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PAPER

Innovative Models of Student Entrepreneurship Education Supported by Mobile Technology in Higher Education

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ABSTRACT

In the context of rapid globalization and digital transformation, entrepreneurship education has become a crucial component of higher education systems. With the swift advancement of mobile technology, leveraging its potential to support student entrepreneurship education has emerged as a significant area of inquiry. Mobile technology not only offers convenient access to learning resources but also fosters entrepreneurial interest and potential through diverse interactive means, enhancing students' entrepreneurial capabilities and innovative thinking. Existing research highlights the notable advantages of mobile technology in education, particularly in resource accessibility and learning interaction. However, traditional studies often focus on the isolated functionalities of technology, lacking a systematic investigation into the overall innovation of entrepreneurship education models. Moreover, current methods show limitations in resource matching and personalized recommendations, failing to fully meet students' diverse entrepreneurial needs. To address these gaps, this paper proposes an intelligent entrepreneurship resource matching model that integrates mobile interactive networks with attention mechanisms. The model consists of five key components: the knowledge embedding layer, attention-enhanced mobile interactive entrepreneurship resource propagation network, attention-based entrepreneurship resource knowledge graph convolutional network, vector fusion layer, and entrepreneurship resource intelligent matching prediction layer. This study not only enriches the theoretical understanding of the integration of entrepreneurship education and mobile technology but also provides practical guidance and reference for educators, offering significant application value.

KEYWORDS

higher education, mobile technology, entrepreneurship education, intelligent matching algorithm, attention mechanism, resource recommendation

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1 INTRODUCTION

In the context of rapid globalization and digital transformation, entrepreneurship education has become an important part of the higher education system [1, 2]. With the rapid advancement of mobile technology, how to effectively utilize mobile technology to support students' entrepreneurship education has become a significant topic in the field of education. Mobile technology not only provides convenient learning resources [3, 4] but also stimulates students' entrepreneurial interest and potential through diverse interactive means [5], enhancing their entrepreneurial abilities and innovative thinking. This paper, set against the background of higher education, explores the application model of mobile technology in student entrepreneurship education, aiming to provide new pathways and ideas for the innovation of entrepreneurship education models through the deep integration of technology and education.

Although existing research has made some progress in educational models supported by mobile technology, there are still some shortcomings in entrepreneurship education [6–10]. Reference [11] focuses on the single function of technology applications, such as resource management or the construction of online learning platforms, lacking a systematic study of the overall innovation of entrepreneurship education models. In addition, the effectiveness of existing methods in resource matching and personalized recommendation is still unsatisfactory [12–17], failing to fully meet students' diverse entrepreneurial needs. Some studies remain at the initial stage of technological implementation [18], neglecting the deep integration of educational theory and practice [19], resulting in limited effectiveness of technology applications. Therefore, there is an urgent need for a systematic method that integrates the latest technology and educational theories to better serve students' entrepreneurship education.

The main content of this paper consists of two parts: first, exploring the design background and objectives of the intelligent matching algorithm for entrepreneurship resources that integrates mobile interactive networks and attention mechanisms in the higher education environment. Second, detailing the five components of the intelligent matching model for entrepreneurship resources that integrates mobile interactive networks and attention mechanisms: the knowledge embedding layer, the attention-enhanced mobile interactive entrepreneurship resource propagation network, the attention-based entrepreneurship resource knowledge graph convolutional network, the vector fusion layer, and the entrepreneurship resource intelligent matching prediction layer. Through these two parts of the study, this paper aims to construct an efficient intelligent matching model for entrepreneurship resources, providing students with personalized and intelligent entrepreneurial support and promoting the innovative development of entrepreneurship education models in higher education. This study not only enriches the relevant research on the integration of entrepreneurship education and mobile technology in theory but also provides concrete guidance and reference for educators in practice, possessing significant application value.

2 DESIGN BACKGROUND AND OBJECTIVES

Traditional methods for intelligent matching of entrepreneurship resources mostly focus on exploring the interaction between students and entrepreneurship resources, ignoring the correlation between students. This omission results in the lack of similar student information with mobile interactive relationships in the student's feature representation, thereby reducing the contribution of student entities to the intelligent matching results of entrepreneurship resources. In real life, when students make decisions in entrepreneurship education, they tend to seek advice through mobile interactive relationships. Most models ignore this similarity effect between students receiving entrepreneurship education and fail to incorporate mobile interactive information into the intelligent matching model for entrepreneurship resources. In practical scenarios, after identifying part of a student's interests, systems often repeatedly recommend fixed entrepreneurship resources to that student, making it difficult to discover new content. Associating students receiving entrepreneurship education with each other can effectively solve this problem.

The intelligent matching algorithm for entrepreneurship resources that integrates mobile interactive networks and attention mechanisms proposed in this paper aims to address the problem of existing models neglecting the interaction relationships between students receiving entrepreneurship education. By introducing the mobile interactive network, the algorithm can capture and analyze the interaction behaviors between students based on mobile devices, such as information sharing, discussions, and suggestions. The mobile interactive network can not only record students' explicit interests in entrepreneurship resources but also reveal implicit knowledge and resource preferences obtained through communication, providing richer contextual information for the intelligent matching system. Moreover, through the attention mechanism, the algorithm can dynamically adjust its focus, allocating more computational resources to the student interaction relationships with significant influence in the mobile interactive network.

Specifically, the model utilizes mobile devices to capture real interaction behaviors between students, and these behavioral data form a rich mobile interactive network. By analyzing this network, the model can identify the friendships between students receiving entrepreneurship education as well as the frequency and depth of their interactions. For example, in the given scenario, although the student-resource bipartite graph cannot directly establish a path between student i_1 and resource u_5, the introduction of mobile interactive relationship e_1 enables the model to identify the friendship between i_1, i_2, and i_4, thereby inferring that i_1 might be interested in the entrepreneurship resource u_5, which i_4 interacts with. Next, the attention mechanism is introduced to dynamically adjust the model's focus on different interaction relationships. Specifically, the attention mechanism assigns different importance weights to student interaction relationships according to the intensity of interaction and the relevance of the interaction content between students. For instance, if i_1 interacts frequently with i_2 and their content is highly relevant, the model tends to pay more attention to the influence of resources recommended by i_2 on i_2. In this way, when the model determines whether entrepreneurship resource u_5 is suitable to be matched with student i_1, it not only considers i_1's own historical interaction data but also emphasizes, through the attention mechanism, the interaction between i_1 and their friends i_2 and i_4, as well as the resources these friends recommend or interact with. Through this approach, the model can capture the complex interaction relationships between students while enhancing its ability to predict potential interests.

3 MODEL STRUCTURE DESIGN

The intelligent matching model for entrepreneurship resources that integrates mobile interactive networks and attention mechanisms proposed in this paper is mainly divided into four parts: knowledge graph embedding layer, graph convolutional layer, vector merging layer, and prediction layer, as shown in Figure 1. The knowledge graph embedding layer processes the unstructured information in the entrepreneurship resource knowledge graph, parameterizing each entity into a low-dimensional vector. Through knowledge embedding, complex semantic information can be transformed into operable vector representations, ensuring that the features of students and entrepreneurship resources are fully captured and expressed. The graph convolutional layer calculates propagation weights using the attention mechanism, propagating and aggregating the interaction information between students and entrepreneurship resources in the mobile interactive network. By introducing the attention mechanism, the model can assign different weights according to students' interest levels in neighboring entrepreneurship resources, thereby more accurately extracting valuable features during message propagation. In the vector merging layer, the model merges the multi-layer feature vectors output by the graph convolutional layer by summing them to generate the final feature vectors representing students receiving entrepreneurship education and entrepreneurship resources. Finally, the prediction layer calculates the vectors of students receiving entrepreneurship education and entrepreneurship resources to obtain a prediction value that reflects students' interest levels in entrepreneurship resources. By calculating the similarity between student feature vectors and entrepreneurship resource feature vectors, the model can generate an interest score to measure students' interest levels in specific entrepreneurship resources.

Specifically, this paper uses the student-entrepreneurship resource interaction matrix B, the mobile interactive network, and the entrepreneurship resource knowledge graph as initial inputs. After processing the initial data, two graphs are obtained. The first graph is the fusion graph H_1 of the student-entrepreneurship resource interaction matrix B and the mobile interactive network, aligning the two and naming it the mobile interactive entrepreneurship resource intelligent matching knowledge graph. This graph stores the mobile interactive relationships between students and the interaction data between students and entrepreneurship resources. Here, H_1 is defined as (i_{v1}, i_{v2}, b_{iv1}, i_{v2}, b_{iu}, u), where b_{iv1} and i_{v2} equal 1 if there is a relationship between students receiving entrepreneurship education and 0 otherwise. Similarly, b_{iv} equals 1 if there is an interaction between the student and the entrepreneurship resource and 0 otherwise, representing whether there is a connection between entities in the graph. H_1 integrates the mobile interactive relationships between students and the interaction data between students and entrepreneurship resources. The other part is the knowledge graph of entrepreneurship resources and their attributes, named the entrepreneurship resource knowledge graph H_2, where b_{iv2} is defined as (g, e, s). H_2 displays the knowledge graph of entrepreneurship resources and their attributes.

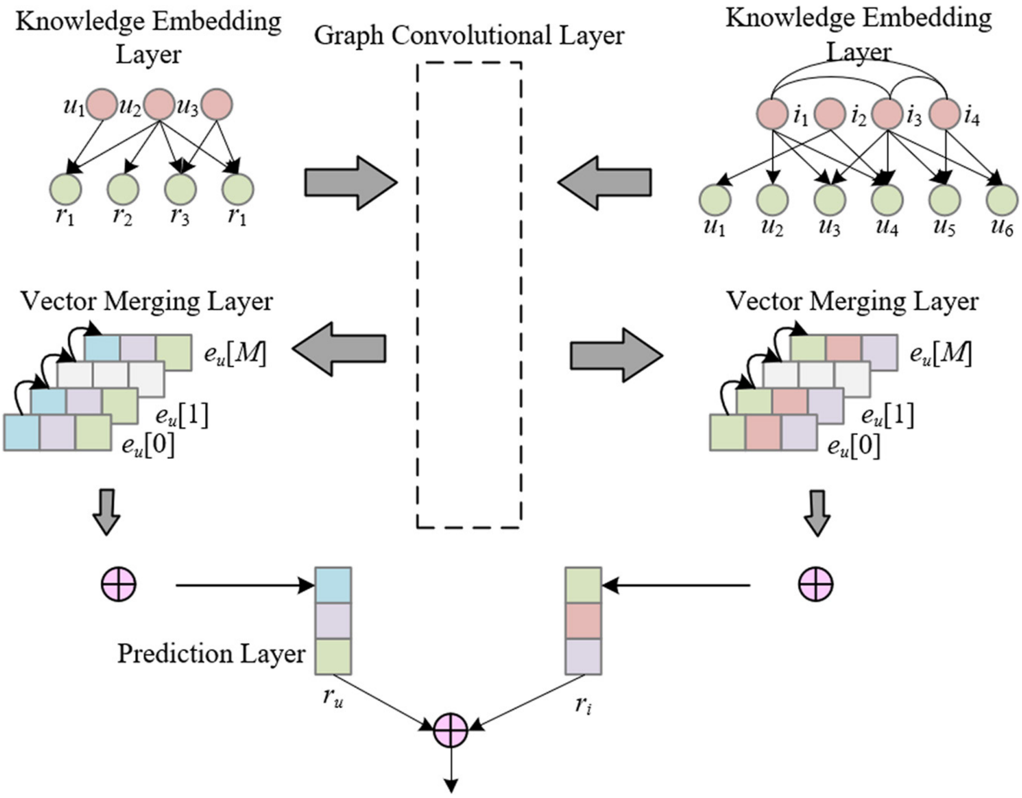

Fig. 1. Entrepreneurship resource intelligent matching model architecture

After defining H_1 and H_2, the prediction function is further trained as $\tilde{b}_{iu} = D\left(i,u \mid \Phi, H_1, H_2\right)$, where b_{iu} represents the predicted score of students receiving entrepreneurship education for entrepreneurship resources, and Φ represents the model parameters under the function.

3.1 Knowledge embedding layer

The knowledge embedding layer adopts the *TransD* model to learn the embeddings of the knowledge graph. The advantage of the *TransD* model lies in its ability to handle many-to-many relationships and optimize the *TransE*, *TransH*, and *TransR* models. *TransD* projects different types of entities and relations into the vector space and uses dynamic mapping matrices for projection. Specifically, for each entity and relation, the *TransD* model defines corresponding projection vectors and mapping matrices. Through these mapping matrices, entity vectors can be projected from the entity space into the relation space, thereby better capturing complex relational structures. In the knowledge graph, the calculation of the embedding score for entities and relations is one of the key steps in the embedding layer. For a knowledge graph triple (g, e, s), where student g is connected to entrepreneurship resource s through relation e, the *TransD* model maps entities g and s into the relation space through mapping matrices generated by projection vectors. Let r_a represent the vector of entity a, then the mapping matrices of entities g and s can be calculated by the formulas $(r_{eo} r_{rg}^T + U^{l\times v})$ and $(r_{eo} r_{go}^T + U^{l\times v})$, respectively. Assuming that the vector of triples (g, e, s) is represented by r_g, r_{go}, r_e, r_{eo}, r_s, and r_{so}, and the projection vector of these vectors is represented by the subscript o, with an identity matrix of $l \times v$ represented by $U^{l\times v}$, the embedding score formula for the knowledge graph triple is:

$$h(g,e,s) = \left\| (r_{eo} r_{go}^T + U^{l\times v}) r_g + r_e - (r_{eo} r_{so}^T + U^{l\times v}) r_s \right\|_2^2 \tag{1}$$

To train the model, positive samples and negative samples need to be constructed. Positive samples consist of real triples, while negative samples are generated by randomly replacing entities or relations to create unreasonable triples. By calculating the embedding scores of positive and negative samples and using an appropriate loss function, the model can learn reasonable embedding vectors, ensuring that the scores of positive samples are higher than those of negative samples. Assuming that the positive sample triple is represented by (g, e, s) and the negative sample triple is represented by (g', e, s') ∈ H', the loss function expression is

$$LOSS = \sum_{(g,e,s)\in H} \sum_{(g',e,s')\in H'} MAX(0, h,(g,e,s) + \varepsilon - h(g',e',s')) \tag{2}$$

3.2 Mobile interactive entrepreneurship resource intelligent matching propagation network with attention mechanism

The mobile interactive entrepreneurship resource intelligent matching propagation network with attention mechanism is one of the key components. It achieves precise matching mainly by assigning different weights to the interaction paths between students and entrepreneurship resources. The application of the attention mechanism in the propagation path is the core innovation of this network. By utilizing the attention mechanism, different weights can be set for different propagation paths, reflecting different levels of association between students and entrepreneurship resources. Specifically, by calculating the score value between student i, who receives entrepreneurship education, and a relation, $e_{g,s}$, the model can identify which paths have a greater impact on the matching results. Assuming that the relationship between entity g and entity s is represented by $e_{g,s}$, and the importance of relation $e_{g,s}$ to student i is represented by $\tau_{e_{g,s}}$, the score value expression is

$$\tau_{e_{g,s}} = r_i \cdot r_e \tag{3}$$

Furthermore, under the effect of the attention mechanism, the set $V_{(g,s)}$ of all tail entities s directly connected to head entity g in the graph is assigned normalized weights. These weights reflect the importance of different entrepreneurship resources to students. When the convolutional network performs aggregation, the attention weights filter entities in the neighborhood to varying degrees according to students' interests. This means that the model not only considers the direct relationship between students and each entrepreneurship resource but also dynamically adjusts these relationship weights according to students' interests, enhancing the flexibility and accuracy of the model. The expression of the model's attention weights is

$$\tilde{\tau}_{e_{g,s}} = \frac{\exp\left(\tilde{\tau}_{e_{g,s}}\right)}{\sum_{g\in V_{(g,s)}} \exp\left(\tilde{\tau}_{e_{g,s}}\right)} \tag{4}$$

In the modeling of the convolutional layer, two processing channels are divided: the mobile interactive entrepreneurship resource intelligent matching propagation network and the entrepreneurship resource knowledge graph convolutional network, which are jointly responsible for outputting the high-order feature vectors of students and entrepreneurship resources. The following section will elaborate on the mobile interactive entrepreneurship resource intelligent matching propagation network.

The structure of the mobile interactive network adopts the nesting of two types of graph convolutional networks, where the first type of network aggregates the interaction information between students receiving entrepreneurship education and entrepreneurship resources. Specifically, in the student-entrepreneurship resource bipartite graph, all entrepreneurship resource information that has interacted with students is propagated and aggregated through the convolutional network. Through a single convolution operation, the model can generate vector representations containing neighborhood entrepreneurship resource information. This process aggregates the dynamic interaction data between students and their associated resources, capturing students' attention and usage of different resources, thereby laying the foundation for further resource matching. Assuming that the connection weight between students and entrepreneurship resources is represented by $\tilde{\tau}_{e_{i,u}}$, and the set of all entrepreneurship resources directly connected to student i in graph H_1 is represented by $V_{(i,u)}$, the vector representation of the neighborhood entrepreneurship resources is

$$r_{V_{(i,s)}} = \sum_{u \in V_{(i,s)}} \tilde{\tau}_{e_{i,u}} r_u \tag{5}$$

After computing the neighborhood representation, the neighborhood vector needs to be merged with the student's own vector. The design of the merging function ensures that the model can comprehensively consider both the student's own characteristics and the characteristics of the entrepreneurship resources in their neighborhood, generating a more comprehensive and accurate representation of the student vector. Assuming that the transformation weight is represented by Q, the bias term is represented by y, and the nonlinear activation function of this layer is represented by δ, then the merging function expression for the first-layer student vector is

$$r_i^{(0)} = \delta\left(Q \cdot \left(r_i + r_{V_{(i,u)}}\right) + y\right) \tag{6}$$

The second type of network aggregates the behavioral information of students receiving entrepreneurship education in a mobile interactive environment. By propagating student information that already contains entrepreneurship resource semantics through the mobile interactive network, the model can further capture interactions and influences among students. Specifically, $V_{(i,i')}$ represents the set of all other students i' directly connected to student i in graph H_1. By propagating and aggregating this type of interaction information, the model generates vector representations that contain neighborhood student information. Assuming that the connection weight between students and other students is represented by $\tilde{\tau}_{e_{i,u}}$, and the number of iterative layers of the convolutional network is represented by m, then the expression is

$$r_{V_{(i,i')}}^{(m-1)} = \sum_{i' \in V_{(i,i')}} \tilde{\tau}_{e_{i,i'}} r_{i'}^{(m-1)} \tag{7}$$

After computing the student neighborhood representation, the neighborhood vector also needs to be merged with the student's own vector. The merging function of the *m* layers ensures that the model can comprehensively integrate the neighborhood student characteristics with the student's own characteristics, generating high-order student vector representations. At this point, the attention mechanism plays a role again, providing the model with fine-grained weighting capabilities for different student interaction information. Through this dynamic adjustment, the model can more flexibly capture students' behavioral patterns and interest changes in the mobile interactive network, thereby achieving more precise and personalized entrepreneurship resource intelligent matching. The merging function expression for the student vector in the *m* layers is

$$r_i^{(m)} = \delta\left(Q \cdot \left(r_i^{(m-1)} + r_{V_{(i,i')}}^{(m-1)}\right) + y\right) \tag{8}$$

3.3 Entrepreneurship resource knowledge graph convolutional network with attention mechanism

The entrepreneurship resource knowledge graph convolutional network constructs the knowledge graph by aggregating the relationships between entrepreneurship resource entities and attribute entities and dynamically weights these relationships using an attention mechanism. Figure 2 shows the model graph convolutional layer architecture. Specifically, each head entity *g* in the entrepreneurship resource knowledge graph represents its neighborhood through the set of directly connected tail entities *s*, denoted as $V_{(g,s)}$. Through the graph convolution operation, the model aggregates this neighborhood information to generate the vector representation of the head entity *h*. The attention mechanism plays a key role in this process—based on the calculated relevance weights of each tail entity *s* to the head entity *g*, the model can highlight the most important relationship information. In this way, the generated head entity vector not only contains its own features but also incorporates the most relevant attribute and relationship information. Assuming that the normalized attention weight is represented by $\tilde{\tau}_{e_{i,u}}$, the specific expression is

$$r_{V_{(g,s)}} = \sum_{r_{V_{(g,s)}}} \tilde{\tau}_{e_{g,s}} r_s \tag{9}$$

After computing the entrepreneurship resource neighborhood representation, it is necessary to merge this neighborhood information with the vector of the entrepreneurship resource itself to generate a higher-order entrepreneurship resource vector representation. The merging function of the *m* layers entrepreneurship resource vector is designed to comprehensively consider both neighborhood features and its own features. The attention mechanism is used to finely weight the neighborhood information, making the final generated entrepreneurship resource vector more comprehensive and precise.

$$r_u^{(m)} = \delta\left(Q \cdot \left(r_u^{(m-1)} + r_{V_{(g,s)}}^{(m-1)}\right) + y\right) \tag{10}$$

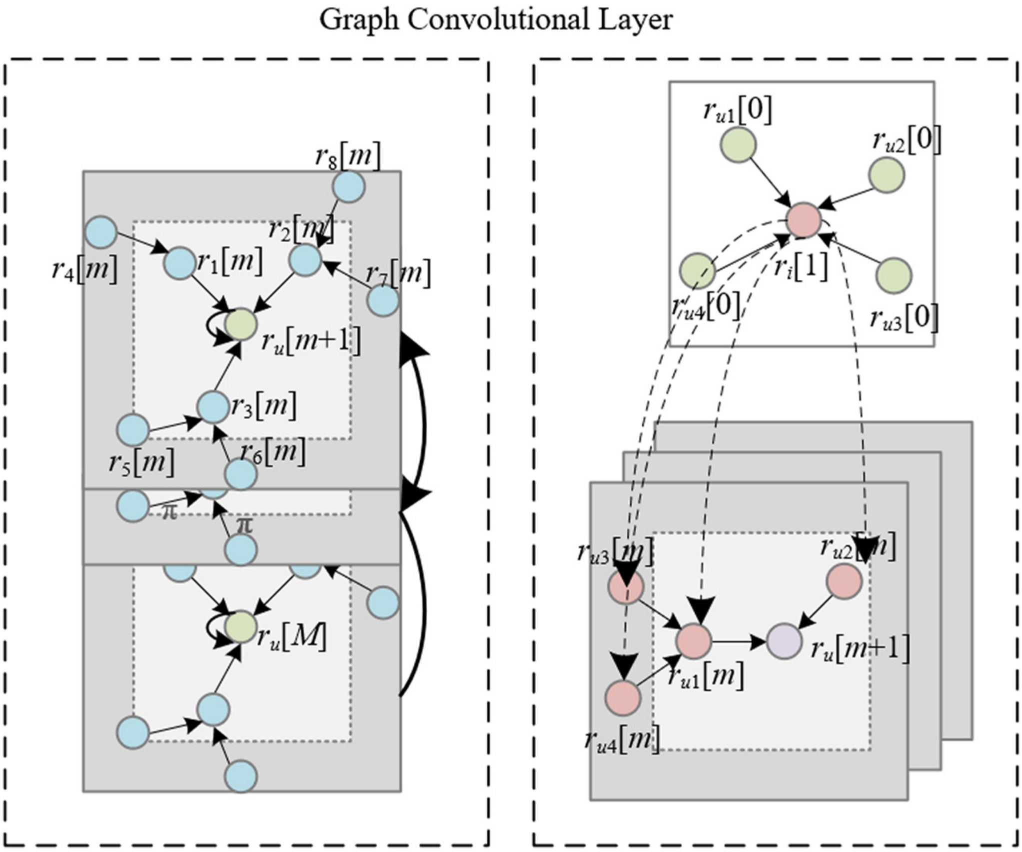

Fig. 2. Model graph convolutional layer architecture

3.4 Vector merging layer

Through one layer of the knowledge graph attention network, the feature vector representing the entity itself and its neighborhood can be obtained, but to further extract higher-order features, it is necessary to expand from one layer to multiple layers. Each layer of graph convolution operation captures increasingly broader neighborhood information, thereby deeply exploring the potential interests of students receiving entrepreneurship education. For example, in the *m*-th layer, the model calculates the aggregated neighborhood information of the entity and then combines it with the entity's own vector to generate a new feature representation. By gradually enhancing the entity representation through multiple iterations, the model can capture students' potential interests and needs, thereby improving the accuracy of entrepreneurship resource matching.

To strengthen the semantic information of the entity vector, the model merges the multi-layer vectors generated by convolution. Specifically, the feature vectors at different levels are accumulated through vector addition. In the mobile interactive network environment, the interactions between students and entrepreneurship resources dynamically change. Through the merging of multi-layer vectors, the model can comprehensively consider students' resource needs and usage behaviors in different times and contexts, ensuring the accuracy and practicality of the recommendation results.

In each layer of convolution operation, the student feature vector is continuously updated and enhanced. By merging the multi-layer feature vectors, the model can capture the evolution of students' interests and changes in needs during the entrepreneurship education process. The merged student vector contains both its own feature information and the comprehensive information of its neighborhood relationships, forming a comprehensive and multi-level student feature representation. The merging function expression for constructing the vector of students receiving entrepreneurship education is

$$r_{uu} = \sum_{m=0}^{M} r_{uu}^{(m)} \tag{11}$$

In each layer of convolution operation, the feature vector of entrepreneurship resources is also continuously updated. Through the merging of multi-layer feature vectors, the model can comprehensively consider the multi-dimensional characteristics and dynamic changes of resources. Particularly in the mobile interactive network environment, the usage and demand for entrepreneurship resources may change over time and contexts. By merging multi-layer vectors, the model can capture these dynamic changes, forming a comprehensive entrepreneurship resource feature representation. The merging function of the entrepreneurship resource vector is

$$r_{u} = \sum_{m=0}^{M} r_{u}^{(m)} \tag{12}$$

3.5 Recommendation result prediction layer

The model calculates the interaction probability score between students receiving entrepreneurship education and entrepreneurship resources through inner product computation. In this process, the feature vectors of students and entrepreneurship resources have already been represented and merged through multi-layer knowledge graph attention networks, forming high-level feature representations. To predict the interaction probability, the model substitutes the student feature vector and the entrepreneurship resource feature vector into the function d for computation. The inner product operation is one of the commonly used methods—by calculating the inner product of the student vector and the resource vector, an interaction score can be obtained, which reflects the potential matching degree between the two. The calculated interaction probability score between students and entrepreneurship resources is

$$\tilde{b}_{iu} = d(r_i, r_u) \tag{13}$$

In this model, methods such as the cross-entropy loss function or the mean square error loss function are used to measure the gap between the model's predicted interaction probability score and the actual interaction label. Assuming the cross-entropy loss function is represented by $\Delta(\cdot)$, the negative sampling set is denoted as O, and the regularization weight coefficient is represented by η, the functional expression is as follows

$$LOSS = \sum_{i \in I} \left(\sum_{u \in (b_{iu}=1)} \Delta\left(b_{iu}, \tilde{b}_{iu}\right) - \sum_{u \in ((i,u) \in O)} \Delta\left(b_{iu}, \tilde{b}_{iu}\right) \right) + \eta D_2^2 \tag{14}$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

From the experimental results presented in Table 1, the proposed method outperforms other methods across all datasets. Specifically, in the benchmark matching dataset, the *AUC* value of the proposed method is 0.812, and the *F*1 value is 0.779, which are about 4.2% and 4.4% higher than those of the second-best method, *DDPG*, respectively. In the dynamic incremental dataset, the *AUC* and *F*1 values of the proposed method reach 0.978 and 0.977, significantly surpassing all other methods, especially outperforming the second-best method, *SupCon*, by about 5.3% and 5.2%, respectively. In the cross-domain mixed dataset, the *AUC* and *F*1 values of the proposed method are 0.921 and 0.889, again exceeding all other methods, with the *AUC* being about 3.6% higher than that of the second-best method, *SupCon*. In the negative sample interference dataset, the *AUC* and *F*1 values of the proposed method are 0.816 and 0.789, respectively. Although the improvement in this dataset is relatively small, the proposed method still maintains a leading position.

Table 1. Comparison of experimental results of different methods

Model	Benchmark Matching Dataset		Dynamic Incremental Dataset		Cross-Domain Mixed Dataset		Negative Sample Interference Dataset	
	AUC	*F*1	*AUC*	*F*1	*AUC*	*F*1	*AUC*	*F*1
Graph-BERT	0.665	0.562	0.745	0.678	0.735	0.659	0.715	0.645
HyperGCN	0.724	0.668	0.879	0.841	0.774	0.732	0.765	0.712
DDPG	0.779	0.735	0.912	0.912	0.836	0.812	0.789	0.748
SupCon	0.769	0.724	0.925	0.925	0.889	0.854	0.812	0.746
The Proposed Method	0.812	0.779	0.978	0.977	0.921	0.889	0.816	0.789

From the recall values of different methods in *Top-K* scenarios across the four datasets—benchmark matching dataset, dynamic incremental dataset, cross-domain mixed dataset, and negative sample interference dataset, as shown in Figure 3—the proposed method outperforms other methods across all datasets and *K* values. In the benchmark matching dataset, as the *K* value increases from 5 to 100, the recall value of the proposed method rises from 0.06 to 0.375, significantly higher than that of other methods, especially being about 6.5% higher than the *DDPG* method at $K = 100$. In the dynamic incremental dataset, the proposed method also shows a clear advantage across all *K* values, reaching a recall value of 0.48 at $K = 100$, which is 7% higher than the *SupCon* method. The results in the cross-domain mixed dataset show that the proposed method achieves significant improvements at every *K* value from 5 to 100, with a recall value of 0.45 at $K = 100$, about 8% higher than that of the second-best method, *SupCon*. In the negative sample interference dataset, the recall value of the proposed method is superior to other methods across all *K* values, particularly achieving a recall value of 0.146 at $K = 100$, about 2.6% higher than the *SupCon* method.

Table 2. *AUC* values of the proposed method under different convolutional network layers

	1 Layer	2 Layers	3 Layers	4 Layers
Benchmark Matching Dataset	0.784	0.775	0.724	0.635
Dynamic Incremental Dataset	0.945	0.975	0.812	0.514
Cross-domain Mixed Dataset	0.879	0.923	0.789	0.612
Negative Sample Interference Dataset	0.826	0.826	0.615	0.578

Table 3. *AUC* values of the proposed method under different sampling times

	2 Times	4 Times	8 Times	16 Times	32 Times	64 Times
Benchmark Matching Dataset	0.712	0.781	0.778	0.678	0.642	0.623
Dynamic Incremental Dataset	0.856	0.953	0.974	0.962	0.932	0.912
Cross-domain Mixed Dataset	0.854	0.885	0.923	0.912	0.832	0.823
Negative Sample Interference Dataset	0.759	0.812	0.812	0.789	0.745	0.724

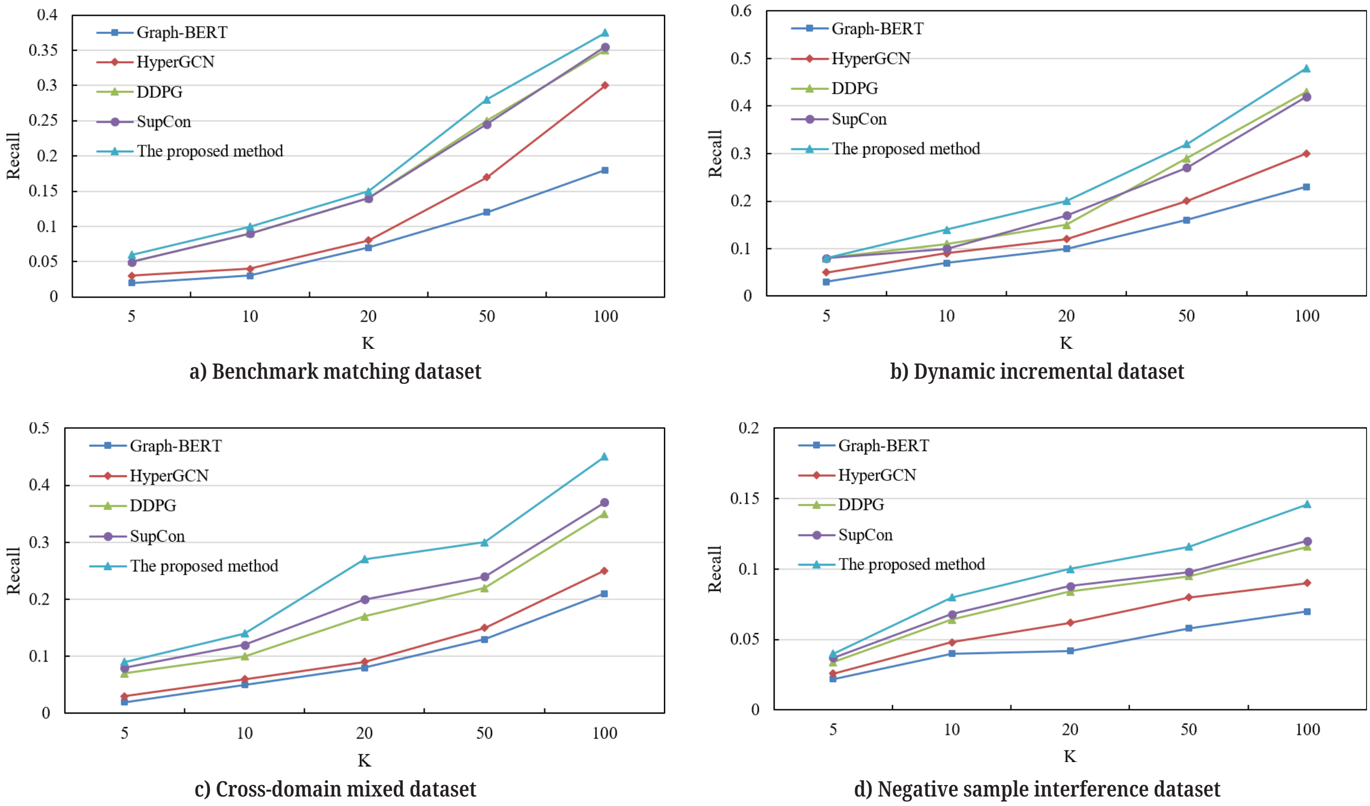

Fig. 3. Comparison results of recall values for intelligent entrepreneurship resource matching under *Top-K* scenarios with different methods

From the data in Table 2, it can be observed that the *AUC* values of the proposed method show significant differences under different datasets and convolutional network layers. In the benchmark matching dataset, as the number of convolutional network layers increases, the *AUC* value gradually decreases from 0.784 at 1 layer to 0.635 at 4 layers, indicating that shallower networks perform better when processing this dataset. In the dynamic incremental dataset, the *AUC* value reaches its highest at two layers with 0.975, while the *AUC* values for 1 and 3 layers are 0.945 and 0.812, respectively, and the *AUC* value for 4 layers significantly drops to 0.514. In the cross-domain mixed dataset, the *AUC* value is highest at 2 layers with 0.923, while the *AUC* values for 1 and 3 layers are 0.879 and 0.789, respectively, and the *AUC* value drops to 0.612 at 4 layers. In the negative sample interference dataset, the *AUC* values for 1 and 2 layers are the same at 0.826, while the *AUC* values for 3 and 4 layers decrease to 0.615 and 0.578, respectively. These results suggest that the proposed method achieves better performance when using shallower networks across different datasets.

From the data in Table 3, it can be observed that the *AUC* values of the proposed method show a significant trend of change under different sampling times. In the benchmark matching dataset, the *AUC* value reaches its highest at 4 times with 0.781, then gradually decreases as the sampling times increase, reaching 0.623 at 64 times. In the dynamic incremental dataset, the *AUC* value reaches its highest at 8 times with 0.974; although it slightly decreases to 0.962 at 16 times, it still maintains a relatively high level, while at 32 and 64 times, the *AUC* values drop to 0.932 and 0.912, respectively. In the cross-domain mixed dataset, the *AUC* value reaches its highest at 8 times with 0.923, while at 16 times it is 0.912, and then it decreases to 0.832 and 0.823 at 32 and 64 times, respectively. In the negative sample interference dataset, the *AUC* values are both 0.812 at 4 and 8 times and then gradually decrease to 0.724 at 64 times. Overall, moderate sampling times, such as 4 and 8 times, can achieve better *AUC* performance across various datasets.

5 CONCLUSION

This paper investigated an intelligent matching algorithm that leverages mobile interactive networks and attention mechanisms to innovate the entrepreneurial education model for students in higher education. The focus of the study is to design and implement an efficient entrepreneurial resource intelligent matching model to provide personalized and intelligent entrepreneurial support for students. The model consists of five main components: knowledge embedding layer, attention-introduced mobile interactive entrepreneurial resource intelligent matching propagation network, attention-introduced entrepreneurial resource knowledge graph convolutional network, vector merging layer, and entrepreneurial resource intelligent matching result prediction layer. This study holds significant theoretical and practical implications. Theoretically, it expands the research field of integrating entrepreneurial education with mobile technology, proposing a novel algorithm that combines attention mechanisms and mobile interactive networks, showcasing the potential of technology in education. Practically, the proposed model provides an intelligent solution for entrepreneurial education in universities, which can significantly improve the efficiency and effectiveness of entrepreneurial resource matching, providing strong support for student entrepreneurship and promoting the innovation and development of entrepreneurial education models in higher education.

Despite the remarkable achievements of this study, there are still some limitations. First, the model's performance varies across different datasets due to data quality and diversity, especially when excessive sampling times may introduce noise. Second, the model's complexity and computational cost are relatively high, which may limit its application in educational institutions with limited resources. Finally, the study mainly verifies the model based on simulated datasets, and its effectiveness in practical applications may be affected by other external factors, requiring further testing and optimization in real-world scenarios. Future research can further explore and deepen the following aspects: First, optimizing the model structure and algorithm to reduce computational costs and improve processing efficiency, enabling its application in more educational institutions. Second, incorporating more real-world data into the model's training and validation to enhance its applicability and robustness in practical scenarios.

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