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PAPER

Design and Implementation of an Intelligent Cross-Border E-Commerce English Learning Platform Based on a Knowledge Map

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ABSTRACT

At present, most online education platforms still have problems such as single learning modes and loose knowledge structures. Using the knowledge map, the study employs a personalized adaptive intelligent adjustment strategy based on the structural expression of the CBEC English subject system. Firstly, the study uses the Scapy framework to crawl the subject knowledge data. Then use the LTP platform to process sentences containing multiple entities. Input the sentence into the dependency parser to analyze and extract the entity relationship. Finally, according to the relevance between knowledge points and topics in the knowledge map, the final learning path recommendation result is obtained. And cluster the similarity of curriculum content to build a complete curriculum system. Based on the above operations, a knowledge map-based smart learning platform for the CBEC English discipline has been designed and implemented to provide a smart, personalized learning environment for learners. According to the experimental analysis, the average satisfaction of learners with the learning platform designed by the study is 81.56%, which can meet the learning needs of learners and provide an excellent mobile learning environment for students.

KEYWORDS

knowledge map, smart learning, online education, cross-border e-commerce (CBEC) English, mobile learning

1 INTRODUCTION

The progressive expansion of online learning has recently reached a certain degree, and it has also helped to solve the issues of uneven distribution and a lack of educational resources [1].

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Knowledge Graph (KG) mainly uses visualization technology to mine, analyze, draw, and display the complex network structure and relationship between knowledge. In the field of education, it is helpful to analyze the development context and research hotspots of the discipline and predict the future development direction of the research [2]. KG is often used to analyze the research situation in a certain discipline. It helps students and teachers understand the development of the discipline and master basic knowledge. Combined with the implicit meaning of knowledge maps, it promotes the efficient use of knowledge and the exploration of new teaching models [3]. Adaptive learning refers to the process by which learners acquire new knowledge and learning abilities through interactive activities with the learning platform based on their original knowledge reserves [4]. In the process of interaction between learners and an intelligent learning platform, the platform can stimulate learners' learning motivation by raising interest. It can also enhance learners' learning abilities with information technology such as the Internet, which can help them realize the significance of learners' active learning activities [5]. To this end, the study aims to build the KG in the field of CBEC English knowledge and use the KG to realize the recommendation of learning paths and the establishment of a curriculum system. This strategy has produced a KG-based intelligent learning platform for the CBEC English topic.

2 RELATED WORKS

Many academics have conducted theoretical research and practical inquiry on smart education in recent times, as the topic has steadily gained popularity. Nusantoro H. and others discussed the key to the early adoption of smart education technology. They first identify the traits of smart education, and then they examine the specifics of the most recent communication technology that will be used in it [6]. Guo Y and others investigated the global and local collaboration of facial expression recognition, which facilitated the implementation of the smart education system. They proposed a condensed framework for multi-region attention transmission. Additionally, they optimize the suggested framework using the unified training technique [7]. Embarak O. H. revealed that machine learning, data mining, and other technologies can all enable personalized learning and tailor material in accordance with individual preferences. Combining XAI and IoB technologies and using the data of student behavior to determine whether the contemporary education system meets the needs of students, a new paradigm of an intelligent education system is proposed [8]. Ateeq K. et al. used regression learning to gradually identify the data generated by students on the intelligent platform and proposed a flexible observation data analysis model (FODAM). Data analysis obtains data relevance and provides interactive education services [9]. Huang Q. et al. developed a training platform and lab experiments to assist students in better understanding the application of electromagnetism and the new research field of current measurement. They use the platform to carry out easy-to-use simulations and tests. Additionally, they computed the overhead power line, visualized the magnetic flux density, and designed the magnetic shielding structure using the platform [10]. From a technical standpoint, Pham Q. D. et al. looked into the difficulties in implementing smart education systems (SES) in underdeveloped nations. It is suggested to use the vSmartEdu separate SES framework and smart classroom design using service-based architecture (SBA) [11]. Hou S. et al. presented an online education model for art education based on the customer behavior theory of the B2B2C platform, along with the technological acceptance model (TAM) and the expectation confirmation model. The three customer decision-making procedures—product owner, content owner, and customer domain—are the foundation of the structure [12]. Designing and putting into use a converged communication platform that combines WebRTC and similar technologies is the goal of Li G. and others. They offer an online learning platform for colleges and institutions and suggest a load-balancing method for a cluster of media servers based on genetic algorithms and consistent hash algorithms [13].

Knowledge Graph is a structured semantic knowledge base that depicts conceptual machine relationships in the real world in a symbolic way. Liu F and colleagues discovered that creating extensive image report matching data sets in the medical industry takes time and money. They introduced an unsupervised model KG encoder to lessen the reliance on paired data (KGAE). During training, this encoder is given separate image and report sets [14]. The implementation of KG in academic and industrial environments has the drawback of not obtaining complete information. Rossi A and others use link prediction (LP) technology to identify the missing facts between entities that already exist in KG [15]. Zheng P. and colleagues developed the industrial KG by combining a significant amount of human-generated and machine-sensing multimodal data with the empirical knowledge that was collected from the manufacturing procedure and the pattern of pattern recognition. On the basis of a thorough examination of the established industrial KG, the embedding algorithm based on graph neural networks is then put into practice. This makes it possible for task breakdown and self-configuring solution search, which is semantic-based [16]. Liu X. et al. used a graphical neural network (GNN) to complete the knowledge map (KGC) and proposed a graph attention network (RAGAT). In this network, relation-specific parameters are introduced to enhance the expression ability of the message function [17]. To model the mapping rules between data and efficient visualization, Li H. et al. introduced the KG framework, which consists of three categories of entities and their relationships. The embedding of two entities as well as the relationship between KG are learned from the existing dataset visualization using embedding technology, which is TransE-based [18]. Liu Y. et al. proposed a new recommendation framework in view of the problem that the existing GNN-based method may not capture the local graph context when it is applied to recommendation using KG. This framework is known as the Up and Down Cultural Graphics Attention Network (CGAT) [19]. Al-Saleem J. et al. constructed CAS Biomedical KG to support drug reuse. They discovered 1350 small compounds that could serve as reusable medicines, host organism proteins, and COVID-19-related illnesses [20]. Lin Q. proposes a unified framework, FTL-LM to implement KG completion. The topological context and logical rules in the medical fusion KG completion language model [21].

According to the comprehensive literature, smart education has become one of the main forms of education at present. The construction and research methods of learning platforms were also different. There was little research on the application of KG to platform practice. Therefore, the research took cross-border e-commerce (CBEC) English as the construction object, and applied the constructed KG to the design of a smart learning platform. This provided a better online learning environment for intelligent education in universities.

3 DESIGN AND IMPLEMENTATION OF CBEC ENGLISH SMART PLATFORM BASED ON KG

3.1 KG construction for intelligent learning platform

They combine KG relations with artificial natural language preprocessing to extract information, establish relevance between knowledge points, and handle complex knowledge associations. This has created a KG for CBEC English. KG, in essence, is a network that can semantically represent the relationship between entities and formalize the description of things and their relationships in real time. The data in KG is mainly organized in the form of triples. Each triplet is a piece of information that helps to explain how things interact in the objective world. The overall technical architecture of KG is shown in Figure 1.

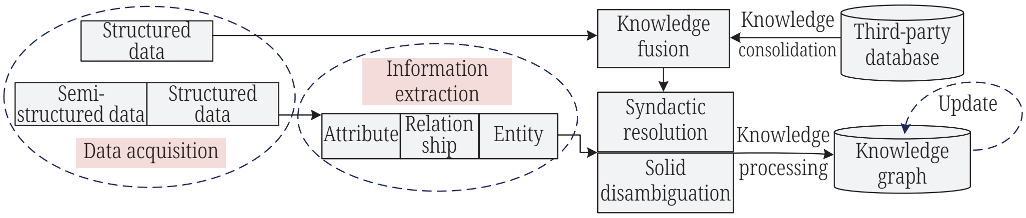


Fig. 1. Technical framework of knowledge map

The study selects the website as the access address of the data source according to the learning content of CBEC English majors. Doccano, a tool supporting multilingual text annotation, is used in the study. It annotates the data to be obtained according to the characteristics of the discipline. Finally, web crawlers use technology based on Python and the Scrapy framework to record and crawl the selected network, respectively. Considering the cost and efficiency of data collection, websites with industry authority, complete data, and standardized data formats are generally preferred in data collection. The FT Chinese website has a lot of good English learning resources, such as bilingual reading, English speed, audio and video, and English radio. Therefore, the FT Chinese website is selected as the data source website. In the crawling process, a URL manager needs to be set, and the URL of the initial content is entered. This will call the parser to parse the web page content in the URL downloader. Word segmentation is the first step of natural language processing and the key to obtaining entity words. The principle of the Scrap crawler is shown in Figure 2.

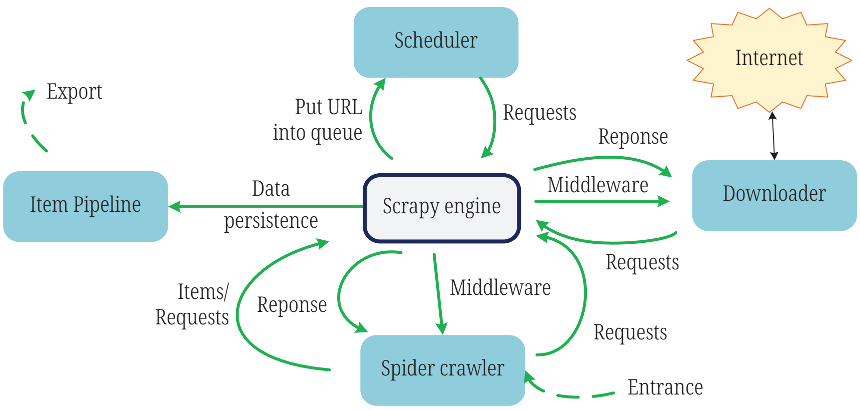


Fig. 2. Principle of Scrap crawler technology

Compared with English, Chinese word segmentation is more complex. Therefore, the LTP natural language platform is used for word segmentation processing in the research. The lexical analysis of LTP incorporates features such as speech tagging and word segmentation. The use the text obtained by crawling and external dictionary files as input. By calling the word segmentation module of LTP, the text is divided into words, punctuation, and other units. The study initially segmented the original corpus and divided a continuous text sequence into sequence fragments in order to discover the particular words with specific meanings in the given text. Then the research will mark the part of speech of each segment and list the part of speech of each word as nouns, verbs, adjectives, etc. Finally, the results of the above segmentation and part-of-speech tagging are filtered, and the entity words needed are obtained according to the actual situation. Entity relation extraction (ERE) can be divided into limited relation extraction and open relation extraction. Restricted relation extraction requires that the relation set be determined in advance, and the relation is regarded as a class label. However, open relation extraction does not have a predefined relation combination. In the process of subject relationship extraction, because the relationship between entities is not fixed, it cannot be used as a classification basis. Based on heuristic rules, the research extracts relationship groups from the text according to the context structure of the phrase. The study uses the LTP platform to process sentences containing multiple entities and input sentences into the dependency parser for analysis. Refer to Table 1 for the syntax relationships of dependency sentences.

Table 1. Dependency syntax

Relationship Type	Relationship Description	Relationship Type	Relationship Description
SBV	s-v relation	COO	Juxtaposition
VOB	verb-object combination	CMP	Relationship between verb and complement
POB	Relationship between intermediary and guest	LAD	Left Attachment
ATT	The relationship between the designated language and the head language	RAD	Right Attachment

According to the syntactic dependency, the noun-centered entity is extracted, and other participles are used as candidate words for entity relationships. Based on the results of part-of-speech tagging, rules are formulated for pattern matching on the dependency syntax tree. It extracts the expression of the original relationship between entity relationships, and if the extraction is successful, it will generate a triplet in the form of "entity, relationship, entity." After the extracted triples, the entities in the triples that connect parts of the prepositional phrases are integrated. If two pairs of triples have the same entity, entity relationship reasoning can be performed. The relationship matching rules used in the study include subject-predicate and verb-object, subject-predicate and preposition-object, fixed-center and right-attachment, and juxtaposition and left-attachment. After obtaining the triples, the researchers use the graph database Neo4J to store them in the form of KG. The research will save the collected data in a CSV file to streamline the data entry process. By importing the CSV file into Neo4J, the information can be rapidly expanded. Nodes and relationships are stored separately to avoid storage confusion caused by large amounts of data. After entity extraction and relationship extraction, CSV files describing the relationship between entities are obtained. From the perspective of discipline structure, knowledge points are the basic units in the discipline knowledge system structure. The basic attributes of knowledge points and the structural relationship between knowledge points are studied to build a knowledge point description model. The coding system is designed using the compound coding method. It is a coding method for recognition based on classification and interpretation. It generally forms a unique identification code by adding a counting number to the classification code. The coding structure is designed into four code segments, which are learning segment information, knowledge structure information, difficulty, and additional count. The degree of difficulty of knowledge points is divided into five levels: simple, basic, medium, difficult, and final, which are expressed by 0.2, 0.4, 0.6, 0.8, and 1.0, respectively. Three digits represent the counting number, corresponding to the technical number information of the knowledge point. Based on the above contents, the study has realized the construction and coding of the knowledge map of CBEC English subject knowledge.

3.2 Design of CBEC English smart learning platform based on KG

First, it is needed to determine the relevance of knowledge points and topics. The calculation of the difficulty of the question depends on the difficulty of the knowledge points contained in the question and the degree of correlation between the knowledge points. The research marks the difficulty coefficient value of each knowledge point, and the difficulty calculation method of each question is shown in formula (1).

$$V = \sum_{i=1}^{N} p_{ij} \cdot v_i \tag{1}$$

In formula (1), p_{ij} is the correlation degree between i and j of each related knowledge point. v_i is the difficulty coefficient value of the knowledge point. Each time the system sets a question for the learners, it ensures that the question has appropriate differentiation. It collects and selects test questions in the question bank associated with the knowledge points that learners have learned. The main examiner of the question extraction algorithm for each set of test papers checks two points: one is whether the difficulty of the test paper meets the set goal, and the other is whether the relationship between the difficulty of the question and the number of questions conforms to the normal distribution characteristics. The study goal is as shown in formula (2).

$$S_v = \sum_{k=1}^{p} V_k \tag{2}$$

In formula (2), p is the number of questions and V is the difficulty of each question. Through the above methods, the study extracts test questions for learners and evaluates the mastery of knowledge points after completion. The evaluation function is shown in formula (3).

$$F_i = \sum_{i=1}^{M} p_{ij} \cdot f \tag{3}$$

In formula (3), f is the learner's answer score, and the value is 1 or 0. For those that meet the requirements of knowledge point mastery, in order to indicate that this knowledge point has been mastered, the acquired knowledge points are summarized and marked in the database stored in the KG. Next, use BFS to find the knowledge points to be learned in the next stage, and select the next level to continue learning. The flow of the recommended learning path is shown in Figure 3.

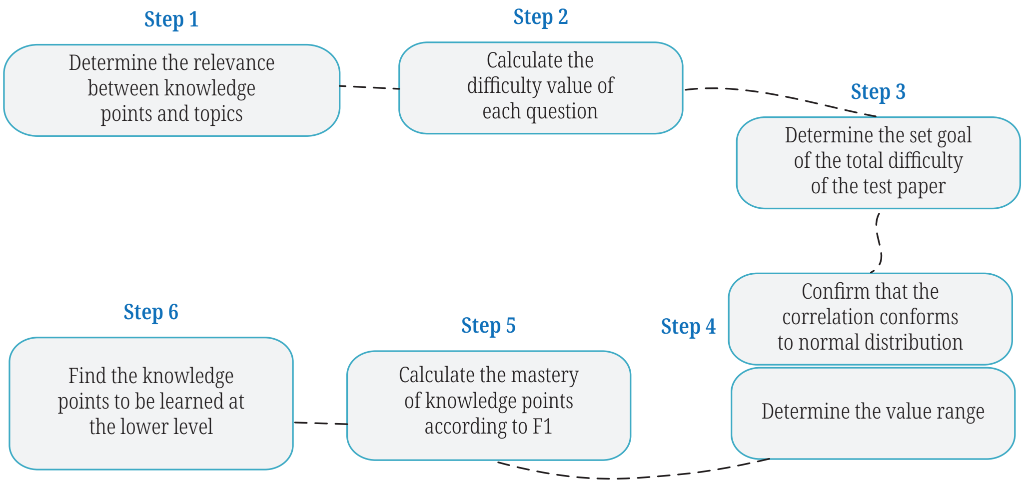


Fig. 3. Recommended learning path flow

The names of many English courses on the learning platform are not uniform professional names. Due to the diversity of course names and content labels, it is difficult for users to identify the specific content of the course. The research uses the nearest neighbor propagation (AP) algorithm to cluster the similarity of curriculum content and optimizes the bias parameters through the differential evolution (DE) algorithm. According to the set of knowledge points, we study and define the horizontal abundance of knowledge points in the curriculum, as shown in formula (4).

$$S_i = \frac{n_i + 1}{t_i} \tag{4}$$

In formula (4), with n_i for the total number of knowledge points referenced in the video, t_i stands for the total number of words in course i. The ratio of the number of core knowledge points at an intersection to the number of essential knowledge points in one course is known as the single-phase similarity of two courses. The calculation method is shown in formula (5).

$$Sim_i = \frac{u'}{m_i} \tag{5}$$

In formula (5), m_i represents related knowledge points, and u' is the intersection of two fundamental concepts. After obtaining the one-way similarity of the two courses, the calculation method of the similarity between the two courses is shown in formula (6).

$$\begin{cases} Sim_{ij} = Sim_i * w_i + Sim_j * w_j \\ w_i = \dfrac{u}{n_i} * S_i \\ w_j = \dfrac{u}{n_i} * S_j \end{cases} \tag{6}$$

In formula (6), w_i and w_j are the weights of course i and course j respectively. After calculating the similarity results, the research will generate the similarity matrix according to the number of courses, as shown in formula (7).

$$M = \begin{bmatrix} Sim_{11} & Sim_{12} & Sim_{1c} \\ Sim_{21} & Sim_{22} & Sim_{2c} \\ & & \\ Sim_{c1} & Sim_{c2} & Sim_{cc} \end{bmatrix} \tag{7}$$

In formula (7), c is the number of courses and generates matrix M. According to the knowledge map generated by each course, the research seeks the connection between courses in the unit of knowledge points, and realizes the construction of curriculum system. On the basis of obtaining the similarity between courses, study and trace the knowledge, and screen out the relevant knowledge points in the two courses, as shown in Figure 4.

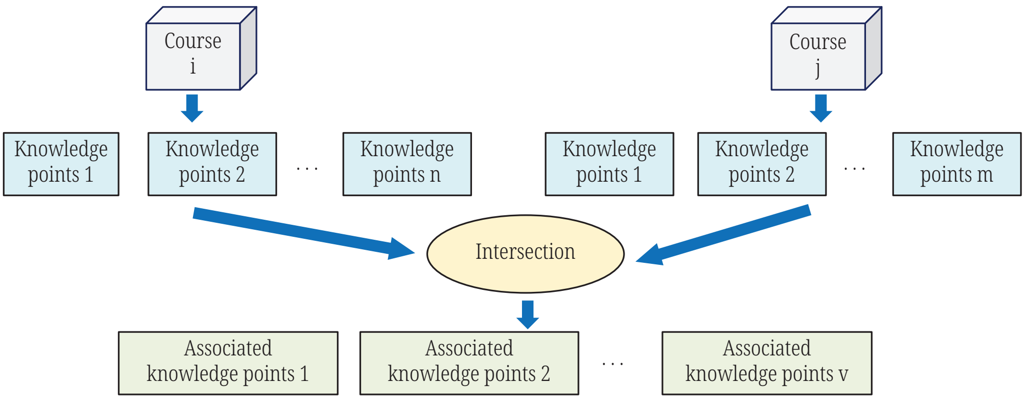


Fig. 4. Screening knowledge points of public courses

Then extract "knowledge points, relations, and knowledge points" from the two courses. Then it matches the common knowledge points in the triad and selects the triad containing the common knowledge points. After getting the association triple, the knowledge map can be fused. Non-public knowledge points in the two courses also have corresponding connections. Taking the curriculum system under the actual teaching environment as an auxiliary reference, we can determine the antecedent and subsequent relationship of knowledge points and trace the source of the emergence of public knowledge points. When learners are learning some content in the course, they can trace the knowledge points involved in the segment to form a knowledge chain. The knowledge points in the knowledge chain correspond to the courses and chapters that have appeared, so as to guide learners to check and fill in gaps and expand their knowledge. When multiple courses have the same knowledge points, make reasonable content recommendations. The recommended courses are ranked according to the similarity algorithm obtained from formula (6). This makes the recommendation result more intelligent. The architecture of a smart platform is shown in Figure 5.

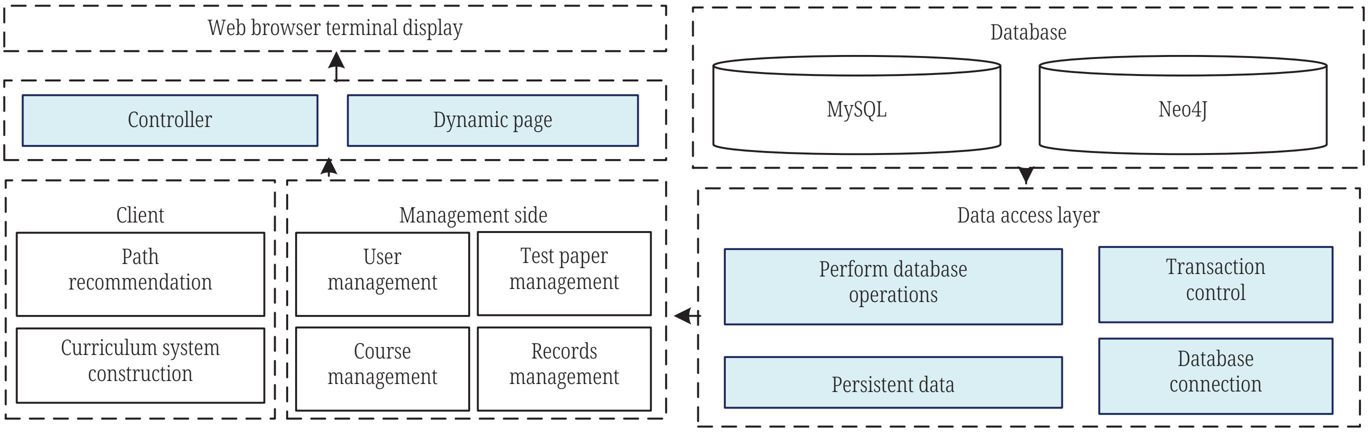
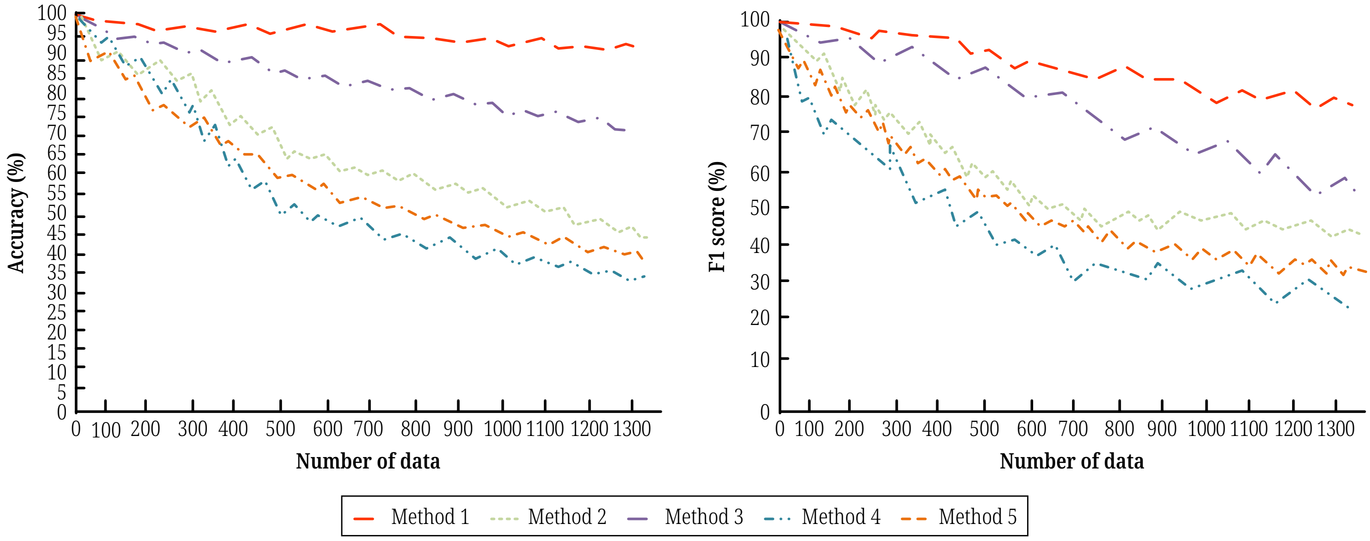


Fig. 5. Intelligent platform architecture

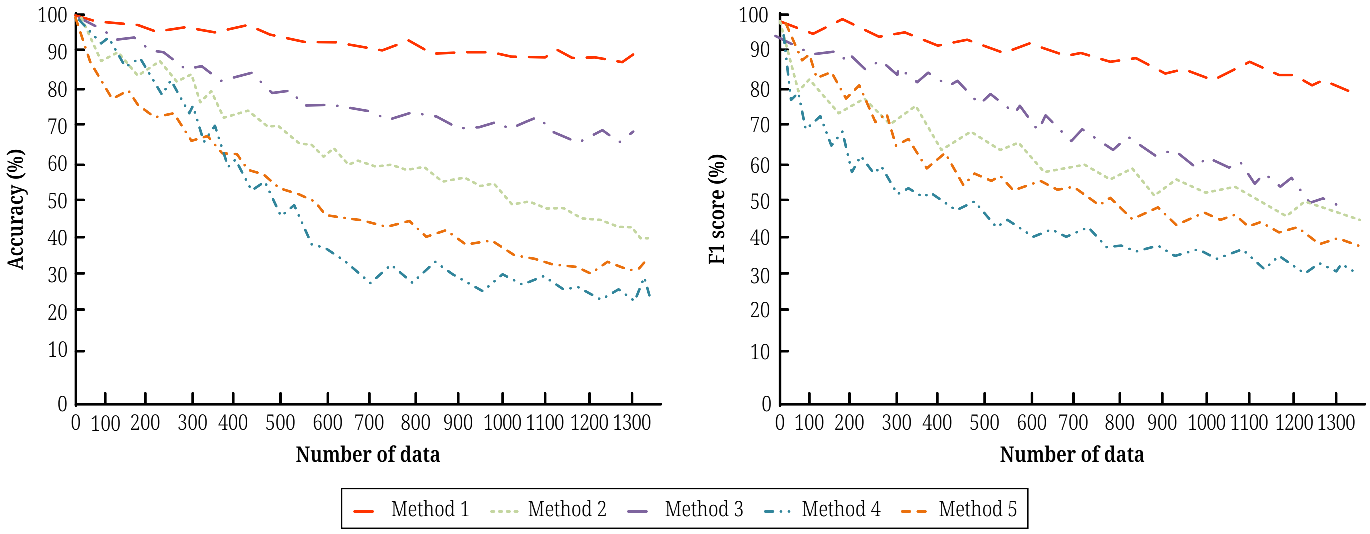
Based on the above contents, the study recommended the establishment of the curriculum system in the smart platform and the learning path of students, which led to the CBEC English smart learning platform based on KG. Finally, students' intelligent experience of online learning will be realized.

4 ANALYSIS OF THE EFFECTIVENESS OF THE IMPLEMENTATION OF KG-BASED INTELLIGENT LEARNING PLATFORMS

As a novel technique of learning in the context of educational information technology, smart learning has been crucial to the reform of education. To realize the intelligence of CBEC English professional education, the study uses KG to design and implement a CBEC English intelligent learning platform. The study employs heuristic rules as a foundation and extracts relationship groups from the text in accordance with the phrase context structure in order to evaluate the performance of the platform. It uses the LTP platform to process sentences containing multiple entities and input the sentences into the dependency parser for analysis and implementation of ERE. To verify the effect of entity recognition and relationship extraction, the extraction method (method 1) and the ERE method based on deep learning (method 2), the ERE method based on multi-task learning (method 3), the ERE method based on dual attention mechanism (method 4), and the ERE method based on multi-feature fusion (method 5) will be used to extract entity relationships from the CLUSTER dataset and the Approaching Science dataset and observe different data scales, accuracy, and F1 values under the data set. See Figure 6 for details.



(a) CLUSTER Dataset



(b) Data set of Approaching Science

Fig. 6. Performance comparison of entity extraction relationship methods

In Figure 6, the accuracy and F1 value of each approach have reduced as data sizes have grown continuously. The change curve of method 1 is the gentlest. The precision value of method 1 is 98.21%, and the F1 value is 94.31% when the volume of data is 100; the precision value of method 2 is 85.74%, which is 12.47% lower than method 1. And the average F1 value is 80.22%, 14.09% lower than method 1; the average F1 value is 90.01%, which is 4.30% below the typical F1 value for method 1, while the average accuracy of method 3 is 91.23%, which is 6.98% lower than that of method 1; the average F1 value is 72.33%, which is 21.98% lower than method 1, whereas the average accuracy of method 4 is 91.00%, which is 7.21% lower than method 1; the average F1 value was 80.02%, 14.29% lower than the average F1 value of method 1, and the accuracy obtained of method 5 was 78.44%, 19.97% poorer compared to method 1. The prediction accuracy and F1 value of technique 1 remain above 90% when the data scale is 1000, whereas those of the other four methods drop to below 75%. A comprehensive analysis of Figure 6 shows that method 1 can better extract the entity relationship from knowledge data.

In order to further compare the performance, recall, F1-score and accuracy (P) are introduced as evaluation indicators. It records the data in Table 2 after comparing the entity relationship recognition and extraction effects of various methods.

Table 2. Average evaluation results of entity relationship extraction

Project	CLUSTER Dataset			Data Set of Approaching Science		
	P(%)	Recall(%)	F1-Score(%)	P(%)	Recall(%)	F1-Score(%)
Method 1	92.53	94.47	93.41	92.46	94.33	93.24
Method 2	71.56	79.85	75.55	71.24	79.66	75.21
Method 3	73.68	80.23	76.39	73.45	80.21	76.48
Method 4	64.12	70.03	68.47	64.15	70.12	68.28
Method 5	68.22	72.46	70.11	68.31	72.47	70.15

From Table 2, the average accuracy of method 1 is 92.50%. The recall rate was 94.40% on average. 93.37% is the average F1 value. The average accuracy, recall rate, and F1 value of the other four methods are less than 80%, which is more than 10% lower than that of method 1. According to the contents of the comprehensive table, method 1 has better performance in entity relationship extraction.

The research makes use of the relevance between knowledge points and topics and uses the breadth of the knowledge map to search first to realize the recommendation of students' learning paths. In order to verify the recommendation effect, study is conducted to crawl the data of compulsory courses for CBEC majors from the learning platform and plan the learning path. At the same time, relevant professional experts in the school are invited to design the path of knowledge points. The results are shown in Figure 7.

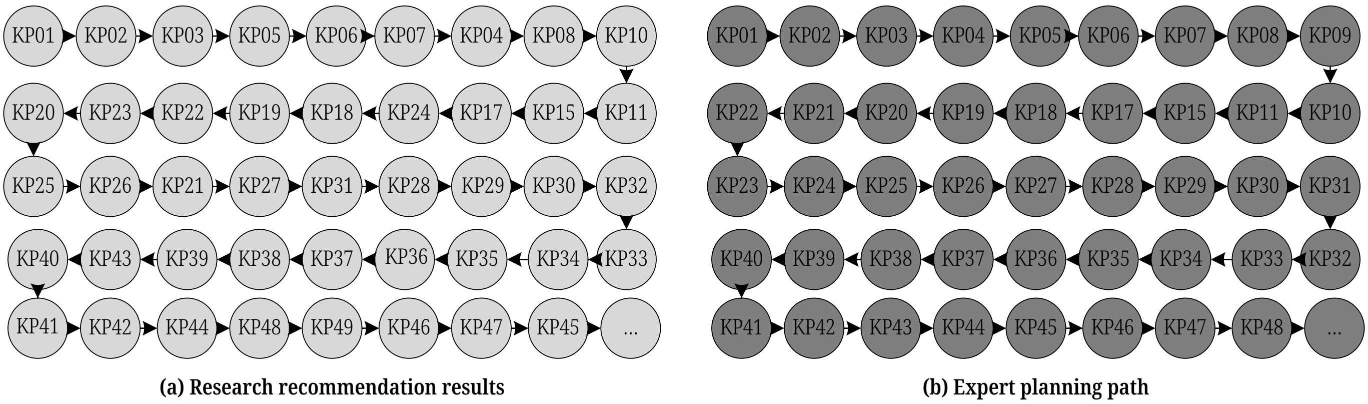


Fig. 7. Recommended learning path results

From Figure 7, the recommendation results obtained according to the research algorithm are similar to the actual expert design path. The study computes the similarity of the two paths to obtain Sim and adds the learning path assessment index fitness to further compare the impacts and make the findings more understandable. The fitness value decreases as the frequency of learning route violations decreases, indicating a higher-quality learning path and a smaller fitness value. The data is recorded in Table 3.

Table 3. Learning path recommendation results

Project	Knowledge Points	Fitness		Sim
	Number	Expert Path	Research Path	
Course 1	72	10	12	81.94%
Course 2	68	9	14	82.02%
Course 3	73	12	15	81.65%
Course 4	81	11	13	82.13%
Course 5	65	8	10	81.92%

In Table 3, the fitness value of the learning path obtained from the study is relatively small, and there is a small gap between the fitness indexes of the expert path. Through the similarity calculation and analysis, it was found that the average similarity between the learning path and the expert path is 83.93%. It can be seen that the quality of the learning path obtained from the study is high and close to the level of the expert design path.

To verify the recommendation effect of the curriculum system formed after clustering, the curriculum system recommendation algorithm (CS), content-based recommendation algorithm (CB), and collaborative filtering recommendation algorithm (CB) are studied. The study evaluates the algorithm's clustering effect for various data sparsities, and Figure 8 shows the comparative findings.

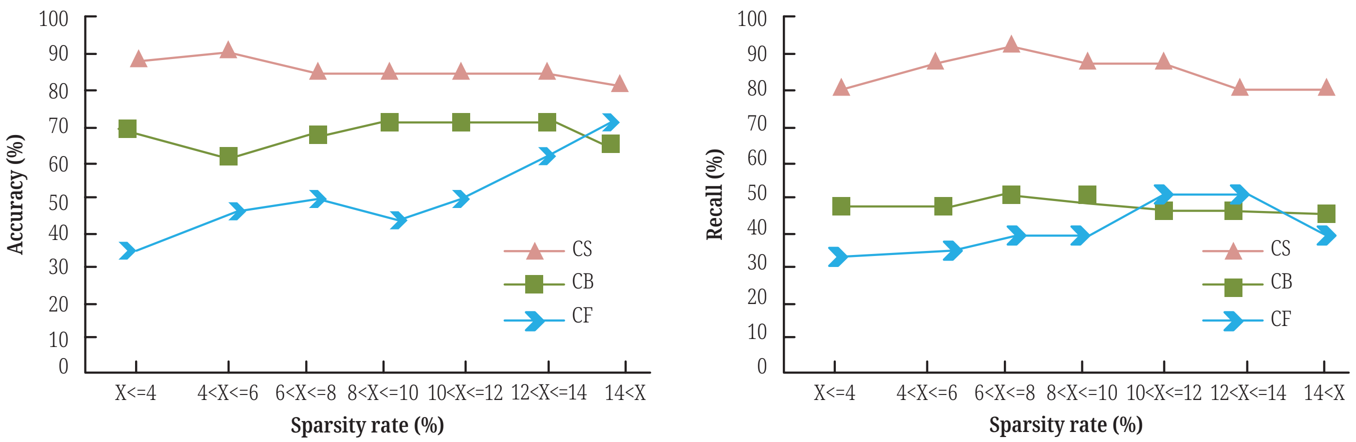


Fig. 8. Change of accuracy and recall rate under different sparsity

In Figure 8, in the case of maximum sparsity, the recommended accuracy of CB is the lowest. As the data density increases slowly, the accuracy of the algorithm improves gradually. The recommendation accuracy and recall rate of CF are less affected by data sparsity. The accuracy and recall rate of CS are least affected by data sparsity, and the average accuracy is 90.83% and the recall rate is 90.22%. The accuracy of the other two algorithms is about 68%, about 22.83% lower than CS, and the recall rate is about 50%, 40.22% lower than CS. According to the contents of Figure 8, CS can better establish the curriculum system and provide suitable curriculum recommendations for learners.

The study looked into satisfaction, personalized learning experience, course recommendation effect, and learning effect to determine whether the platform can meet the demands of educators. The study distributed questionnaires to 38 learners who had used the CBEC English smart learning platform. A total of 33 effective questionnaires were retrieved from the 33 surveys that were gathered. Refer to Table 4 for more details.

Table 4. Survey results of smart learning platform use

Aspect	Survey Results (%)			
	Satisfied	Average	Poor	Dissatisfied
Platform operation	76.32	15.44	4.12	4.12
Personalized learning	80.54	13.23	3.55	2.68
Course recommendation	79.68	14.51	4.02	1.79
Learning effect	81.56	12.42	3.26	2.76

In Table 4, the satisfaction with the use and operation of the platform is 76.32%, the satisfaction with personalized learning is 80.54%, the satisfaction with course recommendation is 79.68%, and the satisfaction with the learning effect is 81.56%. The extensive table shows that the research-based knowledge map-based intelligent learning platform for the CBEC English topic can match learners' learning needs and provide a better online learning environment for students.

5 CONCLUSION

Online education represents an electronic, efficient, and exploratory learning method that provides learners with the possibility of free learning. The KG for CBEC English knowledge is constructed in this study. It also uses KG to recommend learning paths and establish curriculum systems. The intelligent learning platform of the CBEC English discipline based on KG has been designed. According to trials, the mean recall rate is 94.40%, the mean F1 value is 93.37%, and the average accuracy rate for entity relationship extraction is 92.50%. The average similarity between the learning path and the expert path is 83.93%. The satisfaction with the use and operation of the platform is 76.32%, the satisfaction with personalized learning is 80.54%, the satisfaction with course recommendation is 79.68%, and the satisfaction with the learning effect is 81.56%. A thorough examination of the experimental data revealed that the development of an intelligent learning platform has improved entity relationship extraction performance and improved learning path quality. It can provide a better online learning environment for students and satisfy their learning needs. This platform only constructs the knowledge map for CBEC English majors, and the learning content is also limited to this discipline. It is suggested that when the platform content is expanded later, other subject atlases can be added and more comprehensive learning resources can be collected.

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