Exploring the Answering Capability of Large Language Models in Addressing Complex Knowledge in Entrepreneurship Education

Qi Lang, Shengjing Tian, Mo Wang, and Jianan Wang

Abstract—**Entrepreneurship education is critical in encouraging students' innovation, creativity, and entrepreneurial spirit. It provides essential skills and knowledge, enabling them to open their creative potential and apply innovative thinking across diverse professional fields. With the widespread application of large language models in education, intelligent-assisted teaching in entrepreneurship education is stepping into a new learning phase anytime and anywhere. Entrepreneurship education extends across interdisciplinary knowledge fields, incorporating subjects like finance and risk management, which require advanced mathematical computational skills. This complexity presents new challenges for artificial-intelligence-assisted question-and-answer models. The study explores how students can maximize the knowledge repository of current large language models to improve learning efficiency and experimentally validates the performance differences between large language models and graph convolutional reasoning models regarding the complex semantic reasoning and mathematical computational demands in entrepreneurship education questions. Based on case studies, it is found that despite the broad prospects of large language models in entrepreneurship education, they still need to improve in practical applications. Especially in tasks within entrepreneurship education that demand precision, such as mathematical computations and risk assessment, the accuracy and efficiency of existing models still need improvement. Therefore, further exploration into algorithm optimization, model fusion, and other technical enhancements can improve the processing capabilities of intelligent question-and-answer systems for specific domain issues, aiming to meet the practical needs of entrepreneurship education.**

Index Terms—**Entrepreneurship education, intelligence-assisted teaching, large language models, math word problem, question-and-answer models.**

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I. Introduction

THROUGH diverse teaching methodologies and curriculum designs, entrepreneurship education nurtures students' entrepreneurial spirit, innovative abilities, and business acumen [1]. It aims to equip them with the necessary knowledge, skills, and attitudes needed to navigate the complexities of entrepreneurship. This educational approach covers various topics, such as market research, business plan development, resource acquisition, risk management, marketing strategies, and innovation management [2], [3]. Machine question-answering models and chat agents have advanced retrieval capabilities and sophisticated logical understanding, offering crucial technical support for new developments in intelligent education [4]. The emergence of large language models, such as GPT [5], [6],[1] has opened new opportunities in entrepreneurship education. Students can now pose questions to these models anytime and receive immediate answers and solutions, aiding their understanding and application of entrepreneurship theories and practices [7], [8]. Large language models cover various entrepreneurship topics and fields, offering students' diverse and comprehensive knowledge and information about entrepreneurial processes and strategies [9]. Furthermore, they provide numerous entrepreneurship cases and successful experiences, inspiring students' entrepreneurial ideas and interests and fostering their entrepreneurial thinking and innovative abilities [4].

The challenges that large language models encounter in enhancing entrepreneurship education involve an interdisciplinary nature and an emphasis on innovation and risk-taking [10], [11]. The courses often span multiple disciplines, including marketing, financial management, and innovation management, showcasing its multidisciplinary nature [12]. Fig. 1 shows the frequency statistics of words in the entrepreneurship course topics. In contrast, other academic disciplines typically focus more on specific subject areas. Entrepreneurship education encourages students to embrace innovation and experimentation while confronting the risks and challenges inherent in the entrepreneurial process [13]. In comparison, other academic disciplines may

[1][Online]. Available: https://openai.com/index/sora/

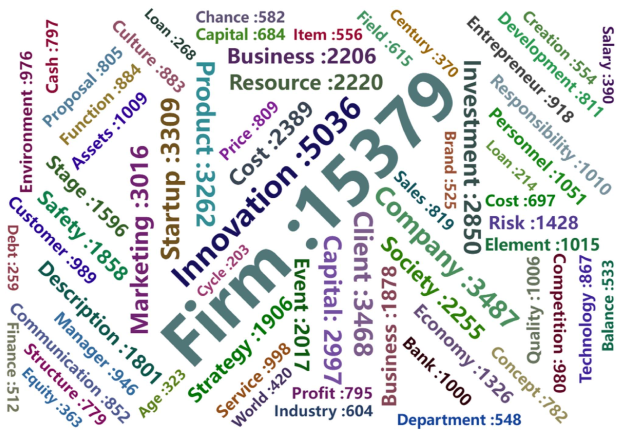

Fig. 1. Entrepreneurship education word cloud.

prioritize knowledge dissemination and skill development with less emphasis on innovation and risk management. Therefore, entrepreneurship education knowledge queries impose significant demands on the knowledge reasoning and computational capabilities of large language models.

With the teaching and comprehension of complex knowledge in entrepreneurship education gaining prominence, there is increasing interest in applying large language models. This study aims to explore the capability of large language models in handling complex knowledge within entrepreneurship education, focusing on their capacity for knowledge reasoning and computational abilities. By analyzing and evaluating their performance in addressing intricate issues in the entrepreneurial domain, we aim to gain deeper insights into the potential roles and limitations of large language models in entrepreneurship education. The article will investigate the following four research topics related to using large language models in querying entrepreneurship education.

1) *RQ1:* What interdisciplinary cultivation and complex computational tasks are involved in entrepreneurial education?
2) *RQ2:* How do intelligent question-answering models address the challenge of solving numerous mathematical word problems in entrepreneurship education?
3) *RQ3:* What are the strengths and weaknesses of large language models and conventional deep learning models in entrepreneurial education question-answering tasks?
4) *RQ4:* What are the differences in abilities and characteristics among various large language models in inferring complex semantic knowledge related to entrepreneurial education?

II. Related Works

This article explores the methodologies and roles of large language models in enhancing question-answering applications within entrepreneurship education. Related research includes an analysis of the interdisciplinary nature of entrepreneurial education, the integration of artificial intelligence models in educational contexts, and an introduction to complex reasoning artificial intelligence models.

Q1: Assume the target customers constitute 5% of the population. Based on the user model, after scoring and sorting, among the top 10% of the 1000 potential customers, there are 25 target customers identified. What is the lift of this model at the 10% threshold?
Q 2 : In which account is the salary of personnel in the company's finance department recorded?
Q3: In what historical context did the jungle of management theories emerge?

Fig. 2. Postlecture exercises in entrepreneurship education.

A. Challenges in Entrepreneurship Knowledge Reasoning

The definition of the task for intelligent knowledge retrieval and reasoning question and answer in entrepreneurial education is provided. For a text-based question Q and a knowledge base KB, the retrieval model identifies and extracts the top-k most relevant candidate documents set C from KB based on the content of the question [14]

$$C = \text{Retriever}(Q, KB). \tag{1}$$

Furthermore, the reasoning model performs deep reading comprehension and logical inference on the semantic information of the retrieved text data, predicting or generating answers according to the task requirements [15]

$$R = \text{Reasoner}(Q, C). \tag{2}$$

Fig. 2 presents questions from three entrepreneurship education courses. *Q1* pertains to using a user scoring model for customer segmentation, involving mathematical operations and knowledge of lift. It challenges reasoning and mathematical skills in educational question-and-answer models. Question *Q2* examines knowledge related to the sources of funding for enterprises and the generation of profits, primarily assessing students' financial abilities. Question *Q3* is derived from the section on the evolution of management theories in the Introduction to Management course, describing the state of Western management studies after World War II. The aforementioned examples demonstrate that entrepreneurship education covers many knowledge areas, is highly specialized, and requires strong mathematical reasoning skills. Therefore, leveraging large language models can significantly aid in meeting the challenges of entrepreneurship education.

B. Large Language Models Empower Intelligent Tutoring

Large language models empower intelligent tutoring by providing robust support and capabilities through instant answering [16], [17], personalized guidance [18], [19], study plan formulation [20], [21], learning resource recommendations [22], [23], and learning process monitoring [24], [25]. Students can pose questions to large language models anytime and receive immediate accurate answers [26]. This instant answering capability aids students in resolving doubts and confusion during learning, enhancing learning efficiency. Large language models can monitor students' learning processes and promptly identify issues and difficulties. By analyzing students' learning behaviors and performances, the models can offer tailored learning advice and assistance, helping students overcome learning obstacles and achieve better academic outcomes [27]. Hu et al. [28] used mathematics teaching as an example to analyze the performance of GPT-4 in generating instructional materials. They found that the large model still needs improvement in interdisciplinary assessment and knowledge of geometry and algebra. Li et al. [29] explored the differences in evaluating the quality of student-generated questions using GPT compared to human experts. They found that GPT can achieve expert-level performance regarding topic relevance and difficulty but needs to assess cognitive level. Zhai et al. [30] found that integrating multiple sources of information using conversational agents powered by large language models can stimulate participants' thinking. Researchers propose node embedding learning models to perceive the evolving implicit cognitive states of learners, addressing multiple intelligent educational application tasks involving non-formatted graphical data in educational big data [17].

There are still many challenges in using large language models for teaching assistance in professional fields. These include the possibility of errors or inaccuracies in responses leading to student misunderstandings and the inadvertent perpetuation of biases present in the training data by large language models. Therefore, ensuring that the responses and guidance provided by the models are fair and unbiased is crucial for providing equal learning opportunities for all students.

C. Educational Knowledge Question-Answering Models

Educational question-answering systems based on large language models offer extensive knowledge coverage, spanning multiple subjects and domains. These models can understand the context and intent behind questions, generating answers through profound semantic comprehension rather than mere keyword matching. Researchers utilize Gradient Boosting Tree classification models to construct a more refined method for evaluating students' free-text responses, further uncovering and explaining the semantic facet matching patterns of different student answers [31]. The Explanations for Textbook Question-Answering model proposes an interpretable paragraph-level sentence combination question-answering model for knowledge reasoning in the complex multimodal task of textbook question answering [32]. The knowledge-based iterative consensus natural language explanation (KICNLE) model integrates additional knowledge and proposes an iterative answer generation method with coherent evidence chaining for visual question answering, achieving high-quality answer generation [33]. Luo et al. [34] investigated the novel task of embodied question answering for personal assistants. They enhanced the model's ability to perform complex reasoning and provide accurate feedback from noisy data through training with a co-regularization learning method. The Feature Crosses Information-Based Knowledge Tracing model focuses on capturing complex higher order relationships between concepts during personalized student modeling, introducing dynamic semantic information to simulate real educational scenarios [35]. The paper [36] addresses the highly challenging task of intelligent tutoring in mathematics learning, focusing on reasoning skills. It utilizes existing manually annotated multidisciplinary learning resources to create training data, enhancing the model's ability to resist interference in context comprehension.

Knowledge question-answering models offer new opportunities to enhance educational experiences and provide customized learning solutions for specific issues. However, applying natural language question-answering models in entrepreneurship education currently faces challenges, including low accuracy of information and incomplete integration of mathematical reasoning with entrepreneurial knowledge.

III. Methods

A. Network Overview

This article explores the application of large language models in assisting with complex problem solving in entrepreneurship education. It primarily includes the analysis of complex semantics and challenging aspects in entrepreneurial education question and answer data, the comprehension of the question and answer model and its application in solving mathematical problems using financial knowledge, and the performance of large language models in entrepreneurship education question and answer. The main technologies used in this article include Chinese word segmentation and word frequency statistics in natural language processing, as well as a graph-to-tree generation model.

B. Analysis of Entrepreneurship Education Questions

The entrepreneurship education question data used in this article are sourced from the dataset MOOCCube [37] and a collection of post-massive open online courses (MOOC) exercise questions, totaling 48 330 question and answer pairs. As the entrepreneurship education data analyzed in this article are in Chinese, they necessitate the incorporation of Chinese word segmentation technology. Common Chinese word segmentation tools include Jieba,[2] hanNLP,[3] pkuseg,[4] and THULAC.[5] Table I summarizes the characteristics of four common word segmentation tools. This article uses the Jieba word segmentation tool to segment and perform frequency statistics on 48 330 entrepreneurship questions. Table II lists the top 26 word frequencies from the segmentation results of these entrepreneurial issues. It can be seen that words like "management," "innovation," "cost," and "marketing" frequently appear, indicating a wide range of issues involved in entrepreneurship. Further analysis revealed that 7% of the questions in entrepreneurial education question and answer tasks require mathematical calculations. These questions demand that models provide theoretical knowledge and calculation formulas, generating the formulas based on semantic analysis of the question.

C. Generating Mathematical Formulas for Entrepreneurial Questions

The article introduces representative graph-to-tree generation models and GPT for solving and comparing discussions on the

[2][Online]. Available: https://github.com/fxsjy/jieba
[3][Online]. Available: https://github.com/hankcs/HanLP
[4][Online]. Available: https://github.com/lancopku/pkuseg-python
[5][Online]. Available: https://github.com/thunlp/THULAC-Python

TABLE I
INTRODUCTION TO FOUR CHINESE WORD SEGMENTATION TOOLS

Models	Characteristics
Jieba	Precise, full, and search engine modes, allows for user-defined dictionaries.
hanNLP	Supports 130 languages, fully functional.
pkuseg	Multidomain segmentation, supports user training.
THULAC	Trained on a large scale with high accuracy.

TABLE II
WORD FREQUENCY RANKING OF ENTREPRENEURIAL QUESTIONS

Word	Frequency	Word	Frequency
Management	15 584	Business	2206
Firm	15 379	Event	2017
Innovation	5036	Strategy	1906
Company	3487	Safety	1858
Client	3468	Description	1801
Startup	3309	Stage	1596
Product	3262	Economy	1326
Marketing	3016	Socialism	1315
Capital	2997	Personnel	1051
Investment	2850	Element	1015
Cost	2389	Responsibility	1010
Society	2255	Assets	1009
Resource	2220	Quality	1006

Q: Given that the operating revenue of the enterprise in 2014 was 45,000 million yuan, the average balance of current assets was 6,000 million yuan, and the average balance of fixed assets was 12,000 million yuan, assuming no other assets.The total asset turnover ratio for the enterprise in 2014 is how many times?

Domain knowledge:
Total asset turnover ratio = Net operating revenue / Average total assets
= Net operating revenue / (Average balance of current assets + Average balance of fixed assets)

Answer:
45,000/(6,000+12,000)=2.5

Fig. 3. Postlecture exercises in entrepreneurship education.

generation of semantically and logically challenging mathematical computation questions and answers in entrepreneurial education. The graph-to-tree generation model is a neural network architecture that transforms textual data into a graph structure with interconnected nodes, capturing semantic logic through graph encoding networks such as graph neural networks and graph convolutional networks (GCNs). Deep features encoded from the graph are used to generate a hierarchical tree structure, connecting numerical values with operators during the generation process, ultimately producing a mathematical formula.

Fig. 3 illustrates an entrepreneurial question and answering example that involves mathematical calculations, specifically focusing on asset turnover ratio. A mathematical problem text mainly consists of word tokens and certain quantities, such as the three numbers 45 000, 6000, and 12 000 shown in Fig. 3, which are crucial pieces of information for calculating the answer. To emphasize the semantic relationships between quantities, this article introduces a GCN, as depicted in Fig. 4, for analyzing and solving entrepreneurial knowledge.

The question embedding vector E_p is initialized graph convolution nodes by bidirectional encoder representations from transformers (BERT) feature learning

$$H = \mathrm{BERT}(\mathrm{Liner}(E_p)). \tag{3}$$

The adjacency matrix A_k of the graph can be constructed based on semantic analysis methods such as syntactic dependence parsing. The GCNs are utilized for encoder (initialize node embedding H_p is H)

$$\begin{aligned} \mathrm{GCN}\left(A_k, H_p\right) &= \mathrm{GConv}_2\left(A_k, \mathrm{GConv}_1\left(A_k, H_p\right)\right) \\ \mathrm{GConv}\left(A_k, H_p\right) &= \mathrm{relu}\left(A_k H_p^T W\right). \end{aligned}$$

D. Data Collection

To investigate the understanding and demand for entrepreneurial knowledge among various professional groups, we designed a questionnaire featuring eight multiple-choice entrepreneurial questions, as illustrated in Fig. 5. The eight questions in the questionnaire cover various subjects such as accounting, financial analysis, customer relations, management, and operations. We collected a total of 92 responses, including 32 undergraduate students, 20 working professionals, 22 recent undergraduate graduates, and 18 recent master's graduates. Fig. 6 displays the distribution of respondents based on the number of questions answered correctly. The data reveal that only two individuals answered all eight questions correctly, whereas the highest number of respondents (23 individuals) answered four questions correctly. Only 12 individuals selected the correct answer for the third question, marking it as having the lowest accuracy rate among all the questions. We also added a question to the survey asking participants to rate their demand for entrepreneurship education on a scale of 1–5. Fig. 7 illustrates the average ratings given by respondents at different career stages. The survey results show that undergraduate students have a higher demand for learning entrepreneurial knowledge. The average score for the demand among working staff is only 2.4, possibly because they already have stable jobs and lives. Meanwhile, we found that recent master's graduates generally have a higher desire to learn entrepreneurial knowledge compared to recent undergraduate graduates.

To further explore the mathematical solving capabilities of different types of entrepreneurial education question-answer models, we conducted comparative experiments on two publicly available datasets: MAWPS [38] and Math23K [39].

IV. EXPERIMENTS AND DISCUSSION

A. Baseline

We conduct comparative experiments on EEH-G2T, ChatGPT-3.5, ChatGPT-4o, and ERNIE Bot Models to analyze their performance.

1) EEH-G2T [40] is a graph-to-tree-type mathematical problem-solving generative model considering long-range graph correlations.

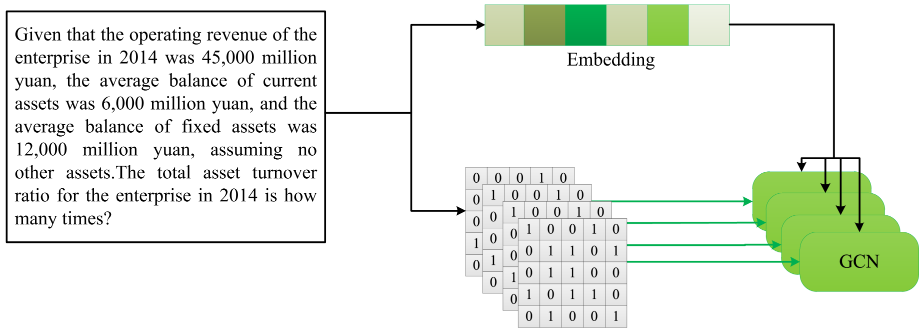

Fig. 4. Schematic diagram of entrepreneurial question graph convolutional encoding.

1. Where are the salaries of employees in the finance department accounted for?
A. Sales expenses **B. Administrative expenses** C. Financial expenses D. Manufacturing costs

2. On September 1st, a certain company had total assets of 30,000 yuan and total liabilities of 10,000 yuan. In September, the company had the following transactions: total income amounted to 15,000 yuan and total expenses amounted to 24,000 yuan. What was the shareholders' equity of the company for September?
A. 20000 B. 9000 **C. 11000** D. 21000

3. Once a new product category is introduced, a flood of competing products emerges. Which of the following options becomes the key determinant of success or failure?
A. Product packaging B. Product pricing **C. Customer choice** D. Technological innovation

4. Which marketing concept is described by the statement "emphasizing salesperson skills and believing that businesses must actively promote products to customers"?
A. Production orientation B. Product orientation **C. Sales orientation** D. Customer orientation

5. What is the essence of management activities?
A. Management of people B. Management of things C. Management of funds D. Management of technology

6. The formation of corporate culture primarily depends on what?
A. The needs of the environment **B. Leadership advocacy** C. Continuous promotion D. Continuous reinforcement

7. Employees in companies with tightly packed work schedules should not adopt which of the following methods for training needs assessment?
A. Questionnaire method B. Observational method **C. Interview method** D. Archival method

8. In the year 20XX, a certain company had interest-bearing liabilities of 800,000 yuan, shareholders' equity of 1,200,000 yuan, post-tax operating net profit of 200,000 yuan, net profit of 150,000 yuan, and an investment capital cost of 9%. What is the economic profit of the company ?
A. 20,000 yuan B.200,000 yuan C. 180,000 yuan D. 30,000 yuan

Fig. 5. Entrepreneurship education test questions.

2) ChatGPT-3.5 is a large model developed by OpenAI with the ability to reinforce learning and reconsider from human feedback.
3) ChatGPT-4o represents OpenAI's versatile breakthrough extending from text to encompass audio and image domains. It holds promising applications across various fields including customer support, content creation, and education.
4) ERNIE Bot, which stands for Enhanced Representation through Knowledge Integration with semantic Bottlenecks, is an advanced language model developed by Baidu. It possesses extensive potential applications in fields such as generative artificial intelligence on education.

B. RQ1: What Interdisciplinary Cultivation and Complex Computational Tasks are Involved in Entrepreneurial Education?

Entrepreneurship education goes beyond business skills to encompass interdisciplinary cultivation. It integrates business knowledge with market analysis skills, demanding that students master market trends, consumer behavior, and competitive analysis. Entrepreneurs typically rely on innovative and

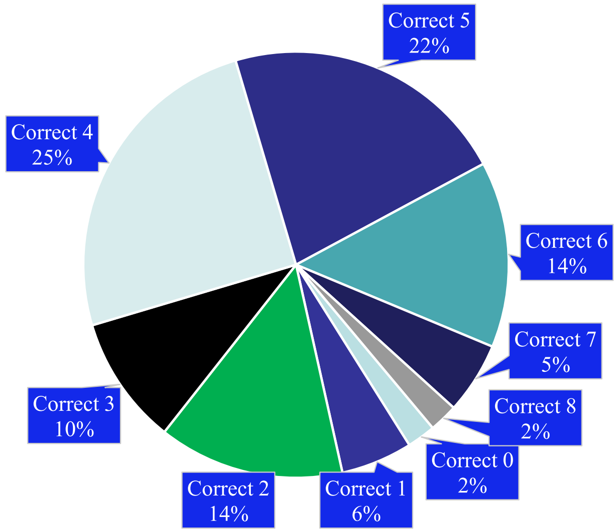

Fig. 6. Pie chart of the distribution of correct answers.

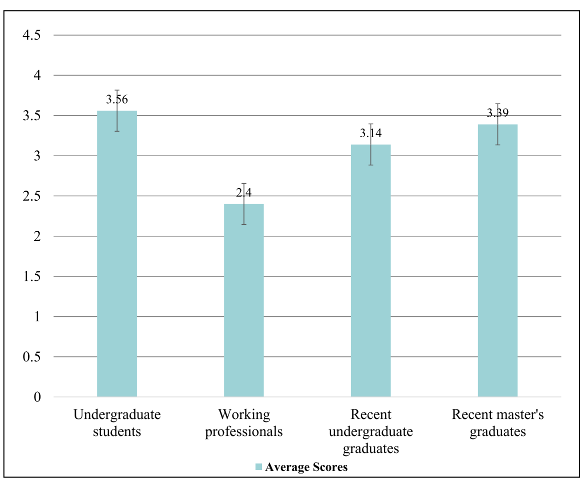

Fig. 7. Bar chart of the average score of entrepreneurial knowledge needs of different groups.

design thinking to develop products and services from conception through execution. Moreover, a thorough understanding of legal and business ethics is essential; entrepreneurs must effectively navigate compliance issues and ethical challenges. The frequency results in Table II validate the need for entrepreneurship education to encompass complex computational tasks, such as data analysis and big data processing, enabling the extraction of insights from large datasets to support decision making. Questions 2 and 8 in Fig. 5 highlight that entrepreneurs must possess financial and mathematical understanding. Hence, entrepreneurial learners encounter the challenge of acquiring and integrating knowledge across multiple domains.

In a comprehensive view, entrepreneurship education goes beyond imparting mere business skills—it is an interdisciplinary curriculum encompassing in-depth learning and integrated application across various domains, including business, mathematics, design, law, and finance. The emergence of intelligent question-answering systems, particularly large language models, has significantly facilitated learning opportunities for

User: Help me create a study guide for entrepreneurial knowledge.

Outline for Entrepreneurship Knowledge Learning

I. Fundamentals of Entrepreneurship
- Introduction to Entrepreneurship:
- Entrepreneurial Mindset and Skills

II. Market Analysis
- Market Research
- Competitive Analysis
- Market Trends

III. Business Planning
- Business Plan Writing
- Financial Planning
- Operational Planning

IV. Legal and Ethical Issues
- Legal Fundamentals
- Business Ethics

V. Finance and Accounting
- Basic Financial Knowledge
- Funding and Investment

VI. Marketing
- Marketing Strategy
- Digital Marketing

VII. Innovation and Technology
- Innovation Management
- Technology Application

VIII. Internationalization and Global Markets
- International Market Entry Strategies
- Cross-Cultural Management

IX. Case Studies and Practice
- Successful Entrepreneurship Cases
- Entrepreneurship Simulation and Practice

Fig. 8. Example of a teacher using a large model to create an entrepreneurship course outline.

TABLE III
RESULTS FOR 120 MATH QUESTIONS

Models	120 Math Questions
EEH-G2T	65.8
ERNIR	74.2
ChatGPT-3.5	86.7

entrepreneurs. Such holistic training aids in the well-rounded development of entrepreneurs, equipping them to succeed in intricate and evolving business landscapes.

During the course design process, teachers can utilize intelligent generative models to develop a structured entrepreneurship knowledge outline that covers core areas and critical content systematically, as illustrated in Fig. 8. When teachers need to consult specialized knowledge and assist with teaching inquiries, they can utilize open-source domain-specific intelligent analysis models (such as those for mathematical problem-solving or risk assessment). These models harness their accuracy and domain expertise to offer more precise knowledge retrieval solutions for educators and students.

C. RQ2: How Do Intelligent Question-Answering Models Address the Challenge of Solving Numerous Mathematical Word Problems in Entrepreneurship Education?

We randomly selected 90 questions from the test set of the Math23 dataset, along with 30 entrepreneurial education homework questions that involve calculations, totaling 120 math problems. Table III displays the accuracy of three artificial intelligence models in answering these 120 questions. It reveals that ChatGPT-3.5 can accurately solve 86.7% of these questions. However, the addition of entrepreneurial questions has lowered the accuracy of the EEH-G2T model, which specializes in solving mathematical application questions. As large language models, such as ChatGPT-4o, have emerged, they have integrated a wealth of global knowledge into intelligent systems, significantly enhancing the capability to intelligently solve entrepreneurial education support questions, especially in the realm of mathematics. In Fig. 9, case 1 represents a mathematical application question. The results reveal that the graph convolutional tree-based EEH-G2T model generated an incorrect

Case 1: A class of students planted 400 sunflowers, and the average yield of each sunflower seed was 0.25 kg. If you can press 0.18 kg of oil per kg of sunflower seeds, how many kilograms of oil can be extracted from the sunflower seeds in this class?

EEH-G2T: X=0.25*0.18; (error) **ChatGPT-3.5: 400×0.25×0.18**

Case 2: On September 1st, a certain company had total assets of 30,000 yuan and total liabilities of 10,000 yuan. In September, the company had the following transactions: total income amounted to 15,000 yuan and total expenses amounted to 24,000 yuan. What was the shareholders' equity of the company for September?

ERNIE Bot: 15000-24000=-90000; (error) **ChatGPT-4o: 30000-10000+(15000-24000)=11000**

Case 3: In the year 20XX, the total liabilities of a company amounted to 1.2 million yuan, of which 300,000 yuan were interest-bearing liabilities. The asset-liability ratio was 50%. The net profit after tax for the year was 150,000 yuan, with a net profit of 120,000 yuan. Please calculate the return on investment capital for the company for that year.

ChatGPT-3.5: 1.5\((1.2\0.5-1.2+0.3)\2)=0.2; (error) **ChatGPT-4o: 15\(30+120)=0.1**

Fig. 9. Comparison of solutions for three mathematical problems.

answer, whereas ChatGPT-3.5 provided the correct answer and outlined the process of computational logical reasoning. Case 2 concerns a calculation problem involving shareholder equity in entrepreneurial issues. The large language models ERNIE Bot and ChatGPT-4o both provide detailed calculation processes. However, due to ambiguities in understanding the question, the ERNIE Bot model generated incorrect results. The mathematical computation and conversational question-answering capabilities of ChatGPT-3.5 have surpassed most deep learning question-answering models and some pretrained large models. The complex calculation question in Case 3, involving investment and financial knowledge, posed a challenge for ChatGPT-3.5. However, the enhanced computational capabilities of ChatGPT-4o successfully provided the correct answer.

With extensive learning and a comprehensive understanding of world knowledge by large models, intelligent question-answering assistants can now provide satisfactory teaching support for entrepreneurship learners. These models accurately answer complex entrepreneurial questions and offer in-depth explanations and personalized learning recommendations, helping users efficiently grasp key concepts and skills during the learning process. Their robust computational abilities and broad knowledge base enable them to address various needs, providing comprehensive learning support and real-time solutions for entrepreneurs.

D. RQ3: What are the Strengths and Weaknesses of Large Language Models and Conventional Deep Learning Models in Entrepreneurial Education Question-Answering Tasks?

Pretrained large models trained on extensive datasets can understand and process complex natural language texts, including specialized terms and contexts in the entrepreneurial domain. This capability is crucial for text parsing and answer generation in entrepreneurial education question-answering tasks. Large models generally demonstrate robust generalization capabilities, allowing them to handle novel tasks or domains without requiring specific retraining. This flexibility and adaptability make large models particularly effective in entrepreneurial education question-answering tasks. Experimental results from Table III indicate that the EEH-G2T model's accuracy declines when new entrepreneurial questions are introduced to the original test dataset. Large-scale models can adapt to specific tasks and data through fine-tuning, enabling them to excel in diverse application scenarios. For instance, models in the GPT series can comprehend context to generate detailed case studies and strategic analyses relevant to entrepreneurship education, offering valuable advice to entrepreneurs. They can address fundamental questions about entrepreneurship education and provide personalized recommendations and guidance based on user input. Deep learning models offer relative flexibility in structural design, allowing for customization and optimization based on specific task requirements. For entrepreneurship education questions and answering tasks, appropriate model architectures can be tailored to accommodate the complexity and diversity of questions. Deploying and utilizing these models in resource-constrained educational environments becomes more straightforward and viable.

In conclusion, both large language models and deep learning models have their respective advantages and disadvantages in entrepreneurship education question and answering tasks. The choice of the appropriate model should take into account specific task requirements, available computational resources, data accessibility, and other relevant factors.

E. RQ4: What are the Differences in Abilities and Characteristics Among Various Large Language Models in Inferring Complex Semantic Knowledge Related to Entrepreneurial Education?

We input the eight entrepreneurship questions from Fig. 5 into the ERNIE Bot and ChatGPT-4o large models to compare how

1. Where are the salaries of employees in the finance department accounted for?
ERNIR：B. Administrative expenses (✓) The salaries of the finance department employees belong to the company's daily operations management expenses and should therefore be recorded under management expenses.
ChatGPT-4o: B. Administrative expenses (✓) The salaries of the finance department employees should be recorded as management expenses.
2. On September 1st, a certain company had total assets of 30,000 yuan and total liabilities of 10,000 yuan. In September, the company had the following transactions: total income amounted to 15,000 yuan and total expenses amounted to 24,000 yuan. What was the shareholders' equity of the company for September?
ERNIR：B. 9000 (×) Shareholder equity = Total assets - Total liabilities. Initial shareholder equity = 30,000 yuan - 10,000 yuan = 20,000 yuan. September transactions resulted in changes in net assets, specifically shareholder equity change = Total revenue - Total expenses = 15,000 yuan - 24,000 yuan = -9,000 yuan. Shareholder equity in September = Initial shareholder equity + Change in shareholder equity for September = 20,000 yuan - 9,000 yuan = 11,000 yuan, but note that this actually represents a decrease of 9,000 yuan, so the final answer reflects the negative change, which is 20,000 yuan - 9,000 yuan = 11,000 yuan (however, the question asks for the changed value, so the answer is option b. 9000, indicating a decrease of 9,000 yuan).
ChatGPT-4o: C. 11000 (✓) 1. Calculate the initial shareholder equity: Initial shareholder equity = Total assets - Total liabilities = 30,000 yuan - 10,000 yuan = 20,000 yuan 2. Calculate the net loss for September: Net loss = Total revenue - Total expenses = 15,000 yuan - 24,000 yuan = -9,000 yuan 3. Calculate the ending shareholder equity: Ending shareholder equity = Initial shareholder equity + Net loss = 20,000 yuan + (-9,000 yuan) = 11,000 yuan
3. Once a new product category is introduced, a flood of competing products emerges. Which of the following options becomes the key determinant of success or failure?
ERNIR：D. Technological innovation (×) In a fiercely competitive market, technological innovation is the key factor determining whether a product can stand out. While packaging, pricing, and customer selection are important, technological innovation often dictates the core competitiveness and market position of a product.
ChatGPT-4o: D. Technological innovation (×) When new product categories emerge, a plethora of competing products often follows suit. In such scenarios, the key determinant of success is typically technological innovation. Technological innovation enables products to distinguish themselves in terms of functionality, quality, or user experience, thereby attracting customers and establishing competitive advantages.
6. The formation of corporate culture primarily depends on what?
ERNIR：B. Leadership advocacy (✓) The formation of corporate culture primarily relies on leadership advocacy and promotion. The values, behaviors, and expectations of leaders profoundly influence the formation and development of corporate culture.
ChatGPT-4o: D. Continuous reinforcement (×) The formation of corporate culture primarily relies on continuous reinforcement. While environmental demands, leadership advocacy, and ongoing promotion all play roles in shaping corporate culture, continuous reinforcement is key. By consistently reinforcing and solidifying core values, behavioral norms, and cultural principles, corporate culture can resonate deeply and be sustained and developed over time.
7. Employees in companies with tightly packed work schedules should not adopt which of the following methods for training needs assessment?
ERNIR：D. Archival method (×) For employees in companies with tight work schedules, using the document-based method for training needs assessment may not be suitable. This approach requires extensive review of historical records, which can be time-consuming. Employees in such companies may not have sufficient time and energy to cooperate with this assessment method.
ChatGPT-4o: C. Interview method (✓) In companies with tight work schedules, time and human resources are typically very limited. The survey method is often efficient in terms of time and less disruptive to work, making it suitable for use in compact work environments. While the observational method is effective, it requires managers or training specialists to spend time observing employees' daily work, which may not be feasible due to time constraints. The interview method involves extensive one-on-one communication and may not be practical in companies with tight work schedules. The document-based method involves reviewing employees' historical records and performance data, which generally does not cause significant disruption to employees' current work arrangements.

Fig. 10. Answers of the ERNIE Bot and ChatGPT-4o models on entrepreneurship questions.

each model responded. Both models provided accurate analyses and generated correct answers for questions 1, 4, 5, and 8. ChatGPT-4o answered six questions correctly, while the ERNIE Bot model answered five questions correctly. Fig. 10 presents partial answer results and the reasoning process. Question 1 pertains to the categorization of financial items, explicitly inquiring about where the salaries of employees in the finance department are recorded or accounted for. It is evident that large-scale models, with comprehensive knowledge inputs, can generally produce accurate answers effectively. Question 2 pertains to arithmetic in accounting and finance, primarily testing understanding and computational skills related to financial statement elements, such as total assets, total liabilities, and shareholder equity. The results of the answer generation show that while the ERNIE model reasoned correctly through the process, it faced ambiguity in understanding the question, leading to an "overinterpretation" and ultimately selecting an incorrect answer. Question 3 examines the critical factors of market competition and product success. Notably, both large models incorrectly chose technological innovation as the determining factor. However, the question specifies that a new product category has emerged, shifting the competitive emphasis to customer choices. This outcome highlights how large models can be susceptible to errors influenced by rigid thinking patterns. Questions 6 and 7, respectively, are about the primary factors in forming corporate culture and selecting and considering training needs assessment methods in busy work environments. ChatGPT-4o incorrectly chose continuous reinforcement as the main factor in creating corporate culture. At the same time, the ERNIE model indicated that document-based methods are more time consuming and labor intensive than interview methods.

Different large-scale models vary in their coverage and depth of specialized knowledge. Some models are trained to focus more on general knowledge and answering common questions, while others may provide more specialized answers through training and fine-tuning in specific domains. Large models may exhibit biases or errors when interpreting complex concepts or reasoning tasks. These biases can stem from biases in training data, inherent limitations of algorithms, or incomplete understanding of the question. Therefore, fine-tuning or training proprietary large models can better support students in entrepreneurship education.

V. Conclusion

This article focuses on intelligent question answering in entrepreneurship education, analyzing the characteristics and challenges of entrepreneurship question-answering data. It identifies the complexity and difficulties of answering the interdisciplinary knowledge question in entrepreneurship education. This article compares classic graph convolution to tree generation models and large language models like ChatGPT for solving mathematical application problems in entrepreneurship question-answering tasks. Further comparisons of these pretrained models in complex entrepreneurship knowledge reasoning reveal significant impacts on generation results from the knowledge coverage in training data and model design principles. Given the uniqueness and specialization of entrepreneurship education, the direct application of general pretrained models may only partially meet the requirements. Models can be fine-tuned on data specific to entrepreneurship education by utilizing transfer learning techniques, building upon general pretrained models to better adapt to entrepreneurship education scenarios and enhance their capability to answer domain-specific questions. Implementing multiturn dialogue mechanisms will enable the system to understand users' continuous queries better, achieving a more natural interaction experience.

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