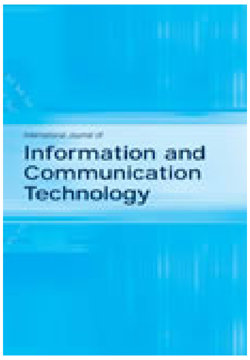

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Vocational education course recommendation based on neighbours under the construction of knowledge graph

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Abstract: Focusing on issues of incomplete user information and inaccurate recommendations in current vocational education course recommendation methods, this paper first constructs a knowledge graph (KG) for vocational education. On this basis, a novel negative sampling approach is employed to enhance the KG representation model TransH (EOTransH), and different weights are given to negative samples assigned different scores contribute to full model training. Then, a bipartite graph of courses and users is constructed, and KG embedding is built through the joint user entity neighbourhood information. Furthermore, higher-order connectivity information between users and courses is mined through attention-based propagation. Finally, an attention network is built in the output prediction layer to explore user preference features. Experimental outcome on the MOOCCourse and MOOCCube datasets indicate that the proposed approach improves F1 by at least 2.05%, 4.09%, effectively solving the problem of inaccurate recommendations.

Keywords: vocational education course recommendation; knowledge graph; nearest neighbour method; TransH model; attention network.

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1 Introduction

In today's knowledge-based economy, vocational education, as an important way to cultivate application-oriented talents, enhance the vocational skills and employment competitiveness of workers, is facing unprecedented development opportunities and challenges. With the continuous upgrading of the industrial structure and the rapid development of emerging technologies, the demand for various professional skills talents is showing diversification and dynamic characteristics (Cerda-Navarro et al., 2017). In order to better adapt to this change, fulfil the unique educational needs of each student, and improve the quality of education and the precision of talent cultivation, the field of vocational education imperatively requires to introduce advanced technologies to optimise course recommendation and learning services (Jia and Zhao, 2022). Due to the late start of vocational education in China, existing online education platforms cannot provide users with precise and efficient course recommendation services. Therefore, how to reduce the cost of course selection and provide users with personalised and diversified course services is a problem that higher vocational colleges urgently need to solve (He, 2023). In the vocational education scenario, KG can cover multi-dimensional information such as course knowledge, skill requirements, job positions, and learner characteristics, constructing a comprehensive and rich knowledge network, providing more precise and intelligent decision-making basis for course recommendation (Qu et al., 2024a).

Wang et al. (2021) built a predictive model based on vocational education data, which combined Bayesian knowledge tracing. In terms of student behaviour modelling, a descriptive model was established using least squares method and ridge regression algorithm. Zhu et al. (2022) built a vocational education recommendation model using a Markov model text classification algorithm, and built a predictive model using a regression algorithm, using key student vocational feature data. Li (2024) fully mined and analysed learner information, and then used the association rule Apriori algorithm to recommend suitable vocational courses to learners. Ma (2022) proposed a course recommendation model based on machine learning algorithms. The model combines vocational course time features and spectral clustering algorithm to achieve automatic classification of courses, which improves the accuracy of the recommendation. Xie (2022) analysed users' past problem-solving behaviour and modelled the user's memory curve, combined with the user's memory ability and cognitive level to enhance the personalisation and effectiveness of the recommendation.

Machine learning models rely on large-scale, high-quality data for training. The quality, quantity and characteristics of the data directly affect the recommendation effect. The recommendation of vocational education courses needs to integrate students' behavioural data, ability data and career goal data to build an accurate user profile. The algorithm automatically extracts patterns from the data through iterative optimisation without the need for explicit manual programming. In vocational education scenarios, the recommendation system can dynamically adjust the recommendation strategy based on students' historical learning behaviours, thereby enhancing the recommendation effect. Recommendation models in light of machine learning algorithms rely on manually extracted features, while recommendation models in light of deep learning algorithms significantly improve recommendation performance by extracting deep features of vocational courses. Li and Kim (2021) suggested a vocational course recommendation model in light of an improved autoencoder, which uses LSTM to extract time features and uses a Softmax function for recommendation. Hassan et al. (2024) used a bidirectional LSTM with an attention mechanism for emotion analysis to construct a learner portrait feature model, which significantly improved recommendation performance. Qu et al. (2024b) extracted user interests from a series of registered courses using a recurrent neural network and used content-based technology to mine relationships between courses to recommend courses. Chen et al. (2025) put forward a course recommendation approach in light of an attention-based convolutional neural network (CNN), which uses the attention mechanism to train the neural network based on the difference between the estimated score and the user's actual rating. Gu (2025) introduced a dynamic attention mechanism combined with hierarchical reinforcement learning for course recommendation systems, which effectively improved the model's adaptability and the accuracy of recommendations.

In recent years, KG, as a type containing a large number of additional facts and semantics of edge information, has achieved certain results in vocational education recommendation algorithms. Knowledge graphs offer core advantages for vocational education recommendation algorithms through their structured semantic representations, cross-domain associations, and explainable reasoning capabilities. These features enable precise capture of complex relationships, support dynamic personalised recommendations, and enhance interpretability. Such benefits directly translate into significant improvements in performance metrics including recommendation accuracy, user satisfaction, and cold-start handling capabilities. Ramazanova et al. (2024) integrated the project's KG using the TransR algorithm, fusing entity information and relationship information into the recommendation system, which has better recommendation effects. Guan (2023) utilised vocational education links to predict tasks, which can enhance the accuracy of recommendations to a certain extent, but due to the neglect of the path connectivity of KG, the final result is difficult to interpret recommendations. Urdaneta-Ponte et al. (2021) modelled the joint text semantics and structure of user and vocational education course interactions using a hierarchical fusion fuzzy deep neural network, which improved recommendation efficiency. Fettach et al. (2024) obtained entity embeddings using TransR, learned the relationships between entities, and aggregated the embeddings of neighbouring domains, and introduced an attention mechanism, which has better recommendation effects. Xu (2025) combined KG and graph neural networks to consider the weights of neighbouring nodes for each entity to mine high-order information in the knowledge graph, capture users' potential interests, and improve recommendation effects. Yang et al. (2025) suggested a recommendation algorithm in light of heterogeneous graphs and KG, which strengthens sub-graph propagation information and can solve the problem of irrelevant neighbours appearing during propagation, and has good interpretability for improving recommendation effects.

Based on the analysis of the current research status, vocational education platforms face two major challenges in recommendation systems: one is how to solve the problems of incomplete new user information and inaccurate recommendations; the other is that users' willingness to learn is diverse and their interests are changeable, how to accurately capture the user's next learning interest point for precise recommendation. Therefore, this paper conducted in-depth research on the above problems and proposed a vocational education course recommendation method based on KG and neighbours. First, a KG containing students, vocational education courses, teaching videos, and concepts and their relationships is constructed. On this basis, novel negative sampling approach is incorporated to enhance the TransH knowledge graph embedding model, weighting various negative samples with different weights to complete the model training of EOTransH. Then, a bipartite graph of courses and users is constructed, and knowledge graph embeddings are constructed by jointly utilising user entity neighbour information. The attention propagation module can obtain more accurate user and course vectors. Finally, through attention prediction, the focus is better focused on the feature information of users and vocational education courses, which can achieve more accurate recommendation effects. Simulation experiments were conducted on the MOOCCourse and MOOCCube datasets, and the outcome showed that the AUC of the proposed approach was 0.9869 and 0.9531 on the two datasets, which can effectively solve the problem of inaccurate recommendation for newly added users and improve the accuracy of recommendations.

2 Relevant technologies

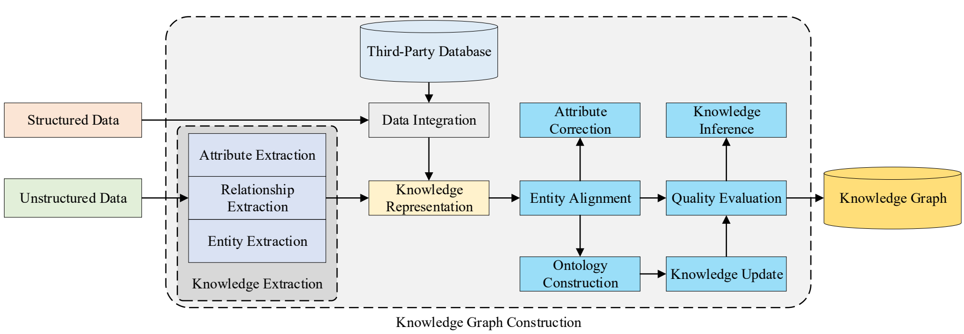
2.1 Knowledge graph

KG is a knowledge base based on graph structure, which structurally describes and represents information about entities, concepts, events, and other aspects of the real world, while also describing the relationships and attributes between them (Peng et al., 2023). KG aims to better organise and understand human knowledge, enabling machines to better understand and process this knowledge, and also allowing people to better utilise and master the knowledge in the world. It is usually represented using Resource Description Framework (RDF) triples, as shown in equation (1). According to the graph structure of the KG, vertices stand for entities, and edges represent the relationships between entities. Where E is the set of vertices in the knowledge graph G, and R is the set of edges in the KG. Each triple (h, r, t) represents a factual relationship between entities specifically, the existence of a relation r between head entity h and tail entity t.

$$G = \{(h, r, t) \mid h \in E, r \in R, t \in E\} \tag{1}$$

Constructing a knowledge graph involves comprehensive consideration of multiple factors, such as the tools and methods used, as well as data accuracy and completeness, knowledge representation modelling, the scale and depth of relationship extraction, and updates and maintenance (Abu-Salih and Alotaibi, 2024). First, determine the application scenario and establish the corresponding basic framework. Secondly, unify the update and processing of data obtained from different channels. After data pre-processing, use machine learning techniques to extract entities and relationships. Then, select a suitable representation method for knowledge representation. Finally, select a suitable storage technology to store KG data. Figure 1 implies the general construction process of the KG.

Figure 1 The general construction process of the KG (see online version for colours)



2.2 Attention mechanism

As a model architecture in the field of machine learning, the attention mechanism imitates the focusing behaviour of human vision, concentrating more attention resources on key objects at a specific moment, while ignoring non-key objects (Brauwers and Frasincar, 2021). In the era of deep learning, it is typically manifested as a special multi-layer neural network structure, which allows the model to simulate biological selective forgetting and context association tasks. This mechanism enables the model to automatically adjust the allocation of attention points, reduce the transmission of useless information, and thus reduce the complexity of the entire model. The attention mechanism represents the importance of information in the whole by calculating the weights of different information, and information with higher weights appears more important. At the same time, assigning low weights to unimportant information reduces the influence of the unimportant information. This can more reasonably utilise resources and quickly lock important information in a large amount of data. The flexibility of its structural design and the modular integration method can be adjusted internally according to specific needs, which is also a key reason why recommendation systems prefer to use the attention mechanism.

The calculation process of the attention mechanism can be mainly summarised in three steps: first, the similarity between *Query* and *Key* is computed (Liu and Guo, 2019). Second, the similarity or relevance score is normalised. Third, Value is weighted and summed according to the weight coefficient (Ataee et al., 2023). In the first step, different functions are usually used to calculate the similarity. In the second step, the Softmax method is usually used for normalisation, calculated as shown in equation (2), where Sim_i represents the similarity between two variables. In the third step, the calculated a_i is used as the weight parameter for the corresponding value.

$$a_i = Softmax\left(Sim_i\right) = \frac{e^{Sim_i}}{\sum_{j=1}^{L_\chi} e^{Sim_j}} \tag{2}$$

Integrating attention mechanisms into deep neural networks can significantly enhance model performance in vocational education scenarios through core advantages such as dynamic information focusing, modelling long-range dependencies, multimodal fusion, and improved interpretability. Its value extends beyond metrics like recommendation accuracy and user satisfaction; it also builds an interpretable bridge between data, models, and users, transforming intelligent education services from black-box operations to transparent decision-making.

3 Knowledge graph construction for vocational education course recommendation

A knowledge graph is a technology that represents knowledge in a graphical structure, mainly including entities and relationships. Entities are the basic units of the KG, typically representing objects in vocational education, such as people, things, etc. Relationships describe the associations and interactions between entities, reflecting the semantic connection of knowledge. For example, in the knowledge graph of vocational education courses, entities can be ‘students’, ‘vocational education courses’, and relationships can be ‘select’, ‘recommend’, ‘prerequisite courses’, etc. These relationships connect related entities through directed edges, forming a complex and organic knowledge network, which not only helps to systematically manage data, but also reveals potential patterns and connections within the data, thereby providing support for subsequent curriculum recommendation scenarios.

As introduced in the previous chapter, the construction process of the vocational education KG includes steps such as data collection, entity extraction, relation extraction, knowledge graph representation, and knowledge graph update. After collecting vocational education course data, entity extraction identifies the basic units from the collected data. For example, student entities E_s and course entities E_c are extracted from the online vocational education registration data. Let S be the student set $S = \{s_1, s_2, \ldots, s_m\}$ and the vocational education course set $C = \{c_1, c_2, \ldots, c_n\}$, then $E_s = \{s_i | s_i \in S\}$, $E_c = \{c_j | c_j \in C\}$.

Relation extraction identifies and extracts associations between entities. Assuming a set of relations $R = \{r_1, r_2, \ldots, r_k\}$ which includes relations such as 'select', 'recommend', and 'prerequisite vocational education courses'. For each pair of entities (e_i, e_j), determine whether a relationship exists r_k, which can be represented as $R(e_i, e_j) = \{r_k | (e_i, e_j) \in R_k\}$, where R_k is the set of specific relation types r_k.

The vocational education KG can be represented as a directed graph $G = (V, E)$, where V is the entity set, and E is the relation set. For each pair of entities (e_i, e_j), if a relationship r_k exists, then there is a directed edge from e_i to e_j. V and E are represented as follows.

$$V = E_s \cup E_c \tag{3}$$

$$E = \left\{ \left(e_i, e_j, r_k \right) \middle| R\left(e_i, e_j \right) = r_k \right\} \tag{4}$$

As data continues to accumulate and change, the vocational education KG needs to be updated regularly to maintain its accuracy and timeliness. The update process includes adding new entities, deleting obsolete entities, and updating relationships. Assuming a set of new entities is E_{new}, a set of entities to be deleted is E_{del}, then the updated entity set V' and the relationship set E' are as follows.

$$V' = \left(V \cup E_{new} \right) \setminus E_{del} \tag{5}$$

$$E' = \left\{ \left(e_i, e_j, r_k \right) \middle| \left(e_i, e_j \right) \in V', R\left(e_i, e_j \right) = r_k \right\} \tag{6}$$

Finally, the entities and relationships of the vocational education KG are stored in the form of tables, and the association relationship between tables is used to represent the structure of the vocational education KG, such as storing in the relational database MySQL.

4 Knowledge representation of vocational education based on improved TransH

The vocational education KG cannot be directly applied to the recommendation system. It needs to be vectorised first, which is knowledge representation. The objective of knowledge graph embedding is to project discrete entities and relations into a dense vector space, constrained by structural preservation and semantic consistency requirements, so that the efficiency of calculating semantic connections is higher, which helps to solve the data sparsity problem. Building upon TransH, this chapter proposes an optimised knowledge representation paradigm (Jia et al., 2017). Traditional negative sampling methods exhibit significant drawbacks in knowledge representation learning. We therefore develop an improved approach and implement it within the TransH paradigm, and an optimised knowledge representation model EOTransH is developed in this study.

Given the vocational education knowledge graph $G = \{(h, r, t)| h, t \in E, r \in R\}$, for the vocational education course triple (h, r, t), first, the head entity, tail entity, and relationship are embedded as model inputs using the TransH representation method. The improved representation learning yields higher-quality embeddings that significantly boost performance across multiple KG tasks including triple categorisation and relation prediction. First, the scoring function of the curriculum knowledge graph is expressed as equation (7).

$$f_r(h, t) = \|h_\perp + r - t_\perp\|_2^2 \tag{7}$$

where $h_\perp$ and $t_\perp$ are vectors obtained after processing with the projection matrix, and the construction methods of the projection matrices are $M_{rh} = r_p h_p^\perp + I$, $M_{rt} = r_p t_p^\perp + I$, where h_p, r_p and t_p are another set of entity vectors used to construct the relationship matrix, I is the identity matrix, $h_\perp = M_{rh} h, t_\perp = M_{rt} t$.

In the traditional TransH model, the traditional negative sampling method has the problems of treating positive triples as negative triples and low quality of negative samples. Inspired by the Rotate model (Huang et al., 2021), the training of this EOTransH model adopts a self-adversarial negative sampling method (Cen et al., 2023), and replaces the operation is completed by calculating the probability according to the different proportions of head and tail entities. Negative samples with different scores are given different weights, and the details of the integrated pipeline of competitive negative sampling and EOTransH parameter learning will be described in detail below.

1 Head-tail entity swapping probabilities in negative sampling. From all positive triple sets, for each relation *r*, compute the mean cardinality of tail entities per head entity across all qualifying triples, represented as *tph*, and expected head entity count associated with each tail entity, represented as *hpt*, subsequently compute the replacement probability through equation (8).

$$p = \frac{tph}{tph + hpt} \tag{8}$$

During negative sampling, the head entity replacement probability is denoted as p and The tail entity replacement probability is complementary at $1 - p$.

2 Weight of negative instances. In the early stages of training, the model cannot effectively differentiate semantic variations and needs obviously incorrect negative examples for training. At this time, the score of negative examples that are confused with positive examples is relatively low. In the middle and later stages of training, the model can accurately represent entities and relations, so it requires to differentiate more subtle semantics, and constructing negative sample pairs that are tough for the model to distinguish is more meaningful. In the later stages of training,

the model's ability to distinguish ambiguous semantics increases, and the scores of negative examples that are confused with positive examples also increase. In light of this idea, higher-scoring negative samples are given higher weights.

Suppose given a positive triple, construct m negative triples, and then score the negative triples using the EOTransH model's scoring function. The higher the score, the higher the corresponding weight, and the calculation of the weight is indicated in equation (9).

$$p\left(h_j', r, t_j'\right) = \frac{\exp \alpha f\left(h_j', r, t_j'\right)}{\sum_{i=1}^{m} \exp \alpha f\left(h_j', r, t_j'\right)} \tag{9}$$

where (h_j', r, t_j') is the *i*-th negative example triple, α is the sampling temperature, when $\alpha > 0$ occurs, the higher the negative example score, the greater its weight, when $\alpha = 0$ occurs, it is equivalent to unif sampling.

Because the goal of setting the loss function is to evaluate the model's performance during training, guide the optimisation and update of model parameters, so that it gradually approaches the optimal solution. The specific loss function setting is implied in equation (10).

$$L = \sum_{(h,r,t)\in S} \sum_{(h',r',t')\in S'} \max\left(0, f_r(h,t) - f_r(h',t') + \gamma\right) \tag{10}$$

where $\gamma > 0$ represents the boundary, S' is the negative sample space, from which negative samples are randomly selected to replace the positive sample, as shown in equation (11).

$$S' = \left\{\left(h', r', t'\right) \mid h' \in E\right\} \cup \left\{(h, r, t) \mid t' \in E\right\} \tag{11}$$

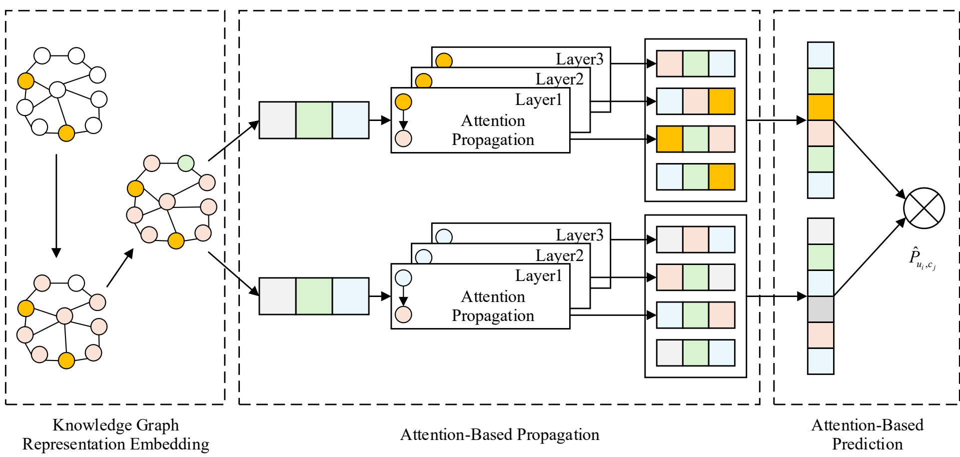
5 Vocational education course recommendations based on knowledge graphs and neighbours

5.1 Vocational education knowledge graph embedding with joint user entity neighbourhood information

The massive amount of occupational education course information provides users with too many choices, leading them to feel lost and find it difficult to obtain the learning resources they need. As the user base gradually increases, the courses recommended to users become increasingly broad, resulting in a sparse interaction density between learners and courses. The problem of inaccurate recommendations for newly added users in the course recommendation system is becoming increasingly prominent. This leads to newly registered users often struggling to efficiently select interesting occupational education courses in the early stages of the platform, resulting in inaccurate recommendations for new users and information overload. The system cannot associate and match courses based on user features, and therefore cannot perform accurate recommendations, resulting in inaccurate recommendations for newly added users.

Therefore, to address the problem of inaccurate recommendations for newly added users in the recommendation system, this chapter proposes a vocational education course recommendation algorithm based on KG and neighbours, as indicated in Figure 2. First, when constructing the user and vocational education course KG, the EOTransH method was adopted for graph representation learning to reduce KG cost and improve algorithm execution efficiency. Secondly, a bipartite graph of vocational education courses and users is constructed, and a KG embedding is built through the joint user entity neighbour information. Subsequently, higher-order connectivity information between users and vocational education courses is mined through attention-based propagation. Finally, an attention network is built in the recommendation module to explore learners' learning preferences, making recommendations more accurate. This method effectively solves the problem of inaccurate recommendations for new users and improves recommendation accuracy.

Figure 2 The structure of the EOTransH method (see online version for colours)



This paper can solve the representation problem of newly added user entities, and can reflect differently according to different neighbour entities. This method consists of three parts: the input layer, the relationship entity transformation embedding layer, and the output layer.

1 *Input layer*. Receives the feature vectors of user entities and neighbouring entities associated with the user entity, and combining these two types of feature vectors can obtain more accurate vector representation. For a given user entity $u = \{s, r_1, e_1, r_2, e_2, \ldots\}$ and neighbouring entities, first calculate the related neighbouring entities based on the user entity, and secondly, through vocational education KG traversal calculation to obtain the related neighbour vectors, we can obtain all neighbouring entities of the user entity $E_n = \{e_1, e_2, \ldots, e_n\}$.

To obtain more similar semantic information between entity vectors and neighbour relationships, this section adopts a relationship transformation mechanism using head entities and tail entities. This method can well represent the impact of relationships on neighbouring entities, as shown in equation (12), where e_j is the j-th neighbouring entity of the user entity, and w_r is the transfer vector.

$$T_r(e_j) = e_j - w_r^T e_j w_r \tag{12}$$

2 *Rule weight aggregation layer*. Using the logic rule module alone cannot accurately identify the optimal neighbouring entities, so an attention network is needed to mine the optimal neighbouring entities. Therefore, this paper combines the attention network, and through calculating the attention weight of the neighbouring entities, mines the optimal neighbouring entities. For the neighbours e_j of the entity e_i, the weight calculation is shown in equation (13) and equation (14), where tanh() represents the activation function, T_r is the relationship transformation function, || represents the concatenation of two vectors, and W is the weight matrix.

$$\alpha_{ji|} = \tanh\left(\left[WT_r\left(e_i\right) \| WT_r\left(e_j\right)\right]\right) \tag{13}$$

$$\alpha_{ji|}^{Att} = \operatorname{softmax}\left(\alpha_{ji}\right) = \frac{\exp\left(\alpha_{ji}\right)}{\sum_{k \in N_i} \exp\left(\alpha_{k|i}\right)} \tag{14}$$

3 *Output layer*. Finally, to obtain an accurate output entity embedding e_i, the logic rule weight and the attention mechanism weight can be added, as shown in equation (15). The final output entity embedding is used for the subsequent attention propagation module.

$$e_i = \sum_{\left(r, e_j \in N_k(i)\right)} \left(\alpha_{ji|}^{L} + \alpha_{ji}^{Att}\right) T_r\left(e_j\right) \tag{15}$$

5.2 Near neighbour node aggregation based on attention mechanism

Attention embeddings in the propagation layer can help effectively aggregate information from neighbouring nodes. By learning the weight distribution of neighbouring nodes, the information from neighbouring nodes can be better integrated during the information propagation process, thereby enriching the representation information of the present node.

First, let $N_h = \{(h, r, t) | (h, r, t) \in G\}$ represent the set of triples where h is the head entity, then the information of all tail entity vectors e_t of the triples (h, r, t) with h as the head entity is propagated as follows.

$$e_{N_h} = \sum_{(h, r, t) \in N_h} \pi(h, r, t) e_t \tag{16}$$

where $\pi(h, r, t)$ represents how much information is transferred from the tail entity vector to e_t to the head entity vector e_h under the condition of r. The more information transferred, the greater the weight. Its specific implementation is as follows, where W_r represents a 'entity-relation' projection matrix, and tanh(·) is an activation function.

$$\pi(h, r, t) = \left(W_r e_t\right)^T \tanh\left(W_r e_h + e_t\right) \tag{17}$$

Secondly, the attention score is normalised using the Softmax function, as shown below.

$$\pi(h, r, t) = \frac{\exp\left(\pi(h, r, t)\right)}{\sum_{(h, r', t') \in N_h} \exp\left(\pi(h, r', t')\right)} \tag{18}$$

Finally, a double interaction aggregator is used to combine the two independent features as follows, where W_1, $W_2 \in R$ is a trainable weight matrix, and ○ represents element-wise product. The first half is a GCN aggregator, and the second half is a Relu transformation after Hadamard product of the features. The double interaction aggregator can better preserve information between neighbour nodes and can better capture the relationships between nodes.

$$f_{Bi-I} = Relu\left(W_1\left(e_h + e_{N_h}\right)\right) + \mathrm{Re}lu\left(W_2(eh \circ eNh)\right) \tag{19}$$

5.3 Vocational education program recommendations and projections

By jointly using user entity neighbour information for vector representation and attention-based propagation, we have already efficiently mined the association features between users and vocational education courses, and mined high-order connectivity information between users and vocational education courses. Taking the user representation and vocational education course representation mined through the above attention-based propagation as input, the user representation and vocational education course representation are concatenated into a vector and input into the attention network. Through the attention mechanism, high-order feature information of users and vocational education courses can be effectively mined, and an accurate prediction that accurately reflects user preferences can be obtained.

Attention-based prediction requires splicing all layers of users and courses to generate e_u^* and e_i^* of users and courses, and output the predicted probability. To obtain the final target course and user's final vector representation, a layer aggregation mechanism is adopted to connect the representations of each step into the final embedding of users and courses, as shown in the formula below, where || is the concatenation function, and L is the number of layers of the course and user vectors. Attention aggregation can better enrich the embedding of vocational education courses.

$$e_i^* = e_i^{(0)} \| \ldots \| e_i^L \tag{20}$$

$$e_u^* = e_u^{(0)} \| \ldots \| e_u^L \tag{21}$$

In addition, it is necessary to deeply study the user's latent preferences for the purpose of achieving more precise recommendation results. Through the attention mechanism in the attention network, high-order feature capture of users can be performed, which can accurately mine the user's preferences, thereby achieving the problem of accurate recommendation. In the processing of users' historical behaviour, the user's historical behaviour can be regarded as implicit feedback, so the user's feature encoding matrix can be represented as $\{c_1^i, c_2^i, \ldots, c_k^i\}$. The attention network uses a Softmax function to calculate weights, as shown in equation (22).

$$\Phi_{c_k^i, c_j} = \mathrm{softmax}\left(\Gamma\left(c_k^i, c_j\right)\right) = \frac{\exp\left(\Gamma\left(c_k^i, c_j\right)\right)}{\sum_{k=1}^{N} \exp\left(\Gamma\left(c_k^i, c_j\right)\right)} \tag{22}$$

According to the similarity calculation weight and the user representation obtained through attention-based propagation, calculate the user embedding u_i, as shown in equation (23).

$$u_i = \sum_{k=1}^{N} \Phi_{c_k^i, c_j} c_k^i \tag{23}$$

Finally, calculate the probability $\hat{P}_{u_i, c_j} = \Theta(u_i, c_j)$ that the user selects the vocational education course, sort these probabilities in descending order, and when performing personalised vocational education course recommendation for the target user u, select the *N* courses corresponding to the probabilities ranked higher, to achieve personalised Top-*N* vocational education course recommendation.

6 Experimental results and analyses

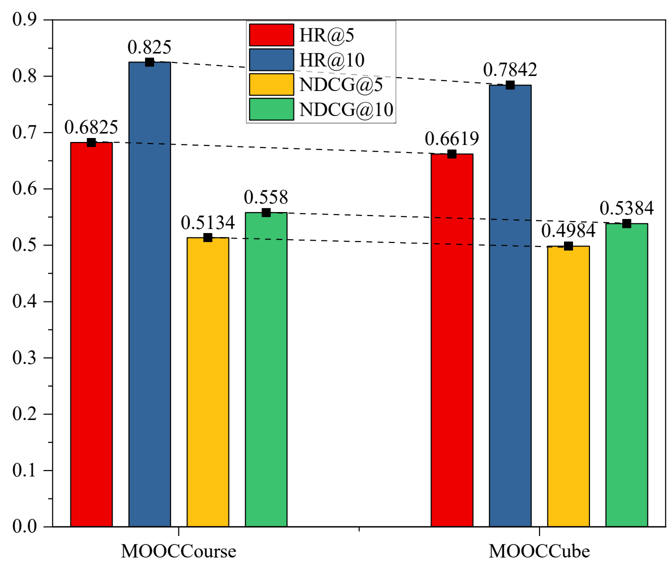
The experiment utilises the deep learning framework TensorFlow, and the training dataset is the Chinese general encyclopaedia knowledge graph CN-DBpedia Dump, which contains 9.13 million encyclopaedia entities and 67.08 million ternary relationship triples. The experimental datasets are MOOCCourse (Xu et al., 2023) and MOOCCube (Wang and Feng, 2024). The MOOCCourse dataset contains 1,302 vocational education courses and 82,535 users, with each user registered for at least three vocational education courses. The MOOCCube dataset collects and processes 706 vocational education courses and 55,203 users, with each user registered for at least two vocational education courses. The experimental data is classified into training set, validation set, and test set, with a split ratio of 8:1:1. Adam optimiser is used for optimisation in the experiment, the batch size is 512, the learning rate is 0.001, and the maximum epochs is set to 1,000.

The proposed model is denoted as NKGV, and the performance of the NKGV model on different datasets is compared in terms of Hit Rate (HR@N) and Normalised Discounted Cumulative Gain (NDCG@N), where N represents the number of neighbours, as shown in Figure 3. It is obvious that the NKGV model performs better on the MOOCCourse dataset. This proves that the NKGV model has a good recommendation effect for users who are interested in multiple vocational education courses. More courses help the model to be fully trained and accurately remove noisy courses, which can more accurately recommend target vocational education courses to users.

To further verify the effectiveness of the NKGV model, this paper selects AE-LSTM (Li and Kim, 2021), CNN-LSTM (Chen et al., 2025), TransR-AM (Fettach et al., 2024), and HGNN-KG (Yang et al., 2025) as comparison models. The evaluation metrics are HR@10, NDCG@10, AUC, and F1. The comparison of various metrics on the two datasets is shown in Figure 4. The HR@10 of NKGV on the two datasets were 0.825 and 0.7842, respectively, which were at least 7.04% and 4.18% higher than other models. The NDCG@10 were 0.556 and 0.5384, respectively, which were at least 8.57% and 8.26% higher than other models. The AUC on the two datasets were 0.9869 and 0.9531, respectively, which were at least 3.6% and 3.62% higher, F1 on the two datasets were 0.9508 and 0.9281, respectively, which were at least 2.05% and 4.09% higher. Compared with other comparison models, NKGV achieved significant improvements in all metrics.

This is because NKGV combines neighbour information of users, which can extract user features most similar to the recommendation user, and updates nodes by recursively propagating the embedded information of neighbour nodes to distinguish more matching neighbour information, thereby improving recommendation accuracy. NKGV has good performance, because the proposed method models the relationships between users, courses, and user-course relationships using knowledge graphs, finds neighbour information of users, explores higher-order connectivity between users and courses through attention-based propagation, mines accurate vector representations of users and courses, alleviates the data sparsity problem, and effectively solves the problem of inaccurate recommendations for newly added users.

Figure 3 Comparison of HR and NDCG of the NKGV model on different datasets (see online version for colours)



To verify the impact of the joint user entity neighbour information knowledge graph embedding module and the attention-based propagation module of NKGV on course recommendation performance, three comparison algorithms were designed for experiments. R1 is to verify the impact of removing the joint user entity neighbour information knowledge graph embedding module on the course recommendation algorithm, and R2 is to verify the impact of removing the attention propagation module on the course recommendation algorithm, as shown in Table 1. Compared with NKGV, R1 and R2 showed a decrease in recommendation accuracy on the MOOCCuce dataset, which also indicates that the joint user entity neighbour information knowledge graph embedding module and the attention-based propagation module can both improve recommendation accuracy.R1 has lower recall, precision, and other indicators than the R2 algorithm, which can explain that the impact of the joint user entity neighbour information knowledge graph embedding module on the vocational education course recommendation algorithm is relatively large.

Figure 4 Comparison of various indicators of different models on two datasets (see online version for colours)

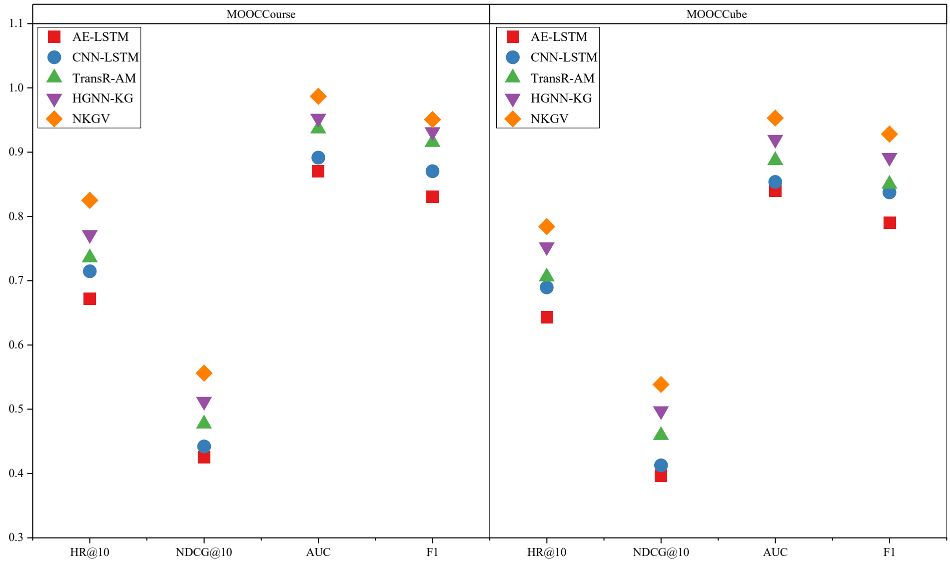


Table 1 Comparison of recommendation performance metrics for different models

Model	*HR@10*	*NDCG@10*	*AUC*	*F1*
R1	0.6231	0.3357	0.7561	0.6795
R2	0.6928	0.3965	0.7924	0.7326
NKGV	0.7842	0.5142	0.9531	0.9281

7 Conclusions

Vocational education platforms, while possessing massive amounts of courses and users, also face issues such as information overload. To address the problems of incomplete user information and inaccurate recommendations in current vocational education course recommendation methods, this paper proposes a vocational education course recommendation method based on KG and neighbours. First, a KG is constructed containing entities such as students, vocational education courses, teaching videos, and concepts, as well as their relationships. On this basis, a new negative sampling approach is adopted to enhance the KG representation model TransH. Using a self-adversarial negative sampling method, replacement operations are performed based on different head-tail entity ratios to calculate probabilities, and negative samples with different scores are given various weights to complete the training of the EOTransH model. Then, a bipartite graph of courses and users is constructed, and KG embeddings are built by combining user entity neighbour information. Furthermore, higher-order connectivity information between users and courses is mined through attention-based propagation. Finally, an attention network is built in the output prediction layer to explore the learner's preference features, making the recommendation more accurate. Experimental outcome implies that the proposed approach achieves F1 values of 0.9508 and 0.9281 on the MOOCCourse dataset and the MOOCCube dataset, respectively, effectively meeting the personalised and diverse course needs of vocational education learners, and providing new ideas for intelligent services in vocational education.

Although the research in this paper has achieved certain results and can meet the requirements of current practical use, there are still some shortcomings. Future research can be carried out in the following aspects.

1 KG can not only be used for vocational education course recommendation, but also for understanding and explaining vocational education course content, error analysis and assisted teaching. In the future, a KG-based intelligent teaching system will become an important auxiliary tool for vocational education teaching and learning, providing more personalised and effective vocational education teaching support for teachers and students.

2 In the user's use process, contextual factors are also important factors for vocational education course recommendation, and can affect the accuracy of personalised recommendations. Incorporating contextual information into the recommendation algorithm can enable the system to more accurately judge user needs and status, provide more appropriate vocational education course suggestions, and thus improve recommendation accuracy and user learning experience. Future research in this direction will focus on exploring contextual awareness technology to achieve a higher level of personalised vocational education course recommendation services.

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Declarations

All authors declare that they have no conflicts of interest.

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