Exploration of Personalized Learning Paths for New Energy Vehicles Based on Knowledge Graphs

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Abstract. With the rapid development of new energy vehicles, it has become an urgent task to cultivate talents with relevant expertise and skills. However, traditional teaching methods struggle to meet the personalized needs of learners, thus necessitating a personalized learning path based on knowledge graphs to provide customized learning support. This study aims to explore personalized learning paths for the field of new energy vehicles based on knowledge graphs and evaluate their effectiveness through empirical experiments. We conducted a series of empirical experiments to evaluate the effectiveness of the personalized learning paths based on knowledge graphs. The experimental results demonstrate that compared to traditional fixed learning paths, the personalized learning paths based on knowledge graphs can significantly improve learners' academic performance, learning efficiency, and satisfaction.

Keywords: New energy vehicles, Personalized learning paths, Knowledge graph, Educational technology

1 Introduction

With the increasing global energy crisis and environmental issues, new energy vehicles are emerging as clean and sustainable transportation solutions, gradually becoming a hot topic and development direction in the global automotive industry. The rapid development of new energy vehicles has led to a growing demand for professionals with relevant expertise in the field.[1] Consequently, higher education institutions and vocational training organizations face the crucial task of nurturing professionals who can meet the demands of the new energy vehicle industry.[2]

However, the knowledge system in the field of new energy vehicles is vast and complex, often leading learners to face information overload and unclear learning paths.[3] Learners come from diverse backgrounds and have different learning needs, making traditional one-size-fits-all teaching models inadequate for personalized

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learning. Therefore, there is an urgent need to address how to provide learners with personalized learning paths to help them efficiently grasp the specialized knowledge of new energy vehicles.[4]

2 The Research Status of Knowledge Graph in the Field of New Energy Vehicles

In the context of the rapid development of the new energy vehicle industry, the cultivation of professionals in the field has become an important task for higher education institutions and vocational training organizations. However, the current traditional educational models have limitations in meeting learners' needs and providing personalized learning paths.[5] These existing problems underscore the significant necessity for research and application of personalized learning paths based on knowledge graphs.[6]

The knowledge system in the field of new energy vehicles is vast and complex. New energy vehicles encompass multiple disciplinary areas, including electric vehicle principles, battery technology, charging infrastructure, intelligent transportation, and various other aspects of knowledge.[7] These areas of knowledge cover a wide range, from fundamental theories to practical applications.[8]

Learners in the field of new energy vehicles come from diverse backgrounds with varying learning needs. They may have different academic backgrounds, work experiences, and skill levels. Additionally, their learning goals and requirements can vary significantly.[9] Traditional teaching models often adopt a one-size-fits-all approach, which fails to provide personalized learning support based on individual differences. As a result, some learners may feel confused, lose interest, and experience subpar learning outcomes during the learning process.[10]

3 Constructing a Knowledge Graph for the Field of New Energy Vehicles

3.1 Data Mining and Machine Learning

Traditional knowledge graph construction methods heavily rely on manual annotation and knowledge extraction. However, in the domain of new energy vehicles, with the widespread availability of big data and advancements in machine learning techniques, data mining and machine learning methods can be utilized for knowledge graph construction. By analyzing and mining large-scale datasets related to new energy vehicles, it is possible to automatically discover entities, relationships, and attributes, and establish connections between them.

In the realm of new energy vehicles, leveraging data mining and machine learning techniques for knowledge graph construction offers significant advantages. The abundance of big data available in this domain presents an opportunity to extract valuable insights and patterns that may not be readily apparent through traditional manual methods. With the rapid advancements in machine learning algorithms, the automated discovery of entities, relationships, and attributes can greatly enhance the efficiency and accuracy of knowledge graph construction. By harnessing the power of data mining and machine learning, researchers and practitioners can unlock new possibilities for understanding and optimizing new energy vehicle technologies.

3.2 Semi-automated Knowledge Extraction

Knowledge extraction from unstructured textual data is often required during the construction of a knowledge graph. Traditional methods involve manually crafting rules or utilizing natural language processing techniques. However, in the domain of new energy vehicles, the knowledge and expertise of domain experts are highly valuable. Therefore, a semi-automated knowledge extraction approach can be adopted, incorporating the expertise of domain experts into the knowledge extraction process.

In the context of new energy vehicles, the collaboration between domain experts and automated knowledge extraction tools can lead to more accurate and efficient knowledge graph construction. By integrating the domain knowledge of experts with the capabilities of natural language processing algorithms, the process of extracting relevant information from unstructured textual data can be streamlined and enhanced. This synergistic approach ensures that the knowledge graph reflects not only the data-driven insights but also the nuanced understanding provided by experts in the field.

3.3 Multimodal Data Fusion

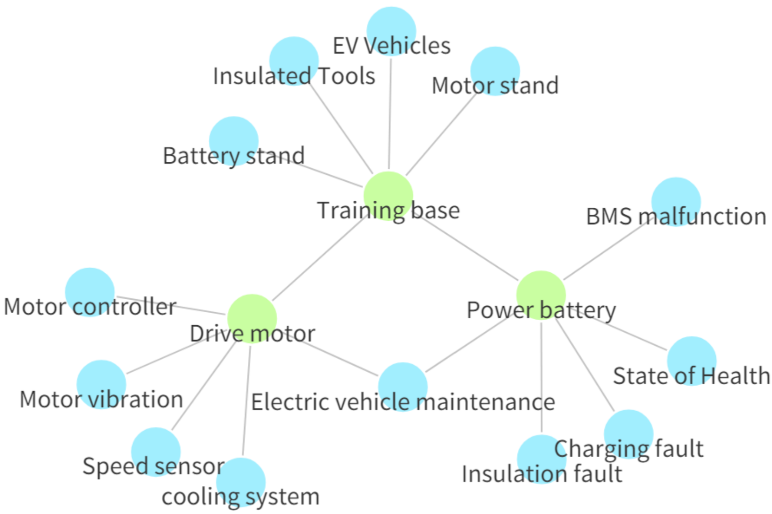

Fig. 1. Example of partial knowledge graph

The field of new energy vehicles encompasses various types of data, including text, images, sensor data, and more. To construct a more comprehensive knowledge graph, the fusion of multimodal data can be employed. Additionally, image recognition and computer vision techniques can be utilized to extract entities and attributes from vehicle photos, which can then be associated with other information in the knowledge graph.As shown in Fig. 1.

4 Personalized Learning Path Recommendation Algorithm

4.1 Learner Interest Modeling and Knowledge Matching

Integrating interests and needs as key factors into the construction and application of knowledge graphs, especially in the integration of interdisciplinary knowledge and personalized matching of learners' needs. The specific implementation methods are as follows: First, interest-tagged knowledge graph: adding interest tags to each knowledge node and relationship in the knowledge graph, indicating the association of the knowledge point or relationship with the fields or topics that learners may be interested in. Second, by analyzing learners' interests and needs, combined with interdisciplinary knowledge graphs, recommending interdisciplinary learning paths and resources that meet their interests and needs to promote interdisciplinary comprehensive learning. Third, interest-driven learning design: teachers can design interest-driven interdisciplinary learning tasks and projects based on learners' interest tags and interdisciplinary connections in the knowledge graph, stimulating learners' interest and motivation in interdisciplinary learning. Fourth, personalized learning needs matching: integrating learners' personalized needs with the interdisciplinary knowledge structure of the knowledge graph to achieve personalized learning needs matching, providing learners with customized learning experiences and resource support.

By integrating learners' interests and needs as important considerations into the construction and application of interdisciplinary knowledge graphs, it can better meet learners' personalized learning needs, promote interdisciplinary comprehensive learning, and the development of knowledge integration capabilities. This interest-driven interdisciplinary knowledge graph application helps expand learners' knowledge perspectives, cultivate comprehensive abilities, and promote interdisciplinary learning and cross-domain innovation.

4.2 Adaptive Learning Model and Personalized Path Generation

For each learner, we can construct an adaptive learning model to assess their understanding and learning needs regarding different knowledge points in the field of new energy vehicles. This model can be built by incorporating multidimensional data such as the learner's learning history, test scores, practical performance, and more. Based on the adaptive learning model, the algorithm can generate personalized learning paths for learners according to their knowledge gaps and learning objectives. This includes determining the learning sequence, recommending learning resources, and providing learning assistance to meet the learner's individualized needs.

For learners who already have a certain foundation in the field of new energy vehicles, personalized learning paths can identify their mastered knowledge points to avoid redundant learning, thus providing more in-depth and specialized learning content. For beginners or learners transitioning from other disciplines, personalized learning paths can gradually guide them to establish a solid foundational knowledge based on their prior learning experiences and backgrounds, enabling a better understanding of the complex concepts in the new energy vehicle field.

5 Experimental Design and Result Analysis

5.1 Experimental Design

We collected a set of learner data in the field of new energy vehicles, including learners' personal information, learning interests, learning history, and learning performance.The learners were randomly divided into an experimental group and a control group. The experimental group used the personalized learning path recommendation algorithm based on the knowledge graph to receive personalized learning path recommendations. In contrast, the control group received recommendations based on traditional learning path recommendation algorithms that relied on the learners' interests and behavioral data.

5.2 Result Analysis

The learners in the experimental group demonstrated improved learning performance. Compared to the control group, learners in the experimental group showed more significant progress in knowledge comprehension, application abilities, and innovative thinking. This indicates that the personalized learning path recommendation algorithm based on the knowledge graph can assist learners in more effectively mastering the knowledge in the field of new energy vehicles.

6 Conclusions

This study has achieved encouraging results in exploring personalized learning paths in the field of new energy vehicles based on the knowledge graph. By constructing a comprehensive knowledge graph of new energy vehicles and integrating personalized learning path recommendation algorithms, we are able to provide customized learning paths for learners, assisting them in learning and mastering the knowledge and skills in the field of new energy vehicles more efficiently.

The experimental results demonstrate that the personalized learning path recommendation algorithm based on the knowledge graph significantly improves learners' learning performance, learning efficiency, and learner satisfaction.The advancement in personalized learning paths tailored to the domain of new energy vehicles represents a significant contribution to the field of education and training. By leveraging the wealth of information stored in the knowledge graph, learners can access curated learning materials and resources that cater to their individual preferences, goals, and learning styles.

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