Intelligent Retrieval and Comprehension of Entrepreneurship Education Resources Based on Semantic Summarization of Knowledge Graphs

Haiyang Yu, Entai Wang, Qi Lang, and Jianan Wang

***Abstract*—The latest technologies in natural language processing provide creative, knowledge retrieval, and question-answering technologies in the design of intelligent education, which can provide learners with personalized feedback and expert guidance. Entrepreneurship education aims to cultivate and develop the innovative thinking and entrepreneurial skills of students, making it a practical form of education. However, a knowledge retrieval and question-answering teaching assistant system for entrepreneurship education has not been proposed. This observation motivated us to develop a reading comprehension framework to address the challenges of domain-specific knowledge gaps and the weak comprehension of complex texts encountered by intelligent education models in practical applications. The proposed framework mainly includes: question understanding, relevant knowledge retrieval, mathematical calculation, and answer prediction. The techniques involved in the aforementioned modules mainly include text embedding, similarity retrieval, graph convolution, and long short-term memory network. By integrating this model into entrepreneurship courses, learners can participate in real-time discussions and receive immediate feedback, creating a more dynamic and interactive learning environment. To assess the effectiveness of the proposed model, this article conducts answer prediction on single-choice exercises related to entrepreneurship education courses. This study employs the potential of using a question-and-answer format to enhance intelligent entrepreneurship education, paving the way for a more effective and engaging online learning experience.**

***Index Terms*—Entrepreneurship education, intelligent assistants, knowledge graph, natural language processing (NLP), personalized learning.**

I. Introduction

ENTREPRENEURSHIP education aims to cultivate and enhance students' entrepreneurial awareness, innovative abilities, and entrepreneurial skills, enabling them to successfully establish and operate their own businesses or engage in entrepreneurial endeavors [1], [2]. This form of education places significant emphasis on fostering innovative thinking, creativity, teamwork, risk management, and market insight among students, equipping them with the potential and competitiveness necessary to thrive across diverse fields and industries [3]. Typically, entrepreneurship education encompasses various essential aspects, including training in creativity and innovation, the development of comprehensive business plans, conducting thorough market research, exploring effective financing strategies, understanding relevant laws and regulations, and mastering essential entrepreneurship management principles [4]. Through engaging methods like classroom instruction, hands-on projects, and visits to established enterprises, students gain valuable insights into fundamental entrepreneurial concepts and acquire the practical skills necessary to confidently apply theoretical knowledge in real-world scenarios.

Entrepreneurship education is gaining popularity around the world and is now conducted in an online, hybrid format with the assistance of artificial intelligence (AI) tools [5], [6]. Online education serves as an excellent tool for knowledge enrichment, offering learners flexible and personalized learning experiences, interactive engagement, access to high-quality teaching resources, practical applications through projects, and all at a low-cost and high-efficiency platform [7], [8]. Luise et al. [9] analyzed the potential of the human–computer interactive tutoring system based on natural language processing (NLP) technology in the field of education. However, while learners have many benefits from online education in terms of innovation and entrepreneurial capacity development, they expect timely and personalized feedback to meet their learning needs [10], [11]. The timely resolution of difficulties encountered during online homework completion is crucial for maintaining a coherent knowledge learning process, particularly for learners facing challenges in this regard [12], [13]. Hence, the exploration of machine question-answering methods as intelligent assistants for entrepreneurship education is of paramount significance, enabling real-time responses to questions and facilitating seamless knowledge dissemination [14], [15]. Furthermore, the intelligent question-answering system offers an additional advantage by analyzing and evaluating learning progress of students [16], [17]. This allows the system to provide teachers with valuable

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Question: What are the five important elements of entrepreneurial team management?

Text: Five elements of an entrepreneurial team: 1. Entrepreneurial goal: The entrepreneurial team has a clear goal, which guides the thinking and behavior of team members. Without goals, the team has no value of existence. 2. Entrepreneurs: People are the core strength of an entrepreneurial team, and three or more people can form a team. 3. The positioning of the entrepreneurial team: The positioning of the entrepreneurial team determines where the team is in the enterprise, who chooses and decides the members of the team, and who should be responsible for the team in the end. 4. Authority: The power of the team leader is related to the development stage of the entrepreneurial team. 5. Entrepreneurship plan: A plan is an arrangement for achieving a goal and a plan for future actions. The plan can be understood as a specific working procedure for the implementation of the goal.

A. Goals Financial Position Authority Plan

B. Goals People Position Authority Plan

C. Goals People Performance Authority Plan

D. Goals People Position Authority Supervision

Fig. 1. Example of entrepreneurship education question answering.

feedback and data, enabling them to gain a deeper understanding of students' individual learning needs. Fig. 1 shows an example of real practice questions from an entrepreneurship education course. Armed with this valuable information, teachers can optimize their teaching content and methods to cater to the specific requirements of their students, ultimately enhancing the overall teaching and learning experience.

Question-answering pipeline in education has witnessed remarkable progress, bringing new vitality to online entrepreneurship education [18], [19]. Many advanced educational information retrieval and question-and-answer models provide technical support for intelligent learning assistants in entrepreneurship education [20], [21], [22]. The researchers utilize the structured knowledge database of the knowledge graph to perform question matching with entities and relationships, thereby achieving a higher level of accuracy in machine question answering [23], [24], [25], [26]. Event-QA [27] model achieves knowledge question answering by integrating graph knowledge with event background information. The concept tagging with both questions and solutions (PQSCT) model designed a question-solution module based on bidirectional encoder representation from transformers (BERT) to extend the content of feature representation vector [28]. Chen et al. [29] utilize Graph2Seq to encode the knowledge graph subgraph and enhanced the decoding by copying mechanism from knowledge subgraphs. The knowledge graph-based models require the question content to include entities. However, when the question pertains to specialized domain knowledge, such as law and investment experience in entrepreneurship education, it presents challenges for the retrieval module to locate relevant evidence information. With the proposal of the transformer [30], AI technology based on pretraining models has made a breakthrough in the field of intelligent entrepreneurship education, such as embeddings from language models (ELMo) [31], BERT [32], OpenAI generative pre-trained transformer (GPT3) [33], and Multiagent [34]. Some pretrained models that are good at dealing with Chinese are also proposed [35], [36]. The pretraining models currently face key challenges and issues, primarily centered around poor interpretability and limited robustness, which cannot be entirely overcome within data-driven deep learning approaches.

Drawing upon the extensive generalization capability of large pretrained embedding models, this article aims to formulate knowledge question answering within the specialized domain of online entrepreneurship education. To complement the distinct semantic details of the question, this study devises a question semantic summarization module grounded in graph structure (QSSG). Subsequently, it accomplishes a comprehensive understanding of entrepreneurial knowledge within the question-answering model by fusing features, employing the generalized attributes present in the feature fusion layer. Furthermore, by incorporating a formula generation module, the model can offer supplementary mathematical expressions for questions that involve computational prerequisites, which serves to bolster the analytical and problem-solving capabilities of the model.

The primary innovations of this study can be summarized as follows.

1) This article innovatively applies intelligent question-answering technology to a smart assistant in entrepreneurial education. It proposes a semantic summarization module based on the text grammar knowledge graph to reveal the knowledge attributes within specific domains of entrepreneurial education texts.
2) A question solver for entrepreneurial education has been developed, featuring a mathematical expression generation module. This contributes to the intelligent education framework by providing capabilities in reading comprehension and mathematical analysis.
3) The proposed model achieves an answer prediction accuracy rate exceeding 97% for practical exercises focused on entrepreneurship education. In addition, it has the capability to offer real-time and professional question-answering services to online learners.

The rest of this article is organized as follows. Section II is for the related work. Section III presents the main methods proposed in this article. Section IV discusses the evaluation results. Finally, Section V concludes this article.

II. Related Work

This section presents three related works: the definition of the entrepreneurship education question-answering task, machine question-answering models, and educational question-answering datasets.

A. Entrepreneurship Education Question-Answering Task

Entrepreneurship education, with its experiential curriculum that places a strong emphasis on fostering innovation, holds substantial significance within the domains of engineering, science, and technology [37]. In the broader context of promoting the comprehensive growth of smart education, the research focus within innovation and entrepreneurship education has progressively gravitated toward harnessing the potential of emerging technologies in AI and Big Data [38], [39], [40]. This shift entails harnessing existing educational resources to facilitate expansion and the delivery of personalized services [41], [42]. Balsa et al. [43] devised a virtual tutor for an online learning platform, encapsulating all course-related information within an ontology. They further translated the original question into an SPARQL protocol and RDF query language (SPARQL) query to facilitate the process of question answering. Question-generation for the educational domain (EduQG) [44] provides a dataset of more than 3000 questions and answers including multiple choice and cloze for educational question and answer generation. Building upon the aforementioned research groundwork, this article delves into the question-answering model within the context of online entrepreneurship education and gives the basic definition of the task. For a given single-choice question Q, knowledge documents set P, a set of candidate answers R, and the correct answer option g, the objective is to train an answer prediction model denoted as F as follows:

$$g = F(Q, P, R). \tag{1}$$

B. Machine Question-Answering Models

The intelligent machine question-answering model holds a diverse range of applications within the fields of smart education, medical diagnosis, and financial analysis [45], [46]. With the rapid advancement of deep learning models and the enhancement of computer processing capabilities, machine reading comprehension models featuring the transformer architecture as central component have been introduced [47], [48]. Qiu et al. [49] proposed a director-actor-critic framework based on knowledge graphs to solve the problem of limited coverage of complex questions and answers. The variational reasoning network [50] model introduces a novel deep learning architecture that leverages knowledge graphs to address noisy expression problems and the intricacies of multihop reasoning. It further integrates a probabilistic logic variational reasoning approach within the model. Xiong et al. [51] proposed an efficient entity linking strategy that combines feature matching with an entity disambiguation model to address subject entity ambiguity expression more effectively. For question answering with constraints, multiple relations, and variables, Shin and Lee [52] presented a semantic graph query method based on question decomposition. The aforementioned question-answering models provide technical support for intelligent assistants.

Furthermore, some specialized question-answering models for online education are proposed. Jenders et al. [53] introduced a machine-learning model designed to predict suitable answers for forum questions by analyzing the responses marked as most satisfactory by users. Macina et al. [54] devised an approach to enhance the productivity of educators and boost community engagement by suggesting fresh questions and answers for students. Mittal et al. [55] implement cognitive technologies in the management of online education to facilitate teachers and students in addressing questions related to course content. Babinec and Srba [56] developed an automated text analysis approach for community question answering within the education domain. They recommended suitable labeling methods to questioners, thereby facilitating efficient question answering for students on the subjects they have studied. Although the aforementioned methods developed for learners have made some progress in smart education, online course-assisted question answering still faces the challenges of professionalism and accuracy.

C. Educational Question-Answering Datasets

As online teaching platforms continue to gain popularity, several education-focused question and answer datasets have emerged, offering foundational sentence support for the advancement of intelligent question and answer support systems. The CLOTH [57] dataset represents the pioneering large-scale cloze test dataset crafted by humans, primarily encompassing questions utilized in language examinations at the middle and high school levels. The reading comprehension dataset from examinations (RACE) [58] dataset comprises approximately 28 000 articles and nearly 100 000 questions meticulously crafted by expert human English tutors. This dataset aims to assess the comprehension and reasoning capabilities of students aged 12–18, gathering English test materials from middle school students. The ReClor [59] is an emerging reading comprehension dataset that places emphasis on logical reasoning, which derived from standardized graduate admissions exams. The LearningQ [60] dataset encompasses an extensive array of educational subjects and includes lengthy and cognitively demanding documents. In this dataset, question generation necessitates logical reasoning regarding the connections between sentences and paragraphs. Notably, around 30% of the questions entail the application of higher order cognitive skills for resolution. The AI reasoning challenge (ARC) [61] dataset is bifurcated into a challenge set and an easier set, primarily comprising science problems from elementary school level. Specifically, massive open online courses cube (MOOCCube) [62] stands as a substantial NLP dataset built upon real data. It amalgamates information from courses, concepts, student interactions, relationships, and external resources. It provides real and rich case data for application fields such as dropout understanding, recommendation, complex question answering, course concept extraction, and video intelligent jumping.

III. Methodology

A. Network Overview

The research focus of this article is to apply the latest research results of NLP to design intelligent-assisted

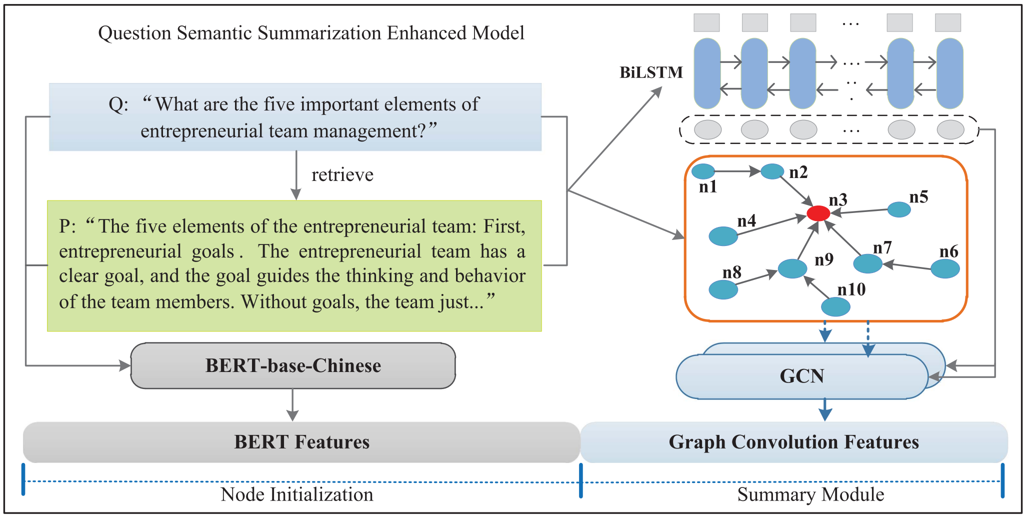

Fig. 2. Overview of the question semantic summarization enhanced model.

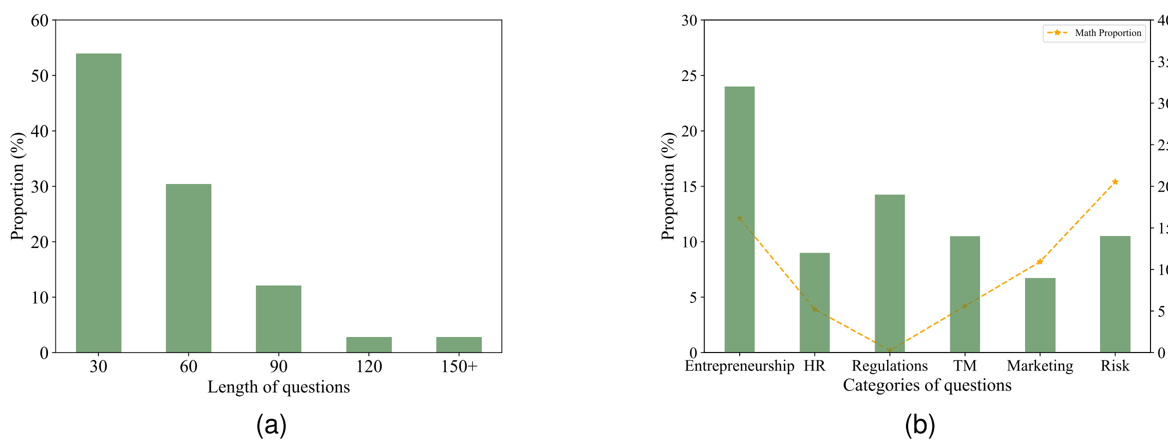

Fig. 3. Data analysis of entrepreneurial education question answering. (a) Length distribution of the questions. (b) Distribution of entrepreneurship education issues across six categories and the distribution of mathematical calculation tasks across each category, where HR represents human resources and TM represents team management.

question-answering models for personalized tutoring and real-time interaction needs in online entrepreneurship education. The article initiates by identifying pertinent topics in entrepreneurship education through keyword queries within datasets. Subsequently, it establishes a supplementary document retrieval approach grounded in online education exercises. Building upon entrepreneurship education data, the study presents an innovative question-answering model enriched with a text semantic summary module. It harnesses the robust capabilities of the extensive Chinese pretraining model BERT to extract text generalization features. Furthermore, it pioneers the development of a unique semantic feature acquisition model, underpinned by graph convolution within the context of text dependence parsing. The primary goal is to enable the provision of intelligent responses for single-choice questions in the domain of entrepreneurship education. Finally, in the model prediction stage, the constraint prediction of the question type is added to improve the reading comprehension ability of the model. Fig. 2 depicts the comprehensive framework and procedural flow of the model introduced in the study.

B. Data Collection for Entrepreneurship Education

The single-choice questions of entrepreneurship education used in this article come from 48 300 questions screened in MOOCCube [62] and 600 final exam questions of entrepreneurship education courses. In total, 3852 questions involve mathematical calculations. Initially, keywords are extracted from a pool of 1000 entrepreneurship-related documents (comprising reports and articles) utilizing the term frequency-inverse document frequency (TFIDF) [63] algorithm as delineated in (2), aimed at extracting pertinent questions. Fig. 3 illustrates the length and type distribution of the collected entrepreneurship education question and answer data in this article. Fig. 3(a) shows that the majority of question lengths do not exceed

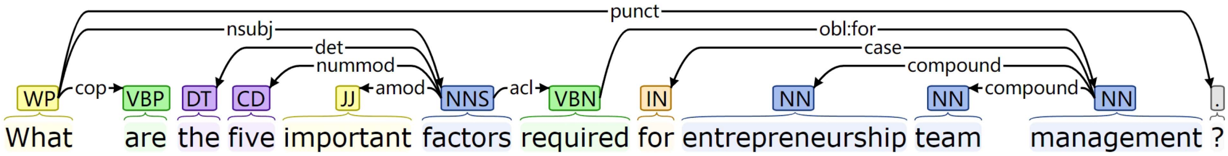

Fig. 4. Syntax dependence parsing results of the question Q.

120 characters. Fig. 3(b) reveals that, apart from topics related to "Entrepreneurship," the data are evenly distributed across various types, each supported by no fewer than 4000 data entries. In addition, over 15% of questions require mathematical calculations in risk-related tasks. Based on the term frequency-weighting algorithm, key terms such as "entrepreneurship," "innovation," "marketing," "business," "management," "investment," "human resources," "capital," "enterprise," "financing," and "customer" are selected. Utilizing these aforementioned keywords, a total of 48 300 entrepreneurship education-related questions are extracted from the dataset

$$\mathrm{tf}_{t,d} = \begin{cases} 1 + \log_{10}\mathrm{count}(t,d), & \text{if}\,\mathrm{count}(t,d) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where t represents the term within the question, while d encompasses all documents. For instance, if a word appears ten times, its term frequency (tf) equals 2.

Since the collected questions only contain option information and have no supporting documents, we designed an evidence document retrieval scheme. For a question and four candidate options, first retrieve the top 50 documents most relevant to the question from Google search as candidates. Subsequently, Flair [64] embeddings are employed to vectorize both the question and candidate documents individually. Flair can directly provide pretrained Chinese vocabulary vector representation, which is simple and convenient to invoke. Similar Chinese embedding methods, such as language technology plantform (LTP) [65] and natural language toolkit (NLTK) [66] can also replace Flair. These vectorized documents are then reorganized based on their cosine similarity values, with the top ten documents selected as supportive documents.

C. Construction of Question-Answering Model

1) Semantic Summarization Encoder: After concatenating question Q, candidate knowledge document P and candidate answers R, the resultant sequence undergoes paragraph embedding and bi-directional long short-term memory (BiLSTM) network processing to yield initial node embeddings

$$H_B = \mathrm{BiLSTM}(\mathrm{Drop}(\mathrm{Linear}(\mathrm{Embedding}(Q, P, R)))). \tag{3}$$

This article constructs two graph structures based on the text of question Q, candidate documents P, and candidate answers R.

a) *Graph 1. Syntactic dependence parsing graph:* The breakdown of questions and documents using the LTP [65] Chinese syntax dependence analysis tool is illustrated in Fig. 4. The subsequent step involves crafting the knowledge graph matrix A_1 grounded in the outcomes of the analysis. Table I lists common syntactic dependence parsing and labeling relationships

TABLE I
DEPENDENCY SYNTAX ANALYSIS ANNOTATION RELATIONS

Tag	Relation type	Tag	Relation type
SBV	subject-verb	VOB	verb-object
IOB	indirect-object	FOB	fronting-object
DBL	double	ATT	abbtribute
ADV	adverbial	CMP	complement
COO	coordinate	POB	preposition-object
HED	head	IS	independent structure

$$A_1 = \begin{Bmatrix} 1 & \mathrm{ATT} & 0 & 0 & 0 & \cdots & 0 \\ 0 & 1 & \mathrm{FOB} & 0 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \mathrm{SBV} & 0 & \cdots & 0 \\ 0 & 0 & 0 & 1 & 0 & \cdots & \mathrm{ATT} \\ 0 & 0 & 0 & \mathrm{VOB} & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 1 & \cdots & \mathrm{WP} \end{Bmatrix}.$$

b) *Graph 2. Interword distance graph:* Adjacent words are assigned a value of 1, while for other words, a value of $\frac{1}{d}$ is assigned (where d represents the positional distance of words). This process culminates in the creation of a graph matrix denoted as A_2 as follows:

$$A_2 = \begin{Bmatrix} 1 & \frac{1}{2} & \frac{1}{3} & \frac{1}{4} & \frac{1}{5} & \cdots & \frac{1}{n} \\ \frac{1}{2} & 1 & \frac{1}{2} & \frac{1}{3} & \frac{1}{4} & \cdots & \frac{1}{n-1} \\ \frac{1}{3} & \frac{1}{2} & 1 & \frac{1}{2} & \frac{1}{3} & \cdots & \frac{1}{n-2} \\ \frac{1}{4} & \frac{1}{3} & \frac{1}{2} & 1 & \frac{1}{2} & \cdots & \frac{1}{n-3} \\ \frac{1}{5} & \frac{1}{4} & \frac{1}{3} & \frac{1}{2} & 1 & \cdots & \frac{1}{n-4} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{1}{n} & \frac{1}{n-1} & \frac{1}{n-2} & \frac{1}{n-3} & \frac{1}{n-4} & \cdots & 1 \end{Bmatrix}.$$

For the knowledge graph matrices A_1 and A_2 and the initialized node feature embedding H_B, a semantic summarization encoding module is constructed using the graph convolutional neural network (GCN) [67]

$$\mathrm{GCN}(A_i, H_B) = \mathrm{GConv}_2(A_i, \mathrm{GConv}_1(A_i, H_B)) \in R^{l \times h}$$
$$\mathrm{GConv}(A_i, H_B) = \mathrm{relu}(A_i H_B^T W)$$
$$H_{\mathrm{sum}} = \Big\Vert_{i=1}^{2} \mathrm{GCN}(A_i, H_B) \in R^{l \times 2h} \tag{4}$$

where $\|$ is the concatenation of the two GCN heads, W is a trainable and learnable weight matrix, l is the sequence length, and h is the number of hidden layer nodes.

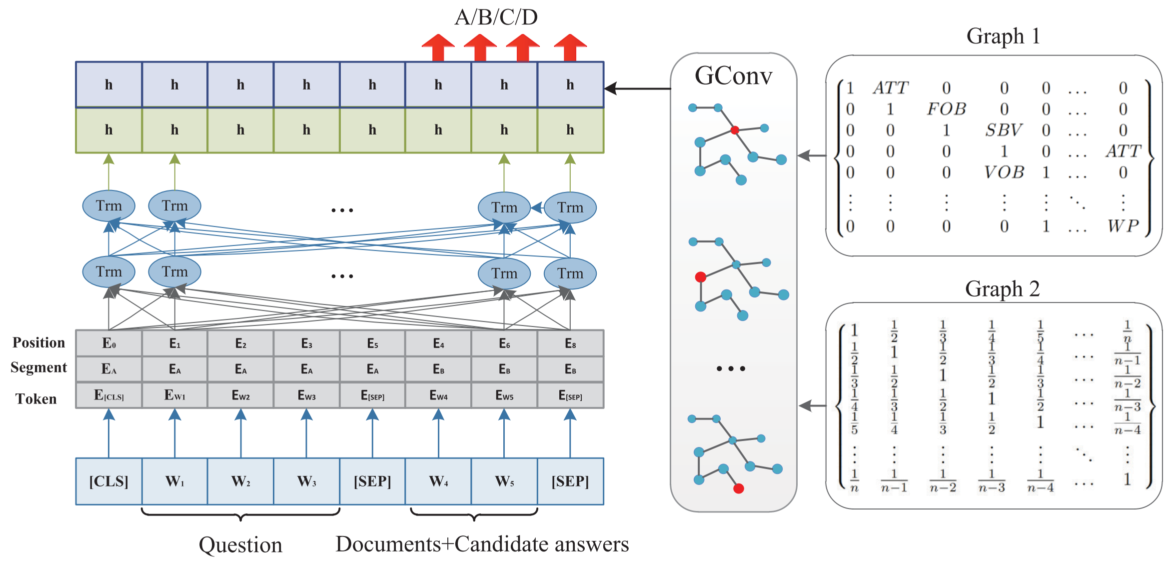

Fig. 5. Answer reading comprehension model diagram.

In addition to the aforementioned two graph structures, a variety of graph structures can be defined in other intelligent educational question-answering tasks, such as the visual graph based on multimodal image pixels, the entity association graph of text, etc.

c) Answer Reading Comprehension: In the reading comprehension stage, the initial step involves utilizing the Chinese pretrained BERT model to extract document features from both the question Q and the candidate documents P as follows:

$$H_T = \text{BERT}(Q, P, R) \in R^{l \times h}. \tag{5}$$

The BERT feature combines the vector feature of the question summary module to predict the answer as follows:

$$P(A|Q, P, R) = \text{Softmax}(W_H^T \cdot (\text{Concat}(H_{\text{sum}}, H_T))) \tag{6}$$

where W_H is the parameter matrix to be learned.

The aforementioned reading comprehension process outputs the probability of answer selection. Fig. 5 shows the internal structure of the answer prediction model, which mainly includes two parts: the BERT generalization feature extraction on the left and the GCN on the right to summarize the questions and document content. The experimental part will further analyze the role of the two feature extraction modules.

d) Mathematical Expression Generation: In the realm of intelligent entrepreneurship education question-and-answer systems, when questions involve financial analysis, budget formulation, or other calculations, the model need to retrieve the pertinent formula and provide the calculation equation to facilitate accurate answer predictions.

Following the graph-to-tree decoder [68], when the question content and the corresponding four options all contain numbers, the graph summary features will be used for expression generation

$$c = \sum_j \frac{\exp(\text{score}(q_{\text{root}}, H_{\text{sum}_j}))}{\sum_i \exp(\text{score}(q_{\text{root}}, H_{\text{sum}_i}))} H_{\text{sum}_j} \tag{7}$$

where $\text{score}(q_{\text{root}}, H_{\text{sum}_j}) = v_s^T \tanh(W_s[q_{\text{root}}, H_{\text{sum}_j}])$, and v_s^T and W_s are trainable parameters.

$$s(y|q_{\text{root}}, c, Q) = v_p^T \tanh(W_p[q_{\text{root}}, c, e(y|Q)]). \tag{8}$$

Taking the token with the highest probability as the final prediction $\hat{y}$ as follows:

$$\hat{y} = \arg \max_{y \in V^{dec}} \frac{\exp(s(y|q_{\text{root}}, c, Q))}{\sum_i \exp(s(y_i|q_{\text{root}}, c, Q))}. \tag{9}$$

If the prediction $\hat{y}$ is an operator, predict the left and right leaf nodes, respectively, with the current goal q as follows:

$$\begin{aligned} h_l &= \sigma(W_{h_1}[q, c, e(\hat{y}|Q)]) \odot \tanh(W_{h_2}[q, c, e(\hat{y}|Q)]) \\ q_l &= \sigma(W_{h_3} h_l) \odot \tanh(W_{h_4} h_l) \end{aligned} \tag{10}$$

where W_{h_1}, W_{h_1}, W_{h_3}, and W_{h_4} are trainable matrices. The prediction results of the left subtree are applied to the prediction of the right subtree

$$\begin{aligned} h_r &= \sigma(W_{h_5}[q, c, e(\hat{y}|Q)]) \odot \tanh(W_{h_6}[q, c, e(\hat{y}|Q)]) \\ q_r &= \sigma(W_{h_7}[h_r, t_l]) \odot \tanh(W_{h_8}[h_l, t_l]) \end{aligned} \tag{11}$$

where t_l is the summarization of the existing prediction sequence with a recursive neural network, and W_{h_5}, W_{h_6}, W_{h_7}, and W_{h_8} are trainable matrices. The model finally outputs the expression F_M and an answer A_M. In particular, when the question requires the generation of a mathematical expression and the model output result A_M is contained in four candidate options, select A_M as the answer prediction result.

e) Candidate Document Prediction Constraints: Supposing the set of candidate documents P comprises n documents (for this experiment, $n = 10$), this article develops a knowledge-supported document prediction module within the question-answering model to enhance the capability for semantic extraction of the model. Based on the accurate response content provided in the question label, the candidate document with the most extensive coverage of the answer text is selected and treated as the pseudolabel $\tilde{p}$. The prediction of the evidence document is then generated using BERT embedding features

$$P(p_i \mid Q, R) = \sigma(W_l^T \cdot (\text{BERT}(Q, p_i, R))) \tag{12}$$

where $P(p_i \mid Q)$ represents the probability that the document p_i is the evidence document, and W_l is a weight matrix. And, take the document with the highest probability as the output of the prediction result

$$\tilde{p}' = \arg\max_{p_i \in P} P(p_i|Q, R). \tag{13}$$

f) Model Training: By employing the cross-entropy loss function, the model parameters are learned through separate calculations for answer choice prediction and evidence document constraint prediction

$$L_{\text{ans}} = \frac{1}{N}\sum_{i=1}^{N}\left(-\sum_{j=1}^{4} g_{i,j}\log_2 P_{i,j}(A|Q, P, R)\right) \tag{14}$$

where $g_{i,j}$ is the probability true value of the ith training data on the jth answer option (if it is the correct option $g_{i,j} = 1$, otherwise $g_{i,j} = 0$), $P_{i,j}$ is the prediction probability of the model on the jth option of the ith data.

The loss function for knowledge-supported document-constrained prediction is

$$L_{\text{constraint}} = \frac{1}{N}\sum_{i=1}^{N}\left(-\sum_{j=1}^{n} \tilde{p}_{i,j}\log_2 \tilde{p}'_{i,j}\right) \tag{15}$$

where $\tilde{p}_{i,j}$ is the probability true value of the ith training data on the jth candidate document, and $\tilde{p}'_{i,j}$ is the prediction probability of the constrain model on the jth candidate document of the ith data.

The final overall loss function for answer prediction is as follows:

$$L = L_{\text{ans}} + \alpha L_{\text{constraint}} \tag{16}$$

where α is a threshold, and this article takes $\alpha = 0.5$ in the experiment.

IV. Evaluation Results and Discussion

A. Baseline

To verify the performance of the proposed model on the professional question-answering data of entrepreneurship education, following the method of previous publications [58], we compared the results of the collected questions with the following methods.

1) *Sliding window algorithm (SW) [69]:* It works by concatenating questions with answers, and then, using the TFIDF algorithm to compute matching scores for documents in a sliding window.
2) *Stanford attentive reader (SA) [70]:* The model first uses the GloVe word embedding tool to embed questions and documents separately. In particular, part of speech, named entities, term frequencies, and question-based attention alignment vectors are spliced during the paragraph embedding process. The embedded questions and documents are, respectively, extracted by BiLSTM for feature extraction and similarity calculation, and the final answer prediction can be obtained. The aligned paragraph embeddings are computed as follows:

$$f_{\text{align}}(p_i) = \sum_i a_{i,j} E(q_j) \tag{17}$$

where q_j is the jth word in the question, $E(q_j) \in R^d$ is its word embedding vector, and $a_{i,j}$ is the degree of association between the ith word p_i and q_j in the document, defined as follows:

$$a_{i,j} = \frac{\exp(\text{MLP}(E(p_i))^{\mathrm{T}}\text{MLP}(E(q_j)))}{\sum_{j'}\exp(\text{MLP}(E(p_i))^{\mathrm{T}}\text{MLP}(E(q_{j'})))} \tag{18}$$

where $\text{MLP}(x) = \max(0, W_{\text{MLP}}x + b_{\text{MLP}})$, and $W_{\text{MLP}} \in R^{d\times d}$ and $b_{\text{MLP}} \in R^d$ are the weight parameters and biases to be trained, respectively.
3) *Gated-attention reader (GA) [71]:* The model proposes a gated attention reader to compute the embedding matrix of the question and documents by integrating the attention mechanism into the multihop structure and further learning the unique embedding representation of the question.
4) *BERT reader [32]:* The BERT model is a deep language representation pretraining model that uses bidirectional transformers to extract contextual features. BERT randomly covers symbols through a masked language model, with the goal of predicting the original vocabulary of covered words based on context only. The "next sentence prediction" task was introduced to enable BERT learning to capture contextual associations between sentences.
5) *Axiomatic fuzzy set (AFS) graph reader [72]:* AFS Graph proposes a method to calculate the similarity between paragraphs, and realizes unsupervised retrieval based on the similarity described by fuzzy concepts. Furthermore, by defining a multidimensional axiom fuzzy set graph inference structure, the membership function is determined by data distribution and semantics. Simple concepts are feature-based basic units whose semantics are used to describe each candidate document. The similarity matrix of the candidate documents is calculated using the axiomatic fuzzy set logic system and the elements in the matrix are edges of the knowledge graph. Combined with the pretrained model efficiently learning an encoder that classifies token replacements accurately (ELECTRA) [73] to achieve open-domain answer reading comprehension.

B. Overall Results

To analyze the performance of the machine question-answering models in different knowledge points of entrepreneurship education, we divided the questions into five categories: human resources, regulations, team management, marketing, and risk management to test the performance of the models, respectively. The experimental results are shown in Table II. The accuracy of the model proposed in this article is 97% on the entire test set of the entrepreneurship data, which is 6.8% and 3.4% higher than BERT reader and the AFS graph, respectively.

TABLE II
PREDICTION RESULTS OF INTELLIGENT QUESTION-ANSWERING MODELS FOR ENTREPRENEURSHIP EDUCATION

Models	Entrepreneurship	Human resources	Regulations	Team management	Marketing	Risk management
Sliding Window ([69])	33.2	34.7	20.1	39.7	34.5	28.1
Stanford Attentive ([70])	72.9	74.9	56.4	81.8	77.0	68.4
Gated-Attention ([71])	78.1	80.9	63.8	86.0	88.2	62.3
BERT Reader ([32])	90.2	88.2	84.8	92.7	91.9	90.0
AFS Graph ([72])	93.6	94.5	**95.1**	95.0	97.2	84.2
QSSG	**97.0**	**95.3**	92.1	**97.8**	**99.0**	**97.6**

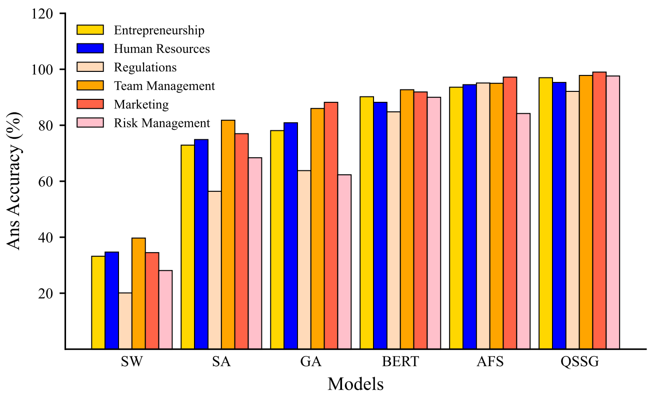

Fig. 6. Accuracy of models in entrepreneurship education question answering.

TABLE III
ABLATION ANALYSIS OF THE QSSG MODEL OF ENTREPRENEURSHIP EDUCATION

Models	Entrepreneurship
QSSG (full model)	**97.0**
remove document-constrain	95.8
remove equation generation	95.6
remove Semantic Summarization Encoder	90.7
remove R from H_B	96.4
remove BERT	82.6
only Graph 1	96.7
only Graph 2	95.2

Since most of the questions of the regulations category require complex multihop reasoning, the accuracy of the QSSG model in the regulations is lower than that of AFSGraph, which is exactly the type of questions that the AFSGraph model is more suitable for handling. It can be intuitively seen from Fig. 6 that the prediction accuracy of most models in the two categories of entrepreneurship regulations and risk management is lower than that of other categories. The reason for the aforementioned results may be that laws and regulations and risk monitoring require more prior information and professional knowledge background, which poses a high challenge to the intelligent question-answering model and is also the focus of subsequent research.

C. Ablation Study

To analyze the validity of each module of the QSSG model, an ablation study was conducted. First, the validity of the supporting document prediction constraint module was verified. As shown in Table III, the performance of the QSSG decreased by 1.2% after the operation of "remove document-constrain."

TABLE IV
COMPARATIVE ANALYSIS OF PR IN ENTREPRENEURSHIP EDUCATION KNOWLEDGE RETRIEVAL

Models	PR
QSSG	**98.2**
TFIDF ([63])	73.2
TextCNN ([74])	80.5
Bi-GRU ([75])	85.9
Bi-LSTM ([76])	86.6
Attention ([77])	95.8
Entity-centric IR ([78])	98.0

After removing the mathematical equation module, the prediction accuracy of the model is 95.6%. Then, after the operation of "remove semantic summarization encoder," the model performance is reduced by 6.3%, indicating that the knowledge semantic summarization module proposed in this article can significantly improve the model prediction effect. Furthermore, the performance of the model decreases significantly after BERT embedding is removed, which shows the importance of generalization features extracted by the pretrained BERT model to the question-answering model. In this article, two graph structures are constructed in the knowledge summary module, and further analysis shows that the prior information covered by graph 1 is more effective for the QSSG model.

The retrieval capability of the model for entrepreneurship education knowledge is the basis for the accuracy of the question-answering model. Therefore, we compare the retrieval part of the QSSG model with the commonly used models shown in Table IV. We evaluate the retrieval capability of the models using the paragraph recall (PR) rate. Specifically, we employ the models listed in Table IV to retrieve the top ten paragraphs most relevant to the questions. If the correct answer is included among them, PR equals 1; otherwise, PR equals 0. Experimental results indicate that compared to directly using the TFIDF model, the proposed model demonstrates a 25% increase in the retrieval PR rate.

D. Case Study

To verify the knowledge retrieval ability of the proposed QSSG model as an intelligent assistant in entrepreneurship education, a case study is applied with examples of the complex topics of entrepreneurship education. Fig. 7 shows three examples of entrepreneurship education question retrieval to analyze the ability of machine question-answering models to retrieve supporting documents. Question 1 mainly involves knowledge of finance and accounting subjects, Question 2 examines business

Question	Supporting Document
Q1: What are the accounting elements that reflect the operating results of an enterprise over a period of time? **A. Income, expenses and profit** B. Assets, liabilities and owners C. Income, assets and liabilities D. Assets, liabilities and profit	Accounting elements are financial accounting objects and basic classifications determined according to the economic characteristics of transactions or events. Accounting elements are divided into assets, liabilities, owner's equity, income, expenses and profits according to their nature. The elements of assets, liabilities and owner's equity focus on reflecting the financial status of the enterprise; the elements of income, expenses and profit focus on reflecting the operating results of the enterprise.
Q2: What is the nature of management activities? A. Management of things **B. Management of people** C. Management of funds D. Management of technology	The essence of management refers to the effective decision-making and planning of human resources, material resources, financial resources, information and other resources owned by the organization through planning, organization, command, coordination, control and innovation under specific environmental conditions, organize, lead, and control in order to efficiently achieve the established organizational goals.
Q3: In the stock issuance, when the investment bank adopts the balance underwriting method, who mainly bears the risk of issuance failure? A. Issuer's responsibility **B. Investment bank commitments** C. Issuers and investment banks undertake D. Is not responsible	The balance underwriting method is a common stock issuance method in which the investment bank will commit to purchase the shares not subscribed by investors to ensure the successful completion of the issuance. If during the balance underwriting issuance process, it is unable to attract enough investors to subscribe for shares, resulting in the failure of the issuance, the investment bank will need to bear the corresponding risks and losses in accordance with the agreement.

Fig. 7. Examples of entrepreneurship education question retrieval.

Q4: Assuming that the target customers account for 5% of the population, the user model is now used to score and sort the top 10% customers among 1000 potential customers, and 25 target customers are found among them. What is the improvement degree of this model at 10%? **A.5**, B.4, C.3, D.2

GPT3.5 Lift = proportion of target customers/total proportion =0.05/0.10=0.5, the lift of the model at 10% is 0.5, corresponding to option B.

QSSG P: lift is the ratio of confidence to expected confidence, which reflects how much the occurrence of item set A changes the occurrence probability of item set B, lift(A=>B)=P(B|A)/P(B).
Equation: (25/(1000*10%))/5%=5

Q5: If enterprise A sells 10 million products to enterprise B, and enterprise B receives the products and pays the payment 3 months later, enterprise A should now record it. **A.Accounts receivable**, B. Monetary funds, C.Accounts payable, D.Accounts received in advance.

GPT3.5 Because enterprise B has received the product but has not yet paid for it, this means that enterprise A has an account receivable (money owed by enterprise B to enterprise A) and should therefore record the account receivable in the assets. Because enterprise B has not yet paid for the goods, enterprise A needs to record accounts payable (money owed by enterprise A to suppliers) in its liabilities to reflect the unpaid goods. So, the correct answer is C. Accounts payable.

QSSG P: Accounts receivable refers to the amount that an enterprise should collect from the purchasing unit in the normal course of business due to the sale of goods, products and provision of services.

Fig. 8. Case studies of the QSSG model with the GPT3.5 model.

management and corporate management principles, and Question 3 includes knowledge of investment risks. The QSSG model has retrieved the correct supporting documents for the three questions in Fig. 7. The underlined content is the core semantic information used to answer the question, and the bold and underlined options are the correct answers. Simultaneously, it can be observed that there are discrepancies between the presentation of entrepreneurship education issues and the supporting documents. Simple direct methods of answer extraction fail to yield the correct options. This necessitates that question-answering models are capable of accomplishing knowledge and logic reasoning.

In addition to the accuracy of retrieval, the knowledge reasoning ability of the question-answering model is also the core ability of an intelligent entrepreneurship education assistant. Fig. 8 shows the comparison between the QSSG model proposed in this article and GPT3.5 on two typical examples of entrepreneurship education questions. Q4 is an application question involving mathematical calculation, the model needs to retrieve the calculation method of lift and correctly bring in values. The answer given by the GPT can be seen that it brings in incorrect values, causing logical errors and failing to find the correct answer. The proposed QSSG model supplements the mathematical reasoning requirements through the equation generation module and gives the correct answer. Q5 is an accounting professional question. The first half of the answer given by GPT is correct, but the second half generates information that is not included in the question, which ultimately results in an incorrect answer. The aforementioned two examples prove the validity of QSSG model's mathematical equation generation module and information summary and retrieval constraint module. The aforementioned case studies verify the superiority of the QSSG model in knowledge retrieval in related fields of entrepreneurship education and prove that the model proposed in this article has robust mathematical calculation and knowledge reasoning ability.

V. Conclusion

In this article, a machine reading comprehension model with semantic summary structure of questions and evidence documents is proposed for online instructor-assisted question-and-answer task in entrepreneurship education. This article collects the questions and answers of entrepreneurship education covering the fields of economy, laws and regulations, management, sales, etc. The model realizes text generalization and unique feature extraction by pretraining BERT and semantic dependence parsing graph structure. The addition of supporting document prediction constraints further improves the inference ability of the model. Furthermore, additional attention to the need for mathematical equations is of great significance to the questions and answers of entrepreneurship education. The experimental results demonstrate the strong predictive capabilities of the proposed model.

The contribution of the question and answer framework in this article mainly includes providing knowledge retrieval assistant for self-learning of learners in the field of innovation and entrepreneurship, and providing timely and accurate answer prediction for intelligent educational guidance. The semantic summary module proposed in this article can be widely used in teaching assistants of other subjects. According to the characteristics of the data of different subjects, graph structures can be constructed to understand and learn the semantics of the question, and realize the intelligent question and answer. In forthcoming research, we intend to delve deeper into the utilization of prior knowledge and intricate logic inherent to answering entrepreneurship education questions. We also aim to tackle the more intricate multihop knowledge questions that present greater challenges.

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