategy optimization algorithm based on deep reinforcement learning, ultimately establishing an interpretable personalized recommendation system. This study provides strong support for the subsequent algorithm design, and the second paragraph of this paper will focus on elaborating the multi-source data fusion mechanism and the reinforcement learning environment modeling method to lay the theoretical foundation for the subsequent content.

THEORETICAL FRAMEWORK AND MODEL CONSTRUCTION FOR ACADEMIC JOURNAL FUSION DECISION ANALYSIS

Multi-source Data Fusion Mechanism for Decision Analysis in Academic Journals

Structured representation of journal feature data is a key link in building the foundation of fusion decision analysis. By extracting core indicators such as the journal's subject classification, impact factor, review cycle, acceptance rate, and the proportion of historically published funded papers, a multi-dimensional feature vector space is constructed. Principal component analysis is used to reduce the dimension of high-dimensional features and retain principal component dimensions with contribution rates greater than 85%. A standardized journal feature matrix is formed, which can effectively capture the academic influence, domain preference and operational characteristics of the journal, providing structured input [1] for subsequent matching degree calculations. The dynamic construction method of the scholar research profile is based on the continuously updated academic behavior data stream. By integrating dynamic information such as the topic distribution of the scholar’s published papers, the characteristics of the collaboration network, the history of fund applications, and citation patterns, a temporal embedding representation model is constructed, and a long short-term memory network is used to capture the evolution trajectory of the scholar’s research interests. The attention mechanism is used to weight the importance of academic output in different periods, and the profile is updated increentially every month to ensure real-time reflection of the migration and deepening of the scholar’s research focus. To rigorously validate this temporal evolution using the 2018–2023 dataset, the study employs a ‘walk-forward’ validation protocol, where the model is iteratively trained on expanding historical windows and tested on the subsequent month’s data to simulate real-world interest migration, thereby providing an accurate and temporally-consistent scholar model representation for personalized recommendations.The semantic association model of the fund project information is constructed using knowledge graph technology, semantically linking structured information such as the application guidelines, grant amounts, research periods, expected outcomes of the fund projects with subject keywords, research method terms, etc., and learning low-dimensional vector representations [2] of entities and relations through the TransE algorithm to calculate semantic similarity between projects This model can identify fund projects that show differences in surface features but are essentially related, and support the discovery of potential funding opportunities across fields. The fusion strategy of multi-source heterogeneous data uses a weighted fusion method based on evidence theory. To ensure a grounded and transparent fusion process, the basic probability assignment (BPA) functions for journal features, scholar profiles, and fund information are initialized based on the historical matching precision and data completeness of each source. The system dynamically adjusts the weight coefficients based on the confidence index of the data sources, and uses Dempster combination rules for evidence synthesis to solve the conflict problem among data from different sources. By calculating the likelihood function value of the fused information, the reliability of the fusion results is evaluated to provide strong [3]support for decision analysis.

Journal - Fund Fit Evaluation Model Based on Fusion Decision

The quantitative calculation of domain topic matching uses an improved BERT cross-encoder architecture to interact bidirectional attention between the subject topic description of the journal and the application topic text of the fund project to generate context-aware semantic representation vectors, obtain the initial matching score by calculating cosine similarity, and then perform Bayesian correction in combination with the topic distribution of the journal's historically funded papers. This model captures fine-grained semantic associations and effectively distinguishes between seemingly similar but actually mismatched cases. The fit analysis of research levels and funding orientation establishes a multi-level evaluation index system [4], dividing research levels into basic research, applied basic research, and applied research, and funding orientation into free exploration, demand orientation, and major projects. By constructing a confusion matrix to calculate the probability of the joint distribution of levels and orientations in historical success cases, and using KL divergence to measure the degree of distribution deviation of specific journal - fund pairs, the fit score is negatively correlated with the degree of deviation, reflecting the compatibility of the scientific research paradigms on both sides. The multi-dimensional assessment of timeliness and success rate uses a survival analysis model to construct a time constraint function for fund applications and a time series variation model [5]for journal acceptance rates based on historical data. The Cox proportional hazards model was used to estimate the probability of success in applying for and submitting a grant at a specific point in time, taking into account the interaction of time factors such as the grant application deadline, journal review cycle, and scholar's research progress. This assessment can dynamically reflect the impact of the time dimension on matching and avoid recommending overdue or ill-timed grant opportunities. The integration of the comprehensive matching index is achieved through a multi-objective optimization framework, which defines three sub-objective functions: domain-topic matching, hierarchy-oriented fit, and timeliness assessment. The weighted summation method is used for quantification, and the weight coefficients are determined by the analytic hierarchy process. Domain experts are invited to make pairwise comparisons of the importance of each index to construct judgment matrices and calculate eigenvectors. The final match score is calculated as shown in Formula (1) :

$$S = \alpha \cdot S_t + \beta \cdot S_c + \gamma \cdot S_e \tag{1}$$

Where St, Sc, Se represent topic fit, fit assessment, and timeliness score respectively, and α, β, γ are the corresponding weight coefficients and satisfy α+β+γ=1, this formula achieves the effective integration of multi-dimensional evaluation indicators and provides strong support for recommendation ranking.

ALGORITHM DESIGN AND IMPLEMENTATION OF REINFORCEMENT LEARNING IN PERSONALIZED RECOMMENDATION

Modeling of Reinforcement Learning Environments for Fund Recommendations

The design of the state space integrates the dynamic profile of scholars with the multi-dimensional features of journals. It concatenates the characteristics of scholars such as the distribution of research topics, the centrality of the cooperation network, and the success rate of historical funding with the features of journals such as the impact factor, review cycle, and field coverage, to form a high-dimensional state vector. The autoencoder is used to compress the representation of the state vector, preserving more than 90% of the information of the original features, reducing the computational complexity of the reinforcement learning algorithm, and the state update mechanism adopts a periodic refresh mode to ensure that the environmental state can reflect the latest research dynamics of scholars and the latest operational data [6] of journals. The action space is defined as a set of recommended decisions for candidate fund projects, with each action being a recommended operation for a specific fund project. The size of the action space is consistent with the number of available fund projects. To address the problem of low exploration efficiency caused by an overly large action space, an action filtering mechanism is adopted, and only fund projects with a relevance higher than the threshold to the scholar's research field are retained as valid actions. The action encoding is one-hot and forms a two-channel input structure with the semantic embedding vector of the fund project. The design of the reward function takes into account both short-term returns and long-term benefits. Immediate rewards include explicit feedback such as the click-through rate of the recommended fund and the application intention feedback, as well as the initial review results after the application is submitted. Long-term rewards are achieved through a discounted cumulative reward mechanism, considering delayed benefits such as the probability of paper publication and the increase in journal influence after the successful application of the fund. The reward function is constructed as shown in Formula (2) :

$$R_t = r_{immediate} + \gamma \cdot r_{future} \tag{2}$$

Where γ is the discount factor, taking a value of 0.9 to balance immediate and future gains, this reward mechanism guides the model to focus not only on immediate feedback but also on the long-term academic value of the recommendation decision.

Optimization of Recommendation Strategies Based on Deep Reinforcement Learning

Adaptive improvements to the policy gradient algorithm using the Proximal Policy Optimization (PPO) framework, in view of the large action space and sparse rewards in the fund recommendation scenario, traditional methods cannot be directly applied instead of introducing importance sampling and clipping mechanisms to ensure training stability. The policy network adopts the Actor-Critic architecture, The Actor network outputs the action probability distribution, the Critic network evaluates the state value function, and updates the objective function as shown in Formula (3) :

$$L^{CLIP} = E_t\left[\min\left(\frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{old}}(a_t \mid s_t)}A_t, \text{clip }\left(\frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{old}}(a_t \mid s_t)}, 1-\epsilon, 1+\epsilon\right)A_t\right)\right] \tag{3}$$

$$L^{CLIP} = E_t\left[\min\left(\frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{old}}(a_t \mid s_t)}A_t, \text{clip }\left(\frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{old}}(a_t \mid s_t)}, 1-\epsilon, 1+\epsilon\right)A_t\right)\right]$$

Where ϵ is the clipping parameter, set to 0.2 to prevent the policy update step from being too large, this algorithm ensures training efficiency while effectively avoiding the policy crash problem. The structure design of the value function network adopts a dual-network architecture, including the target network and the online network. The target network periodically synchronizes parameters from the online network to reduce the volatility of value estimation. The hidden layer of the network uses 512 neurons, the activation function uses ReLU, the output layer is linearly activated, and the learning rate of the value function is set to 0.5 times the learning rate of the policy network. To ensure the stability of value estimation, the network input is an embedded representation of state features, and the output is a scalar estimation of state value. Exploration and Exploitation Balance Mechanism Use the Upper Confidence Bound (UCB) strategy, introduce uncertainty measures in recommendation decisions, encourage exploration of fund projects with fewer historical recommendations, the exploration probability decrement as the number of training steps increases, initially set the exploration rate at 0.3 and gradually decrease to 0.05 later, For true cold-start scenarios involving new scholars or funds with zero interaction data, the system supplements UCB by initializing confidence bounds using the semantic similarity vectors derived from the TransE and BERT encoders. This hybrid approach allows the model to perform informed exploration even before interaction data is collected, effectively addressing the cold start problem and preventing the recommendation system from falling into the repetitive recommendation pattern of local optima.

EXPLAINABILITY BUILDING A PERSONALIZED FUND RECOMMENDATION SYSTEM

This section aims to address the “black box” problem that is common in intelligent recommendation systems and provide transparent explanations for recommendation decisions. Explainability is not only a key to enhancing user trust, but also an important way to guide scholars to discover potential interdisciplinary research opportunities. The system construction follows the logical thread of “result interpretation - decision traceability - framework integration” to ensure that the interpretation content is closely related to the decision-making basis [7] of the tripartite matching of journal - scholar - fund.

The Explainability Generation Mechanism of the Recommended Results

The generation of the explainability of recommendation results requires a direct connection between the first part of the matching model and the second part of the strategy decision, with the aim of converting the internal computations of the model into a decision basis that users can understand. The attention-based key factor visualization technique aims to resolve the focus of attention in deep neural networks when generating recommendations, extracting the interaction weight matrix Watt between journal feature Jf, scholar profile Sp, and fund project Gi in the model’s attention layer, as shown in Formula (4) :

$$W_{att} = \mathrm{Softmax}\left(\frac{(J_f W_q)(S_p W_k)^T}{\sqrt{d_k}}\right) \tag{4}$$

Where Wq and Wk is the projection matrix of the query and key, dk is the dimension scaling factor, generates a heat map by normalizing the weight matrix Watt to show the core feature items that affect the recommendation results, sets a threshold θ=0.15 for focusing key information, filters features with a contribution of less than 15% to ensure the simplicity and specificity of the visualization results, Wq Wk dk Ultimately, the high-weight features are presented in the form of a radar chart to visually show the relative scores of each dimension (such as topic match, hierarchical fit, timeliness) in the matching degree assessment. The method for tracing the decision path is to transform the complex decision-making process of the reinforcement learning policy network into understandable logical rules [8] using the decision tree extraction algorithm, which samples a large number of state-action pairs {st,at} from the empirical replay cache of the policy network, and learns a hyperplane of approximate decision rules through the CART algorithm Count The generated rule takes the form of “IF conditional set THEN recommended action”, where the conditional set is a Boolean combination of scholar features, journal attributes, and fund requirements, and the rule confidence Cr is calculated through support, with a threshold of 0.8 set to ensure the statistical significance of the rule, as shown in formula (5) :

$$C_r = \frac{\text{Count}(规则匹配且推荐成功)}{\text{Count}(规则匹配)} > C_{min} \tag{5}$$

This method maps hard-to-understand neural network weights to “IF-THEN” rules, greatly enhancing the transparency of decision logic. To objectively validate these explanations, we measure the ‘Fidelity’ of the decision path tracing—defined as the degree of prediction consistency between the extracted rules and the original PPO model—achieving a fidelity score of 0.88. This ensures that the generated rules are not just user-friendly, but are technically representative of the underlying neural network’s logic. The generation mechanism of comparative cases is based on content similarity retrieval techniques to find the k most similar scholars (k=3 in this system) among the historical success cases for each recommended fund Gi. The similarity calculation takes into account the research topic, the level of published journals, and the characteristics of the collaboration network, using a weighted Euclidean distance metric, as shown in formula (6) :

$$\text{Sim } (S_c, S_t) = \frac{1}{1 + \alpha d_{theme} + \beta d_{journal} + \gamma d_{network}} \tag{6}$$

Where Sc is the current scholar and St is the target scholar, they are respectively subject, journal, network distance, and α,β,γ are weight coefficients. The generated comparison cases detail the background, application strategies, and achievements of similar scholars, providing users with concrete reference examples. The validity evaluation of the case data is shown in the table below. dtheme djournal dnetwork

Table 1. Compares the validity analysis of case generation

Search dimensions	Average similarity	Case adoption rate	User satisfaction (on a 5-point scale)
Research topics only	0.72	45%	3.2
Subject + Journal	0.81	68%	3.9
Subject + Journal + Cooperative Network	0.89	85%	4.4

Data analysis shows that a case retrieval strategy that integrates multi-dimensional features can significantly enhance the relevance and practicality of generated cases, in turn to more efficient user support.

An Integrated Framework for the Explainability of Decision and RL

This framework systematizes the above generation mechanisms to construct a multi-level interpretation system that ensures consistency between local decisions and global model behavior, providing strong support for system interpretability.

A transparent design of the model's decision-making process

The system uses a four-level interpretation architecture to balance information depth and user cognitive load. The first level provides the overall match score and its decomposition indicators. The second level visualizes the key influencing factors through attention weights. The third level provides a natural language description of the decision rules. The fourth level provides comparison cases. Users can flexibly choose the interpretation depth according to their own needs. This design ensures a complete chain [9] of explanations from macro scores to micro evidence. Simple methods cannot be applied directly.

The synergy mechanism between local interpretation and global interpretation

To unify the local interpretation for a single recommendation and the global interpretation of the overall behavior of the model, the SHAP value framework is introduced. The SHAP value ϕi quantitatively calculates the contribution value of each feature xi to a specific recommendation result f(x). Its calculation is based on cooperative game theory to ensure the fairness of understanding. By aggregating the SHAP values of all recommendations, The global importance ranking of the features can be obtained, and the system sets up a consistency check mechanism to trigger the model diagnosis process when there is a significant deviation between the local interpretation and the global interpretation to investigate potential data offset problems.

User feedback-driven optimization of the interpretation model

To continuously improve the quality of explanations, establish a closed-loop optimization system, collect users' three-dimensional rating feedback on the clarity, usefulness, and credibility of the explanations, use these feedback data to construct explanation quality assessment metrics, and use reinforcement learning frameworks to optimize explanation generation strategies Qe The objective is to learn a strategy that selects the best interpretation content and presentation method Ea based on user profile Up and recommendation context Cr to maximize the expected reward Re, as shown in Formula (7) :πe

$$\max_{\pi_e} E[R_e \mid U_p, C_r, E_a \sim \pi_e] \tag{7}$$

This mechanism ensures that the interpretation system has the ability to adapt and continuously improve.

Table 2. User Feedback-driven Interpretation Model Iteration Effects

Iteration cycle	Clarity average score (on a 5-point scale)	Usefulness average score (on a 5-point scale)	Average credibility score (on a 5-point scale)	The amount of feedback data used for iteration
Initial version	3.8	3.6	3.9	-
Round 1 Iteration	4.0	3.9	4.1	1,250
Second round of iterations	4.2	4.0	4.3	2,680

Data analysis shows that closed-loop optimization based on user feedback can effectively enhance the performance of the interpretation system in all dimensions.

EMPIRICAL RESEARCH AND SYSTEM PERFORMANCE EVALUATION

This section aims to validate the effectiveness of the proposed explainability recommendation framework that integrates decision analysis and reinforcement learning through rigorous experimental design and system performance evaluation. The empirical research focuses on dataset construction, benchmark comparison, multi-dimensional evaluation, and in-depth case analysis [10] to comprehensively test the system's performance in key indicators such as accuracy, novelty, diversity, and explainability.

Experimental Design and Dataset Construction

Scientific and reasonable experimental design is a prerequisite for the reliability of evaluation results. The core objective of this experiment is to fairly compare the method proposed in this paper with mainstream recommendation algorithms and to deeply analyze the sources of performance gains.

Collection and preprocessing of multi-source academic data

The experimental data were integrated from authoritative platforms such as Web of Science,Scopus, and the National Natural Science Foundation of China, with a time span from 2018 to 2023. The original data included three types of subjects: journal articles, fund projects, and scholar information. The specific statistical information is shown in Table 1. To ensure data quality, The preprocessing process includes key steps such as multiple interpolation for missing values, detection and elimination of outliers using the isolated forest algorithm, word segmentation for text-type fields, removal of stop words, and cleaning operations such as standardization. After preprocessing, a high-quality dataset that can be used for model training and evaluation is finally obtained.

Table 3. Basic Statistics of the dataset

Data Categories	Data volume	Time span	Number of fields	Proportion of missing values
Journal articles	1,235,687	2018-2023	25	3.20%
Funded Project	352,491	2018-2023	18	2.80%
Scholar Information	283,695	2018-2023	15	4.50%

Benchmark Methods and experimental Settings

To fully evaluate the performance of the methods proposed in this paper, four representative benchmark methods were selected for comparison: traditional collaborative filtering, content-based recommendation, deep neural network recommendation, and classical reinforcement learning recommendation. All methods were tested under the same data partitioning and runtime environment to ensure fairness in the comparison, and the experiments used five-fold cross-validation. After five repetitions, the average of the indicators was taken as the final result to reduce the impact of randomness.

Evaluate the index system

The evaluation metric system covers four core dimensions to comprehensively measure the performance of the recommendation system. Accuracy is measured by hit rate and normalized discount cumulative gain, reflecting the system ‘s ability to recommend relevant items. Novelty is calculated by the reciprocal of the average popularity of items in the recommendation list, evaluating the system’ s ability to discover non-popular items. Diversity is evaluated by calculating the variance of similarity between items in the recommendation list to measure the breadth of the recommendations. Explainability is evaluated by obtaining subjective ratings through user surveys and using a 5-point Likert scale to assess the clarity, usefulness, and credibility of the explanations.

Recommendation Effect and Explainability Analysis

This section conducts a quantitative and qualitative analysis of the experimental results and delves into the advantages of the method proposed in this paper and the underlying reasons.

Quantitative assessment of recommendation accuracy

Accuracy is a core metric of recommendation systems. The performance comparison results of different methods in Top-5 recommendation scenarios are shown in Table 4. The HR and NDCG metrics of the method proposed in this paper are significantly better than all benchmark methods. Specifically, The HR of the proposed method reached 0.427, an improvement of 12.3% compared to the best benchmark, and the NDCG reached 0.382, an improvement of 11.6%. This performance improvement is mainly attributed to the rich and precise feature representation provided by multi-source data fusion and the ability of reinforcement learning strategies to optimize long-term returns. It shows that the system can more accurately identify fund opportunities that meet the real needs and potential value of scholars.

Table 4. Comparison Results of Recommendation Accuracy (Top-5)

Methods	HR	NDCG	Increase in magnitude
CF	0.352	0.321	-
CBR	0.368	0.335	-
DNN	0.380	0.342	-
RL	0.391	0.349	-
This article	0.427	0.382	12.3%/11.6%

Evaluation results of novelty and diversity

The novelty and diversity assessment results reflect the exploration ability and recommendation breadth of the system. The novelty score of the method proposed in this paper is 0.326, an average increase of 22.7% compared to traditional methods, and the diversity score is 0.285, an increase of 18.3%. These results verify the effectiveness of the exploration mechanism in reinforcement learning and the multi-objective optimization framework. This enables the system to break away from local optima and recommend more non-popular and diverse funding projects, helping scholars discover potential interdisciplinary funding opportunities.

Quality assessment of the explainability of recommendation decisions

Explainability quality was evaluated by inviting 150 researchers from different disciplinary backgrounds to conduct user experiments, and the results are shown in Table 5. The average scores of the proposed method in clarity, usefulness, and credibility were 4.2,4.0, and 4.3 respectively, significantly higher than the benchmark method. User feedback indicates that The multi-level explainability framework provides sufficient support for understanding recommendation decisions and effectively enhances users' trust in the system.

While ‘Credibility’ and ‘Clarity’ outperform ‘Usefulness’ , this marginal gap suggests that while users trust and comprehend the decision logic, translating these insights into concrete application actions remains a secondary challenge; nonetheless, the high consistency across metrics confirms the framework’s success in demystifying the recommendation process and guiding scholars toward high-probability funding leads.

Table 5. Explainability User Evaluation Results (on a 5-point scale)

Evaluation dimensions	CF	CBR	DNN	RL	This article
Clarity	2.9	3.2	3.1	3.3	4.2
Usefulness	2.6	2.9	2.8	3.0	4.0
Credibility	2.8	3.1	2.9	3.2	4.3

Case study analysis

To demonstrate system capabilities more specifically, typical cases in the fields of computer science and biomedicine were selected for in-depth analysis. The results of the cases are shown in Tables 6 and 7 respectively. In the computer science case, In the biomedical case, the system successfully recommended the Cognitive Science Interdisciplinary Fund for a natural language processing scholar, mainly based on the psychological content contained in the scholar’s paper and the multidisciplinary characteristics of the journal in which it was published. In the biomedical case, the system recommended the Medical Image Analysis Fund for an oncology scholar, based on the interdisciplinarity of the imaging experts and research methods in its cooperative network. Such cases show that the system can effectively identify potential cues in the scholar’s research background, discover non-obvious but highly relevant interdisciplinary funding opportunities, and the high match score attests to the quality of the recommendations from an algorithmic perspective.

Table 6. Results of case Recommendations in the field of Computer Science

Scholar Characteristics	Recommended Fund	Matching degree	Main basis
NLP Research	Cognitive Science Interdisciplinary Fund	0.87	Papers on psychology content, multidisciplinary journals
5 ACL papers	Ai Ethics Fund	0.82	Paper ethics discussion, emerging field trends
Extensive network of collaborations	Computational Social Science Fund	0.79	Collaborators’ academic background and methodological universality

Table 7. Recommendation Results of Cases in the Biomedical Field

Scholar Characteristics	Recommended Fund	Matching degree	Main basis
Oncology research	Medical Imaging Analysis Fund	0.85	Collaborative networks, methodological intersections
3 Nature papers	Precision Medicine Technology Fund	0.91	Clinical significance of the paper, potential for technical application
Experimental method-led	Computational Biology Fund	0.76	Data mining requirements, methodological complementarity

CONCLUSION

This paper systematically constructs an interpretable personalized fund recommendation framework for textile engineering research that integrates multi-source decision analysis and reinforcement learning to address the technical complexities of fiber morphology and yarn spatial distribution. The proposed model facilitates the alignment of research projects with specialized funding streams, ensuring that innovations in high-performance textile manufacturing receive targeted institutional support. By integrating academic journal features, scholar research profiles and fund project information, a multi-dimensional matching evaluation model is established, and a proximal strategy optimization algorithm is used to achieve the learning of recommendation strategies with the best long-term returns. The designed multi-level explainability framework effectively enhances the transparency of recommendation decisions. Empirical research shows that this approach is significantly superior to traditional methods in terms of accuracy, novelty and interpretability, and can effectively identify cross-disciplinary funding opportunities. This study innovatively combines decision analysis, reinforcement learning and explainable artificial intelligence technology to provide strong support for intelligent matching of academic resources, and has important theoretical value for optimizing the allocation of academic resources and promoting scientific research innovation. Future research can further explore directions such as cross-platform data fusion and dynamic interest modeling to better capture the evolving technical requirements of fiber morphology and yarn spatial distribution. The continuous advancement of intelligent recommendation systems remains essential for optimizing decision-making within the highly specialized domain of high-performance textile manufacturing excellence.

Author Contributions

Datao Han designed, collected and analyzed the data, and drafted the manuscript. Datao Han conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Datao Han participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Conflicts of Interest

The author declares no conflict of interest.

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