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Research on intelligent recommendation method for electric power scientific literature driven by integration of knowledge graph and DKN

Wenyao Wen*

Chengdu Productivity Promotion Center, Chengdu, 610031, China

* Correspondence author; E-mail: wenwy02@126.com.

Abstract: Aiming at the increasingly active power science and technology innovation under the new power system construction, as well as the problems of information silos and difficulty in accurate personalized recommendation in research literature management, this paper proposes an intelligent recommendation method for power scientific literature driven by the integration of Knowledge Graph (KG) and Deep Knowledge-Aware Network (DKN). First, a four-layer system architecture (data layer, knowledge layer, model layer, and functional application layer) is designed to support full-link data-driven services. Second, for multi-source heterogeneous academic documents, a joint knowledge extraction algorithm combining LayoutLM and Conditional Random Field (CRF) is proposed. To resolve entity conflicts in KG construction, an author name disambiguation algorithm integrating LINE and content features is developed. Finally, the DKN model is adopted to build a multi-channel feature extraction framework fused with KG entities, and an attention mechanism is applied for dynamic user interest modeling, achieving accurate recommendation of academic achievements. Experimental results show that the proposed disambiguation algorithm achieves an average F1 of 0.582 on public datasets, and the DKN-based recommendation algorithm obtains 0.741 and 0.679, demonstrating superior comprehensive performance.

Keywords: knowledge graph; deep knowledge-aware network (DKN); literature recommendation system; joint knowledge extraction; author name disambiguation; electric power scientific and technological innovation.

1. Introduction

The profound advancement of the new round of global scientific and technological revolution and industrial transformation has produced a profound impact on the power industry, a fundamental and strategic industry [1]. Currently, the power industry is in a major transition period of building a new power system and realizing the “dual carbon” goals; scientific and



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technological innovation activities are becoming increasingly active, and the number of scientific research projects and types of output achievements are showing a multidimensional growth trend [2,3]. In the daily management of electric power science and technology projects, scientific research teams produce massive amounts of literature, patents, and other achievements when overcoming major technical projects, and simultaneously need to track and digest a large number of external cutting-edge academic documents. However, traditional electric power scientific and technological innovation management methods mainly rely on manual registration, tabular statistics, and empirical evaluation, or adopt fragmented single information systems for project tracking and achievement management [4]. This model, which treats scientific research data as isolated files for physical archiving, ignores the rich knowledge units (such as research methods, key technologies, citation relationships, author collaboration networks, etc.) hidden within literature and patents, resulting in poor correlation and low utilization of electric power scientific and technological information [4,5].

In addition, existing systems usually can only passively provide users with existing information within the team, and cannot proactively recommend external cutting-edge academic literature to power research personnel based on their unique research interests, making it difficult to meet personalized and timely needs.

In response to the above challenges, the combination of knowledge graphs and recommendation systems provides a completely new solution for the deep mining and precise distribution of electric power scientific and technological innovation information [6,7]. Knowledge graphs can provide knowledge extraction and knowledge association for multivariate and heterogeneous power data, mining hidden connections between scientific research information [6]; while personalized recommendation algorithms based on knowledge graphs can effectively solve the cold start problem faced by traditional recommendation systems, significantly improving the diversity and interpretability of recommendation results [7].

Based on this, this paper focuses deeply on the knowledge extraction of electric power scientific literature, system architecture design, and personalized recommendation algorithms [8]. It discusses in detail how to construct an electric power science and technology knowledge graph from multi-source heterogeneous unstructured texts, design a hybrid-driven intelligent management system overall architecture, and introduce a Deep Knowledge-Aware Network (DKN) to achieve the precise reach of cutting-edge academic achievements and electric power science and technology project resources.

2. Overall architecture of the electric power scientific and technological innovation management system

In order to organically integrate multi-source heterogeneous literature knowledge extraction technology with intelligent recommendation algorithms and serve refined electric power scientific and technological project management, an overall architecture for a knowledge graph hybrid-driven electric power scientific and technological innovation management

system was designed. The system as a whole adopts a layered architecture design, divided from bottom to top into a data layer, knowledge and corpus layer, model layer, and functional application layer, and is supplemented by an information security and privacy protection module running through the whole system [9].

The data layer is the basic support layer of the system, responsible for uniformly collecting and storing full-cycle data and achievement data of internal electric power science and technology projects, as well as external academic papers, patents, and industry standards [5]. Due to the coexistence of structured, semi-structured, and unstructured data, considering the coexistence of structured, semi-structured, and unstructured data, the system adopts a Data Lakehouse architecture to achieve unified storage and efficient access of heterogeneous scientific research data. The knowledge and corpus layer serves as a key intermediate layer, responsible for standardized cleaning, entity resolution, and semantic alignment of raw data, eliminating formatting inconsistencies and noise interference caused by multi-source heterogeneity, and generating high-quality basic corpora in the field of electric power science and technology [10].

The model layer is the intelligent core engine of the system, which is jointly constituted by the knowledge graph in the field of electric power science and technology and deep learning algorithm models. Among them, large language models and deep neural networks are responsible for natural language understanding and content generation, while the knowledge graph provides structured fact querying and logical constraints [11].

The functional application layer focuses on the actual scenarios of electric power scientific and technological innovation management, building core modules such as science and technology project management, science and technology achievement management, and science and technology talent management [12]. This layer achieves full-link data drive from project initiation novelty search, process monitoring to achievement transformation by calling the standardized intelligent recommendation and knowledge extraction services provided by the model layer, upgrading traditional science and technology project management from “passive registration” to “proactive collaboration and precise distribution”.

3. Construction of electric power scientific and technological innovation knowledge graph

The construction of the electric power scientific and technological innovation knowledge graph is the underlying foundation for achieving upper-layer intelligent applications and precise matching of resources [6]. Its core task is to automatically extract structured triplets containing entities, relations, and attributes from multi-source heterogeneous unstructured electric power scientific research documents [10].

3.1. Design of knowledge graph schema layer

Targeting the management characteristics of the electric power science and technology field, this paper defines 9 core entity types: scientific research personnel, scientific research

institutions, scientific research projects, literature, keywords, patents, copyrights, journals, and conferences. At the same time, 7 core semantic relations are defined to cover all elements of the electric power scientific and technological innovation scenario [13], as shown in Table 1.

Table 1. relationship types.

Meaning	Example of Relationship
Affiliation	(Researcher, Affiliation, Research Institution)
Publish	(Researcher, Publish, Literature)
Apply	(Researcher, Apply, Patent) (Researcher, Apply, Copyright)
Output	(Research Project, Output, Literature) (Research Project, Output, Patent) (Research Project, Output, Copyright)
Published In	(Literature, Published In, Journal) (Literature, Published In, Conference)
Cite	(Literature, Cite, Literature)
Contain	(Literature, Contain, Keyword)

Among them, the affiliation relationship is mainly directed at scientific research personnel and scientific research units, used to represent the scientific research unit information where the scientific research personnel are located; the publish relationship is mainly directed at scientific research personnel and literature, used to declare the authors of the literature; the apply relationship is mainly directed at scientific research personnel, patents, and copyrights, used to represent that scientific research personnel applied for or own a certain patent and copyright information; the output relationship is mainly used to represent what scientific research achievements were produced during the process of overcoming scientific research projects; the published in relationship is used to represent which journals or conferences the literature was published in or included in. The cite relationship is used to indicate whether there is a citation between two academic documents. The contain relationship is mainly used to represent what keywords are contained in the literature.

3.2. Knowledge extraction for multi-source heterogeneous electric power academic documents

For electric power academic literature with diverse layouts, this paper proposes a joint knowledge extraction algorithm integrating document region recognition and sequence labeling. Aiming at unstructured chapters, an efficient extraction scheme based on LayoutLM is specially built, and its overall underlying metadata processing flow and computing architecture are shown in Figure 1.

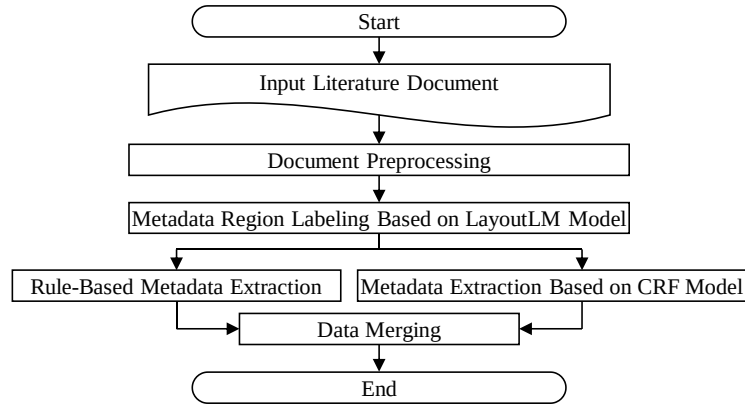


Figure 1. Framework for literature document metadata extraction.

First, according to the structural features of the literature, the algorithm adopts the LayoutLM pre-training model for document region classification. LayoutLM can add the two-dimensional position information of the text on the page in the embedding layer, which is extremely suitable for processing PDF parsing tasks with rich layout information [14]. For the character set $T = \{t_1, t_2, \dots, t_n\}$ in the literature, it undergoes LayoutLM encoding to output the feature vector matrix E . Subsequently, it outputs the score S for each predefined region label through a fully connected layer:

$$S = w \times E + b \quad (1)$$

where w is the learnable weight matrix, and b is the bias vector.

Normalize using the Softmax function to calculate the predicted probability p_i :

$$p_i = \frac{\exp(s_i)}{\sum_{j=1}^t \exp(s_j)} \quad (2)$$

where t represents the number of categories for predefined region labels.

Thus, the system can accurately identify regions such as the title, abstract, keywords, authors, and bibliographic citations of the literature.

On the basis of region recognition, regular string matching is adopted for regions with obvious characteristic patterns such as titles and abstracts; while for regions with complex formats and multiple fine-grained entities such as authors, affiliations, and references, a linear conditional random field model is introduced for sequence labeling extraction. Given an input sequence x , the conditional random field model finds the label sequence y that maximizes the conditional probability $P(y|x)$:

$$P(y|x) = (1/Z(x)) \exp(\sum \lambda_k t_k + \sum \mu_l s_l) \quad (3)$$

where $Z(x)$ is the normalization factor, and t_k and s_l respectively represent the transition feature function and state feature function, with λ_k and μ_k being the corresponding learning weights.

Finally, integrate the extraction results and establish the mapping relationship between each metadata attribute of the literature and the corresponding entities and relationships in the knowledge graph.

3.3. Author Name Disambiguation Based on Heterogeneous Networks and Content Features

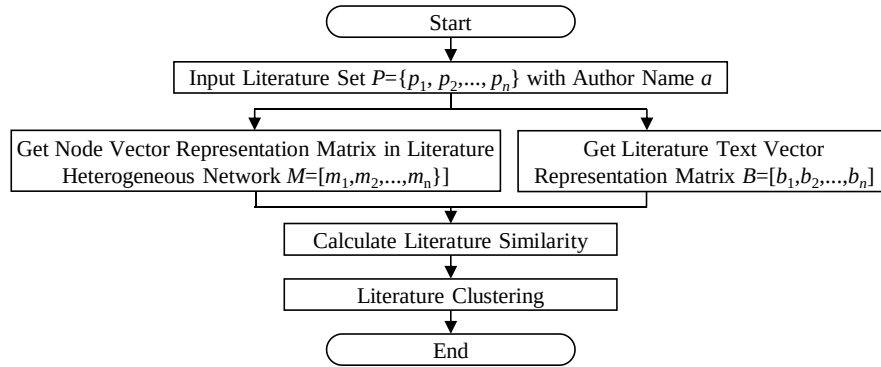


Figure 2. Author Name Disambiguation Based on Heterogeneous Networks and Content Features.

After the knowledge extraction is completed, the power technology innovation management system often encounters a serious problem of author name duplication (entities with the same name may refer to different power researchers). Relying solely on the text features of the literature is difficult to distinguish them completely. Therefore, this paper proposes an author name disambiguation algorithm based on the fusion of heterogeneous literature networks and content features. The overall processing flow and topological association network are shown in Figure. 2.

First, for the author name to be disambiguated and its associated literature set $P = \{p_1, p_2, \dots, p_n\}$, a literature heterogeneous network is constructed. The nodes in the network are literature entities, and four types of associative relations are defined: same publication location, presence of other co-authors, similar titles, and containing common keywords. Then, the LINE algorithm is adopted to perform representation learning on this heterogeneous network, comprehensively considering the first-order and second-order similarities of nodes to obtain the literature relationship feature matrix M containing high-order topological information.

In terms of content features, Word2Vec is used to extract word vectors of literature titles, abstracts, and keywords, and weighted average fusion is performed through Term Frequency–Inverse Document Frequency (TF–IDF):

$$b_i = \sum (TF - IDF_{i,j} \times v_{i,j}) / \sum TF - IDF_{i,j} \quad (4)$$

where $v_{i,j}$ represents the word vector of the j -th word in the literature i .

Thus, the content feature matrix B of the literature is obtained. Finally, the cosine similarities of M and B are calculated separately and added to obtain the fused similarity matrix, and the unsupervised Density–Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm is used for clustering. Literature in the same cluster is attributed to the same real existing author entity, thereby completing disambiguation [15].

4. Personalized recommendation algorithm for electric power scientific literature

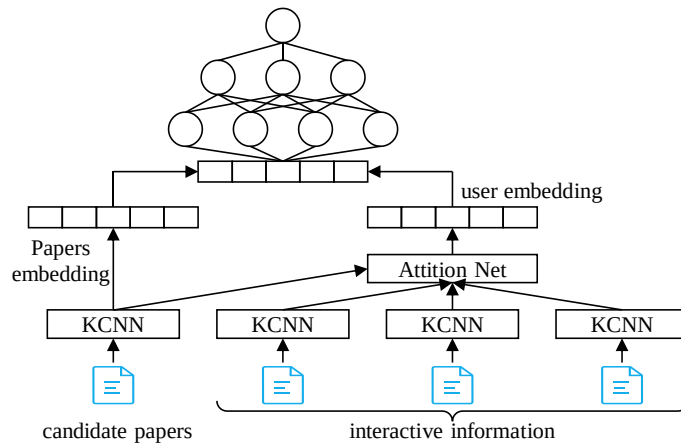


Figure 3. Overall architecture of recommendation system based on DKN.

To address the issue of “information overload” faced by power researchers in project follow-up and frontier tracking, this paper introduces a personalized recommendation mechanism based on the Deep Knowledge-Aware Network (DKN) on the basis of constructing a knowledge graph. The top-level collaborative control and computing architecture of the recommendation subsystem is shown in Figure 3.

4.1. Multi-channel literature feature extraction

The text of electric power scientific literature is highly concentrated and contains rich background knowledge. The DKN model not only utilizes the words of the literature itself but also introduces entities in the knowledge graph and the local graph network context of the entities. This paper designs a multi-channel feature extraction process integrating word vectors and knowledge entities.

For any candidate literature, the TextRank algorithm is first used to extract key sentences for long abstracts, and then word segmentation and entity linking processing are completed, mapping the text words to the pre-constructed electric power science and technology knowledge graph entities. In the literature representation stage, the model builds three parallel data channels, which are respectively the word vector channel, the entity vector channel relying on graph embedding algorithms like TransD to obtain entity feature vectors, and the entity context channel extracting the average representation of one-hop neighbor nodes of corresponding entities within the knowledge graph. After transforming the dimensions using a linear mapping matrix, they are stacked to form a multi-channel tensor W :

$$W = [[w_1, e_1, c_1], \dots, [w_n, e_n, c_n]] \quad (5)$$

where w_i is the word vector of the i -th word in the literature, e_i is the corresponding graph entity feature vector, and c_i is the context feature vector of the entity.

This tensor is input to the knowledge-aware multi-channel convolutional neural network (KCNN), and comprehensive deep features of the candidate literature are extracted through

convolution kernels of different sizes. The whole process of parallel interaction and feature aggregation of these channels is shown in Figure 4.

Literature titles, abstracts, and keywords highly summarize the literature content and contain a large number of knowledge entities; therefore, this paper combines them as the input text for content features. Considering that literature abstracts are usually too long, this paper first uses the TextRank algorithm to extract key sentences of the abstract, and then concatenates them with the title and keywords. For the word segmentation results, a word vector embedding model is first used for word vector representation, and then an entity linking method is utilized to identify the entity corresponding to each word in the knowledge graph, and embedding representation is performed for the entity and entity context. Finally, the word vectors, entity vectors, and entity context vectors are aligned and fed into the KCNN for feature extraction to obtain the final literature vector representation.

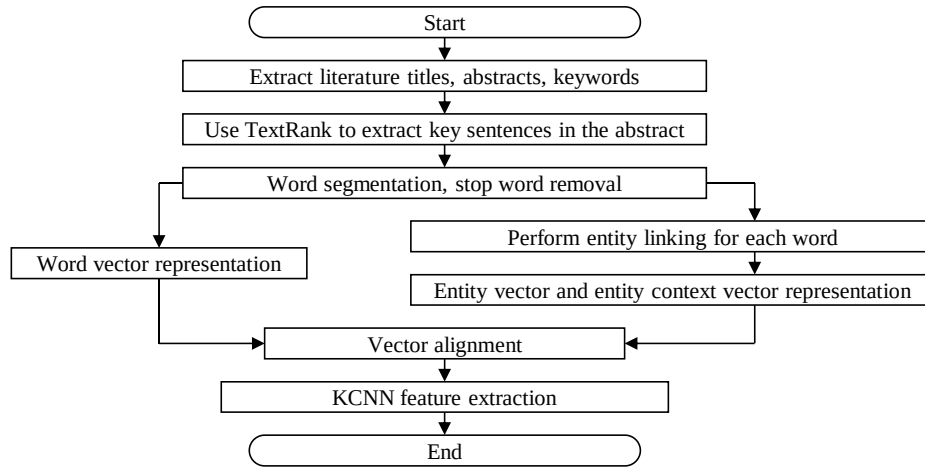


Figure 4. Multi-channel literature feature extraction combined with knowledge graph.

4.2. User interest modeling based on attention mechanism

Because the research interests of electric power researchers evolve dynamically with the execution stages of different science and technology projects, their historical reading records have varying weight influences on current reading intentions. For this reason, an attention network is introduced for user interest modeling.

The features of the candidate literature and the features of each literature historically clicked by the user are concatenated, and calculated through a multi-layer perceptron to obtain the attention formula:

$$\alpha_{e_j, e_i} = \text{softmax}(H(e_j, e_i)) = \frac{\exp(H(e_j, e_i))}{\sum_{k=1}^N \exp(H(e_j, e_k))} \quad (6)$$

Where $H(\cdot)$ is the multi-layer perceptron calculation function, and $\alpha_{j,i}$ represents the attention weight of the historical literature i to the candidate literature j .

The user's final interest representation is the weighted average of the historical literature features. Finally, after the user features and candidate literature features are concatenated,

they are sent to the prediction layer to calculate the probability of the user clicking or paying attention to the candidate electric power scientific literature.

5. Experimental analysis

5.1. Experimental evaluation of author disambiguation in electric power scientific literature

In order to verify the effectiveness of the author name disambiguation algorithm based on the fusion of literature heterogeneous networks and content features proposed in this paper oriented towards electric power scientific literature, the experiment adopts the AMiner public dataset enhanced with electric power scientific literature for performance evaluation. This study conducted a comparative experiment between the proposed algorithm and industry-mainstream graph representation algorithms DeepWalk, Node2Vec, and the traditional GHOST algorithm under the same test environment for electric power scientific literature author disambiguation. The experimental environment configuration is as follows: Python 3.10 and PyTorch 2.0 frameworks are used for model training, and the GPU is NVIDIA RTX4070. In the author disambiguation task, the training set, validation set, and test set are divided according to 8:1:1; the DKN recommendation model training epoch is set to 50, batch size is set to 64, and both word vector dimensions and entity vector dimensions are set to 128. The experimental evaluation metric adopts the average F1 value commonly used in clustering tasks. The performance comparison results of each algorithm are shown in Table 2.

Table 2. Average F1 value comparison of different disambiguation algorithms on public datasets.

Disambiguation Algorithm	Average F1 Value
Disambiguation Algorithm Based on DeepWalk	0.573
Disambiguation Algorithm Based on Node2Vec	0.560
Disambiguation Algorithm Based on Literature Content Feature Representation	0.543
GHOST Algorithm	0.424
Algorithm of This Paper	0.582

As can be seen from Table 2, the performance of the algorithm based on literature content feature representation (average F1 value of 0.543) and the GHOST algorithm (average F1 value of 0.424) are relatively poor. Compared with the above two algorithms, the F1 value of the algorithm in this paper (average F1 value of 0.582) increased by about 7.2% and 37.3% respectively, proving that the introduction of electric power scientific literature heterogeneous networks can effectively enrich the feature information of electric power scientific literature and significantly improve the performance of the electric power scientific literature disambiguation algorithm.

At the same time, this paper also compared the impact of different network representation learning algorithms on the disambiguation effect: among them, the average F1 value of the disambiguation algorithm based on DeepWalk is 0.573, and the average F1 value of the disambiguation algorithm based on Node2Vec is 0.560. The performance gap between the two and the algorithm in this paper is small; compared to the two, the algorithm in this

paper only improved by about 1.6% and 3.9% respectively. However, because neither the DeepWalk nor the Node2Vec algorithm considers the edge weight information in the heterogeneous network, they cannot fully utilize the weight features of the network. Therefore, the actual disambiguation effect in the electric power scientific literature author disambiguation scenario is slightly inferior to the algorithm in this paper.

5.2. Experiment and analysis of personalized literature recommendation

In the personalized recommendation evaluation of electric power scientific literature and electric power scientific and technological innovation project resources, the experiment selects the CiteULike—a dataset annotated with electric power scientific literature and the Acemap academic knowledge graph data in the field of electric power scientific and technological innovation together to construct a simulated recommendation environment. Classic Factorization Machine model LibFM and deep wide network Deep Wide are selected as baseline algorithms to verify their adaptability in the electric power science and technology resource recommendation scenario.

The experiment adopts Area Under Curve (AUC) and Accuracy (ACC) as quantitative evaluation metrics for recommendation effectiveness. The comprehensive recommendation performance of each algorithm is shown in Table 3.

Table 3. Literature recommendation algorithm comparison experiment results.

Recommendation Algorithm	AUC	ACC
LibFM	0.692	0.648
Deep Wide	0.655	0.611
DKN(Method of This Paper)	0.741	0.679

From the above experimental results, it can be seen that compared to traditional recommendation algorithms such as LibFM and Deep Wide, the electric power scientific literature recommendation algorithm based on DKN achieves better results on both core indicators of AUC and ACC: its AUC value increased by about 7.1% and about 13.1% respectively compared to the LibFM and Deep Wide algorithms, and the ACC value increased by about 4.8% and about 11.1% respectively compared to the two algorithms. Thus, it can be seen that after the introduction of the knowledge graph, the recommendation algorithm utilizes the additional information provided by the knowledge graph, enriching the feature representation of electric power scientific literature and electric power scientific and technological innovation projects, and effectively improving the accuracy of recommendations. Therefore, compared with traditional deep learning recommendation algorithms, the knowledge graph-based DKN model is more adaptable to the personalized recommendation tasks of electric power scientific literature and electric power scientific and technological innovation projects.

6. Conclusion

This paper focuses deeply on the issues of deep knowledge mining and precise distribution in the management of electric power scientific literature, and constructs an intelligent

management platform integrating knowledge graphs and recommendation systems. The main contributions and conclusions are as follows:

(1) In terms of system architecture design: a bottom–up four–layer system architecture is proposed, breaking through the full–link data drive mechanism of electric power scientific research data from bottom–layer Data Lakehouse storage to upper–layer science and technology project, achievement, and talent management, realizing the unified standardization and collaboration of internal project data and external academic resources.

(2) In terms of knowledge graph construction and extraction: defined 9 core entities and 7 semantic relations covering all elements of the electric power scientific and technological innovation scenario. The proposed joint model based on LayoutLM and CRF can effectively process academic literature with complex layouts; the designed author disambiguation algorithm based on the fusion of literature heterogeneous networks and content features has an average F1 value of 0.582 verified by experiments, significantly improving the accuracy and data quality of the graph foundation.

(3) In terms of personalized recommendation applications: aiming at the dynamically changing reading intentions of electric power researchers as projects advance, the DKN model is introduced and combined with graph entity information for multi–channel feature extraction, while an attention mechanism is utilized to conduct precise interest modeling of users' historical reading behaviors. Recommendation simulation experiment results show that the model is significantly superior to mainstream recommendation algorithms such as LibFM and Deep Wide on both the AUC (0.741) and ACC (0.679) core evaluation metrics, effectively alleviating the “information overload” problem faced by scientific research personnel in project follow–up and frontier tracking.

In summary, the hybrid–driven framework proposed in this paper not only realizes the precise matching and reach of cutting–edge academic achievements and electric power scientific and technological innovation project resources, but also promotes the intelligent upgrading of traditional electric power science and technology project management from “passive registration” to “proactive collaboration and precise distribution”.

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Authors' contribution

Author Contributions: Conceptualization, Wenyao Wen; methodology, Wenyao Wen; software, Wenyao Wen; validation, Wenyao Wen; formal analysis, Wenyao Wen; investigation, Wenyao Wen; data curation, Wenyao Wen; writing—original draft preparation, Wenyao Wen; writing—review and editing, Wenyao Wen; visualization, Wenyao Wen. The author has read and agreed to the published version of the manuscript.

Conflicts of interests

The authors declare no conflicts of interest.

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