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Intelligent Assisted Decision-Making System for Project Review Integrating Deep Learning Algorithms

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Abstract: With the increasing number and complexity of research projects, traditional manual review methods have significant limitations in terms of efficiency and consistency. To improve the scientific rigor and intelligence of project review, this paper introduces deep learning algorithms and multi-source data processing technology to construct an intelligent auxiliary decision-making system for project review. The system performs semantic encoding and indicator mapping on the application materials, attachments, and historical scoring data to achieve multi-indicator collaborative reasoning and comprehensive score generation, and dynamically corrects the results by incorporating implicit expert scoring logic. Experimental results show that the system demonstrates good discriminative ability in project semantic mapping and indicator scoring. Taking project P3 as an example, its innovation score is 0.90, and its feasibility score is 0.85. The system exhibits good performance in project semantic understanding, scoring accuracy, and ranking consistency, providing a scalable, efficient, and interpretable intelligent auxiliary tool for research project review.

1. Introduction

With the continuous increase in the number and complexity of scientific research projects, traditional manual review methods face significant challenges in terms of efficiency and consistency. To address these issues, this paper proposes and develops an intelligent auxiliary decision-making system for project review that integrates deep learning algorithms. The system automatically generates a comprehensive project score and priority ranking by semantically encoding application materials, mapping key indicators, and performing multi-indicator collaborative reasoning, and dynamically adjusts the score based on implicit expert scoring logic. Simultaneously, the system designs a human-computer interaction interface and a multi-expert opinion fusion mechanism to achieve efficient collaboration between experts and the system during the review process. This research not only improves the efficiency and consistency of project review but also provides scalable and interpretable technical support for intelligent scientific research management and offers methodological references for the design and application of related multi-indicator decision-making systems.

2. Related Work

In recent years, the application of intelligent concepts, artificial intelligence and multi-criteria decision-making methods in project management and engineering decision-making has received increasing attention. Related research continues to explore its practical value in performance optimization, risk management and sustainable development. Amhaimedi et al. explored the application of intelligent concepts in building energy conservation management, used cost deviation and schedule deviation to monitor project performance, compared the decision-making limitations of BIM (Building Information Modeling) and CDM (Critical Decision Method), and screened 19 key cost factors using the Delphi method. The results showed that the number of floors, structural design and building shading scale had a significant impact [1]. ABADI et al. proposed a knowledge-driven intelligent system for Industry 4.0 agile project management, which realizes project knowledge management, interoperability and decision support by constructing an APM (Agile Project Management) ontology and integrating SWRL (Semantic Web Rule Language) rule reasoning [2]. Rodrigues et al., through systematic literature review and quantitative analysis, sorted out the role mechanism of emotional intelligence in project management decision-making, and explored the impact of managers' ability to identify, understand and regulate their own and team's emotions on project performance. They pointed out that emotional factors are generally involved in the decision-making process, but existing literature lacks a clear empirical causal relationship between emotional intelligence and decision-making effect [3]. Torkayesh et al. reviewed the application of Multi-Criteria Decision Making (MCDM) in sustainable development and circular economy. In response to the problem of insufficient research on the MABAC (Multi-Attributive Border Approximation area Comparison) method, they systematically reviewed 117 articles, analyzed its principle progress and application status in intelligent decision-making systems, summarized the main research hotspots and technical characteristics, and proposed future research prospects in combination with current challenges and development trends [4]. Nenni et al. systematically analyzed 215 articles based on the PRISMA method to explore the application status and development trend of artificial intelligence in project risk management. The results showed that AI and machine learning can significantly improve the risk identification, assessment and control capabilities throughout the project life cycle and reshape the traditional management model [5]. Sahoo and Goswami conducted a comprehensive review of the multi-criteria decision making (MCDM) method, emphasizing the importance of MCDM in complex decision-making scenarios. They also explored the diverse applications of MCDM in business, engineering environment, healthcare and public policy [6]. Although existing research has achieved certain results in intelligent project management, artificial intelligence applications, and multi-criteria decision-making methods, there are still significant shortcomings in empirical verification, cross-method integration, and systematic application.

3. Method

3.1 Overall Architecture Design of Intelligent Assisted Decision-Making System for Project Review

3.1.1 Modeling the Review Business Process

To standardize system operation logic, a business process model coupled with state transitions and task scheduling is constructed. A project review state set ($S=s_1,s_2,s_3,s_4,s_5$) is defined, representing "material receipt, semantic parsing, indicator mapping, comprehensive reasoning, and auxiliary sorting," respectively. The operational trajectory of any project instance (p_i) in the system can be represented as a state sequence ($\Gamma(p_i)=s_1\rightarrow s_2\rightarrow s_3\rightarrow s_4\rightarrow s_5$).

The system controls process advancement using an event-triggered mechanism. The transition condition for any state node (s_k) is defined as ($T(s_k)=f(D_k,C_k,R_k)$), where (D_k) represents the stage data completeness constraint, (C_k) represents the business rule control condition, and (R_k) represents the manual review intervention or verification requirement. When ($T(s_k)=1$), the project instance enters the next review state.

Assuming the batch of participating projects is set as ($P=p_1,p_2,\ldots,p_n$), the system promotes projects in parallel based on a unified process scheduling function. Its overall processing is described as follows:

$$\Phi(\mathrm{P})=\sum_{i=1}^{n}\Gamma(\mathrm{p_i}) \tag{1}$$

This enables simultaneous monitoring of the review process and concurrent management of multiple projects.

3.1.2 Multi-source Review Data Processing Architecture

The review data sources include project application text (d_t), feature data of supporting documents (d_f), structured data of expert scores and opinions (d_s), and historical review semantic data (d_h), forming a multi-source heterogeneous data set ($D=d_t,d_f,d_s,d_\mathrm{h}$). The system constructs a unified semantic mapping function ($\Psi:D\rightarrow X$) to transform various heterogeneous inputs into a unified feature space ($X=x_1,x_2,\ldots,x_m$).

For any project (p_i), its comprehensive feature vector is represented as ($X_{p_i}=\Psi(d_t^i,d_f^i,d_s^i,d_\mathrm{h}^i)$), achieving multi-dimensional feature integration of text description, supporting document information, and expert evaluation.

In the feature fusion stage, the system constructs a weighted semantic aggregation model to generate a comprehensive evaluation vector.

$$\mathrm{Z_{p_i}}=\sum_{k=1}^{4}\mathrm{w_k\,x_k} \tag{2}$$

Where (w_k) represents the importance weight coefficient of different data sources in the review decision, satisfying the constraint condition ($\sum_{k=1}^{4}w_k=1$). The comprehensive feature vector (Z_{p_i}) serves as the unified input for subsequent indicator semantic mapping, collaborative reasoning, and project ranking modules, realizing intelligent review support driven by multi-source data collaboration.

3.2 Project Text Semantic Understanding and Indicator Mapping Model

3.2.1 Semantic Coding Modeling of Project Application Materials

To address the long text characteristics of project application materials, the system constructs a domain-adaptive deep semantic coding model, which segments and embeds the project objectives, technical routes, implementation plans, and expected outcomes. For a set of text segments ($T_{p_i}=t_1,t_2,\ldots,t_l$) of a project ($p_i$), each segment is transformed into a vector using a semantic coding function ($E(\cdot)$).

$$x_j=E(t_j),\quad j=1,2,\ldots,l \tag{3}$$

The overall semantic representation of the item (p_i) is a weighted aggregation of segment vectors:

$$X^{sem}p_i=\sum j=1^l\,\alpha_j x_j \tag{4}$$

Where (α_j) represents the importance weight of the paragraph in the overall project review semantics, which can be adaptively adjusted according to the paragraph category, length and historical review data.

3.2.2 Semantic Mapping Mechanism for Key Review Indicators

To align the semantic representation of the project with specific evaluation metrics, a two-way matching mechanism between metrics and text paragraphs is constructed. Let the set of evaluation metrics be $(I=i_1,i_2,\ldots,i_m)$, where each metric is represented by a semantic embedding vector (v_k). The metric mapping function is defined as follows:

$$\mu_{i_k,p_i}=\mathrm{sim}(v_k,X^{sem}_{p_i}) \tag{5}$$

$(\mathrm{sim}(\cdot))$ represents the cosine similarity or other semantic similarity metric function, used to quantify the degree of fit between the metric and the item's text content. Finally, the mapping score vector of item (p_i) across all metrics is:

$$M_{p_i}=[\mu_{i_1,p_i},\mu_{i_2,p_i},\ldots,\mu_{i_m,p_i}] \tag{6}$$

This vector provides direct input for subsequent multi-indicator reasoning and comprehensive ranking.

3.2.3 Simulation of Implicit Expert Scoring Logic

To address the implicit experience-based judgments and preference differences among experts during the review process, a scoring logic simulation model based on historical review corpora is constructed. The expert set $(E=e_1,e_2,\ldots,e_s)$ is defined, and the predicted score for item (p_i) can be expressed as:

$$S^{e_k}_{p_i}=f(M_{p_i},\theta_k) \tag{7}$$

$(f(\cdot))$ represents the rating mapping function, and (θ_k) represents the behavioral parameters of the expert (e_k), including risk preference, emphasis on innovation, and industry experience weights. The system generates implicitly logically corrected indicator weights by aggregating and calculating the rating vectors of multiple experts, thereby modeling the expert decision-making behavior.

$$\widetilde{M}p_i=\sum k=1^s\,\beta_k S^{e_k}_{p_i},\quad \sum_{k=1}^{s}\beta_k=1 \tag{8}$$

(β_k) is the expert weight coefficient, which can be dynamically adjusted based on the consistency and reliability of its review history. Finally, $(\widetilde{M}_{p_i})$ serves as the input for the comprehensive evaluation reasoning of the project, taking into account both textual semantic features and implicit expert preferences, thus achieving a deep integration of intelligent decision-making assistance and human experience.

3.3 Comprehensive Decision-Making Reasoning and Ranking Recommendation Model

3.3.1 Construction of Multi-Indicator Collaborative Reasoning Network

To address the cross-influence and hierarchical coupling among evaluation indicators, a multi-indicator collaborative reasoning network is constructed. Let the semantic mapping score vector of item (p_i) on each indicator be ($\widetilde{M}p_i=[\tilde{\mu}i_1,\tilde{\mu}i_2,\ldots,\tilde{\mu}i_m]$), and define the collaborative weight matrix among indicators ($W=[w_{jk}]$), representing the degree of influence of indicator (i_j) on indicator (i_k). The comprehensive vector after collaborative adjustment of indicators is:

$$\widehat{M}p_i=\widetilde{M}p_i+\widetilde{M}_{p_i}W \tag{9}$$

3.3.2 Comprehensive Scoring Adaptive Mapping Mechanism

To adapt to different project types and varying review focuses, the system is designed with an adaptive mapping mechanism for comprehensive scoring. The comprehensive scoring function ($F(\cdot)$) maps the collaboratively adjusted indicator vector ($\widehat{M}_{p_i}$) to a single score value:

$$S_{p_i}=F(\widehat{M}p_i)=\sum j=1^m \gamma_j\hat{\mu}i_j,\quad \sum j=1^m \gamma_j=1 \tag{10}$$

Where (γ_j) represents the indicator weight coefficient, which can be dynamically adjusted according to project type, historical review preferences, or expert corrections to achieve steady-state adaptation of scores under different review scenarios.

3.3.3 Project Priority Ranking and Decision Interpretation Model

After obtaining the comprehensive score (S_{p_i}), the system generates a project priority ranking (R):

$$R=\mathrm{sort}(S_{p_1},S_{p_2},\ldots,S_{p_n}) \tag{11}$$

Meanwhile, to enhance the interpretability of the decision support, the system outputs a contribution analysis of each item's score to the final ranking, including the contribution rate (ρ_{i_j}) of each indicator:

$$\rho_{i_j}=\frac{\gamma_j\hat{\mu}i_j}{Sp_i} \tag{12}$$

The system still integrates expert feedback processing and dynamic adjustment mechanisms in the comprehensive decision-making reasoning and ranking recommendation module to ensure the interpretability of the review results and the efficiency of optimization.

4. Results and Discussion

4.1 Experimental Subject

The experimental subjects mainly consisted of two parts: project application materials and expert reviewers. The project application materials included several batches of real or simulated project data, covering text descriptions, supporting documents, and historical scoring records, ensuring the data's multi-source and heterogeneous nature to fully verify the system's ability to process different types of information. The expert reviewers were composed of several experts with practical review experience, ensuring the diversity and professionalism of their review opinions, while also providing human reference and verification for the system's generated scoring and ranking results. The experiment was conducted in a fully deployed intelligent auxiliary decision-making system environment, ensuring that the system's semantic parsing, indicator mapping, comprehensive reasoning, ranking recommendation, and interactive interface functional modules all functioned normally.

4.2 Results Analysis

The comprehensive scores and ranking results generated by the system are compared and organized. By analyzing the differences between the system output and the results of human review, the effectiveness of multi-expert opinion fusion is evaluated, and the system's operational efficiency and stability when processing large-scale project data are observed. This stage also includes recording and organizing the system's response time, task concurrency processing capacity, and resource consumption, providing a reference for system optimization and subsequent improvements.

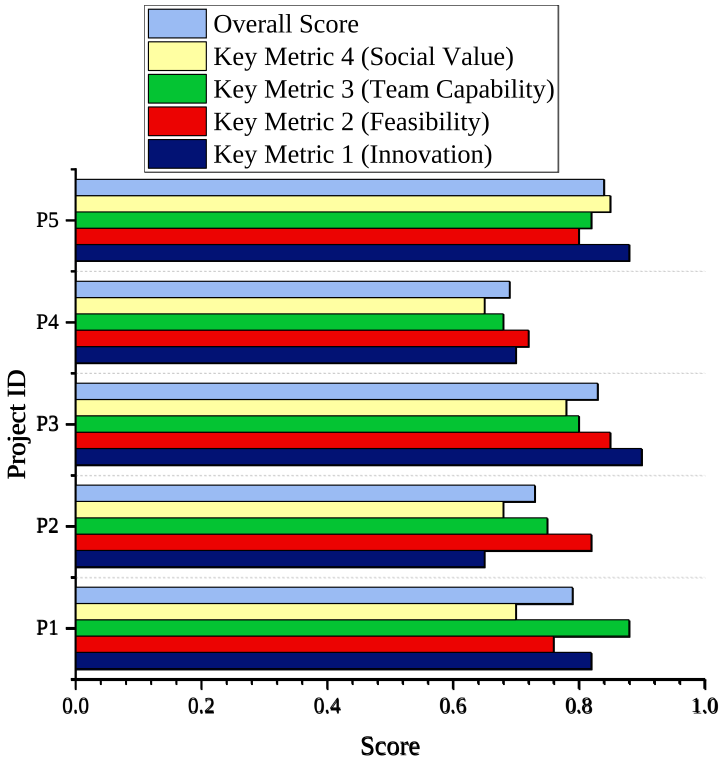

Figure 1. Item Semantic Mapping and Indicator Scoring

As shown in Figure 1, the system demonstrates good discriminative ability in project semantic mapping and indicator scoring. Taking project P3 as an example, it scores 0.90 for innovation, 0.85 for feasibility, 0.80 for team capability, and 0.78 for social value, resulting in a final comprehensive score of 0.83. This demonstrates that the system can effectively integrate the performance of each key indicator to generate a reasonable overall score. Overall, the system scores relatively high on core indicators such as innovation and team capability, while scoring slightly lower on feasibility and social value, reflecting the system's sensitivity and weighting across different indicator dimensions.

5. Conclusion

This paper focuses on the development and application of an intelligent auxiliary decision-making system for project review, proposing a multi-source data processing and comprehensive decision-making framework that integrates deep learning algorithms. The system achieves multi-indicator collaborative reasoning and comprehensive score generation by semantically encoding and mapping key indicators into project application materials, and dynamically corrects the results by incorporating implicit expert scoring logic, thus realizing efficient human-machine collaborative review. However, this research still has certain limitations: firstly, the limited scale of experimental data and the limited number of expert samples may affect the system's wider applicability. Future work could further improve the algorithm's adaptability and enhance the system's interpretability and robustness by expanding the dataset and the scale of expert participation.

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