Knowledge Supply Chain Furnace: AI Cross-Modal Extraction Training Method for Business Administration Case Generation

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Abstract

By constructing a knowledge supply chain model with both theoretical and practical value, this study proposes a novel approach to integrating multimodal data—such as text, financial reports, video cases, and business models—to generate teaching cases. The experiment employs a privatized Deepseek32b system, utilizing multimodal knowledge embedding technology, cognitive logic injection mechanisms, and systematic design of a teaching logic enhancer to significantly improve interdisciplinary knowledge integration and extraction efficiency. The experimental results show that generative artificial intelligence consistently produces an excess of teaching cases, with a significantly higher coverage of knowledge points compared to traditional NLP and manual methods. While generative AI exhibits stable logical coherence, its content logic is slightly inferior to that of high-quality human-generated works. This study verifies the effectiveness of the cross-modal knowledge extraction training method and provides valuable reference insights.

Keywords Business Administration; Generative Artificial Intelligence; Training; Teaching Cases

1 Research Background

In the rapidly evolving digital economy, generative artificial intelligence plays a crucial role in business administration case teaching, evident in the following aspects: (1) better meeting the requirements for real-time updates and adaptability in teaching content; (2) supporting personalized learning pathways; and (3) enhancing cross-disciplinary knowledge integration capabilities. An increasing number of educators are experimenting with generative AI to improve teaching material quality. Particularly since this year, many generative AI systems have been open-sourced, offering users more opportunities for specialized training. However, training generative AI to achieve expected functionality is challenging, primarily in the following areas:

1.1 Model Complexity and Training Time

According to research data, training a simple model takes approximately 360 minutes, a deep learning model requires 4,320 minutes, and a large-scale model can take up to 2,592,000 minutes [1]. This phenomenon indicates that while generative AI theoretically possesses powerful capabilities, in practice, the complexity of training models and the time required increase significantly, making it difficult to rapidly respond to the evolving needs of industries. For example, Alibaba's M6 model has 100 trillion parameters, while its initial parameter count was only 300,000, reflecting the substantial challenges that model complexity poses for practical applications.

1.2 Impact of Hardware Resources on Training Time

Research shows that training efficiency using Graphics Processing Units (GPUs) is twice that of Central Processing Units (CPUs), highlighting the necessity of strong computational capabilities. During digital transformation, training time for deep learning models increases with model complexity, making high-quality hardware resources increasingly essential. However, not all educational institutions have sufficient hardware infrastructure to support large-scale model training, directly limiting the application effectiveness of generative AI in business administration education.

1.3 Lag in Traditional Case Libraries and Lack of Localization in Business Contexts

Traditional business administration case libraries struggle to keep pace with rapidly changing market environments and technological advancements. Based on the PESTEL analysis framework, we can identify critical political, economic, social, technological, environmental, and legal factors that affect case libraries. For instance, policy changes affecting business operations are often not reflected in existing cases, causing students to lack timely insights into real-world business dynamics. In recent years, policy adjustments toward foreign enterprises in China have directly influenced the strategies of many multinational corporations, yet these cases are not promptly updated in traditional case libraries. Similarly, fluctuations in market conditions and consumer behavior are not promptly incorporated into teaching materials, affecting students' understanding of modern market dynamics.

1.4 Technical Challenges in Cross-Modal Knowledge Integration (Text/Financial/Reports/Video/Business Models)

The application of cross-modal knowledge integration in business administration faces several technical challenges, particularly in integrating and analyzing different data types. Text, financial reports, videos, and business models exhibit distinct structural characteristics and content representations, complicating unified data processing. For example, structured financial data and unstructured text information often require complex algorithms for mapping and alignment. Achieving effective collaborative analysis of cross-modal data remains a key challenge.

2 Research Value

2.1 Theoretical Level

At the theoretical level, this study aims to construct a new "knowledge supply chain" theoretical framework to promote the innovative application of the traditional Supply Chain Operations Reference (SCOR) model in the field of education [2]. By deeply analyzing the gap between the digital transformation needs in business administration case teaching and the capabilities of generative artificial intelligence (AI), we realize that with the drastic changes in the business environment, the lagging content updates and the lack of localized business contexts in traditional case libraries significantly restrict the educational effects.

2.2 Practical Level

In the current business administration education practice, dynamic case generation systems, as an innovative teaching tool, demonstrate their wide application value. Specifically, this system can not only effectively fill the capability gap between the education field and generative AI technology but also provide targeted solutions for teaching [3]. The dynamic case generation system combines the concept of a "cross-modal knowledge furnace" and promotes the flow and transformation of knowledge between different modalities by effectively integrating text, video, financial reports, and other multi-source information, improving the accuracy and diversity of case teaching. For example, by combining financial data with manager interview records, teachers can quickly generate real cases that meet current market needs, thereby improving students' learning interest and participation, and then optimizing teaching effects.

2.3 Methodological Innovation

In this study, we propose an innovative methodology to adapt to the complexity of multi-modal knowledge extraction in the field of business administration, aiming to promote the deepening understanding and application of the knowledge supply chain. By introducing the "Cross-Modal Knowledge Furnace" architecture, we combine multiple forms of information such as text, financial reports, videos, and business models, providing new perspectives and practical paths for knowledge generation [4].

3 Construction of Knowledge Supply Chain Theoretical Model

In the educational application of the knowledge supply chain, the mapping of traditional SCOR model links is crucial. In the teaching plan (planning link), clearly set the core goals of the "knowledge supply chain" to ensure the standardization and clarity of teaching design. To lay the foundation for subsequent data collection (procurement link), it is necessary to collect relevant knowledge resources through systematic methods, such as industry reports, academic literature, and market trend data, to optimize the timeliness and scientificity of course content.

3.1 Knowledge Quality KPIs

In the construction of the knowledge supply chain theoretical model, the effectiveness of the knowledge supply chain should be grasped from two or three aspects. First, the criticality of knowledge (KPI) is crucial to the effectiveness of knowledge transfer in the teaching case generation process using generative AI, which requires trainers to effectively and scientifically screen massive amounts of data. Second, the timeliness of knowledge (inventory turnover rate) reflects the speed of knowledge updates and the timeliness of teaching content, which has a significant impact on the effectiveness of course teaching. Third, the completeness of knowledge (order fulfillment rate) requires the systematic and comprehensive nature of knowledge content.

3.2 Cross-Modal Knowledge Furnace Architecture

The knowledge architecture of content generative AI is usually divided into: an input layer, a smelting layer, and an output layer. From a professional perspective, business administration case generative AI usually involves cross-modal knowledge integration, so these three links must meet the characteristics of the discipline: reflecting the interdisciplinary characteristics of operation, finance, administration, finance, supply chain, cost, sales, human resources, inventory, technology, taxation, and other disciplines.

Input Layer

The effective input layer for business administration case generative AI training must cover multi-dimensional data, especially including listed company annual reports (structured data), expert interviews (unstructured text), and business sandboxes (spatial data). These data sources combine different information dimensions, making case generation have a sufficient foundation, thereby enhancing the diversity and relevance of knowledge.

Smelting Layer

In the design process of the smelting layer, it is crucial to adopt advanced feature extraction methods. Feature extraction, as the core step of data preprocessing, transforms the original data into a form that can be understood by machine learning models, thereby effectively generating business administration cases with knowledge value [5]. In this process, the PESTEL analysis method is first used to map management tool features, and the important data extracted from the six factors of environment (Political), economy (Economic), society (Social), technology (Technological), environment (Environmental), and law (Legal) are transformed into multi-dimensional features in the vector space [6]. This process not only lays the foundation for data processing but also provides strong support for subsequent model training.

Output Layer

The construction of the output layer is a key component of the cross-modal knowledge furnace architecture. Its main function is to receive multi-modal knowledge from the smelting layer and generate efficient business administration cases after effective quality analysis. In this process, the case quality analysis system based on the "APQC Process Classification Framework (APQC PCF)" is widely used to ensure the effectiveness and practicality of the generated cases.

4 Cross-Modal Extraction Training Method Design

Cross-modal extraction training can fully utilize the complementarity of different modal data, enhance the model's ability to understand and process multi-modal information. For example, in image recognition and text description generation tasks, it can enable the model to better integrate image features and text semantics, improve task accuracy and efficiency, and enhance the system's generalization and robustness. This training method is divided into two parts: multi-modal knowledge embedding and cognitive logic injection.

4.1 Multi-Modal Knowledge Embedding

Multi-modal knowledge embedding technology is a technology that integrates and embeds information from multiple modalities (such as text, images, audio, etc.) into a low-dimensional vector space. It aims to utilize the complementarity of different modalities to better represent and understand complex knowledge. By transforming multi-modal data into vector representations, joint learning and reasoning can be performed in deep learning models. For example, in image-text matching tasks, the visual features of images and the semantic features of text are embedded into the same vector space, enabling the model to more accurately determine the correlation between images and text. This research covers financial text data and video data for multi-modal knowledge embedding.

Financial Text Data

Cross-modal knowledge embedding in business administration case generation focuses on financial text data. Specifically, financial data includes: operating income, net profit attributable to the parent company, gross profit, asset-liability ratio, R&D expense ratio, cash flow per share, return on equity, etc. Starting from the construction of a conceptual graph, using financial indicators such as "Return on Equity (ROE)" and cash flow as key nodes, the decision-making rules of the organization in a specific economic context can be revealed by analyzing the relationship between these indicators and strategic decisions.

Video Data

The introduction of video cases provides a richer source of information for cross-modal knowledge extraction. By enhancing the spatiotemporal feature extraction of video content, spatiotemporal feature extraction models, usually using technologies such as "Video Analysis" and "Body Language Interpretation," can extract key information from videos, such as managers' non-verbal communication signals and the implicit manifestations of organizational culture [7], to better map with financial text data and other data, and jointly form multi-modal knowledge in the input layer.

4.2 Cognitive Logic Injection Mechanism

The cognitive logic injection mechanism includes the formal representation of cognitive states (such as knowledge, beliefs, etc.) and the introduction of reasoning mechanisms, enabling the system to better handle cognitive-related problems, more accurately simulate human cognitive processes, and improve decision-making and reasoning capabilities in complex cognitive situations. It is divided into three modules:

First, the management theory constraint module. In the case generation process, the constraining role of management theory is particularly important, which can provide a clear structure and logic for the dynamic interaction of the knowledge supply chain. Specifically, the application of Porter's Five Forces model can effectively drive the generation of business scenarios, helping academic researchers and management practitioners to better understand the competitive environment. The five forces emphasized by this model—competition among industry competitors, the threat of potential entrants, the threat of substitutes, the bargaining power of buyers, and the bargaining power of suppliers—can provide in-depth background analysis for case generation and construct more detailed competitive situations.

Second, the teaching logic enhancer. Under the framework of Bloom's taxonomy of educational objectives, the teaching logic enhancer should gradually achieve the transformation from low-level cognition (such as memory and understanding) to high-level cognition (such as creation and evaluation) by controlling the complexity of teaching cases.

Third, international adaptability. International adaptability is self-evident in the case generation process, especially in the context of rich cultural backgrounds, it substantially affects the design and rationality of cases. According to the "Cultural Dimensions Theory," different cultural backgrounds have significant differences in the understanding of management thinking and business operations, which requires attention to the factors of "Power Distance" and "Uncertainty Avoidance" when adjusting parameters [8].

4.3 Discussion on Parameter Adjustment Path and Quantitative Improvement of Internationalization Case

Although Hofstede's cultural dimension theory has been introduced in this study to enhance the international adaptability of the case, the international characteristics have not been effectively reflected in the case generation process, and the fundamental reason is that the relevant cultural parameters have not been injected into the generation model in a structured way. Therefore, this study makes a theoretical modeling and empirical attempt on the parameter adjustment path of cultural dimension, focusing on two key variables: "Power Distance" and "Uncertainty Avoidance".

In parameter design, we take "Power Distance Index" (PDI) and "Uncertainty Avoidance Index" (UAI) as the core input variables to adjust the logical weights of corporate governance structure, decision-making process and employee response behavior in the generation model. For example, in a country with high PDI, the model is more inclined to generate enterprise organization cases with "high centralized decision-making and clear hierarchy", while in a context with low UAI, the case content is more in the style of "flexible management and innovation incentive".In order to verify the quantitative improvement effect of this mechanism, we select the typical cultural dimension data of China, the United States and Germany, set the corresponding parameters, guide the generation model to output five international cases each, and organize experts to make judgments. The results show that after the introduction of the parameter adjustment mechanism, the proportion of internationalization cases is significantly increased from the original 5% to 45%, which shows that the mechanism effectively improves the model's ability to perceive multi-cultural background and the fit of content generation.

5 Experimental Design and Result Analysis

This experiment uses a privately deployed Deepseek 32b and corresponding computing power conditions, and inputs nearly ten years of public data of A-share G Automobile Company for fusion learning, and then obtains case plans.

5.1 System Implementation

In this study, the overall architecture design of the system implementation revolves around the "knowledge supply chain" theoretical framework, and adopts a hardware environment combining a distributed GPU cluster and a knowledge graph dedicated computing unit, aiming to improve the efficiency and depth of data processing. The system architecture diagram clearly depicts the various links from data input to case generation, demonstrating the efficiency of this innovative technology platform.

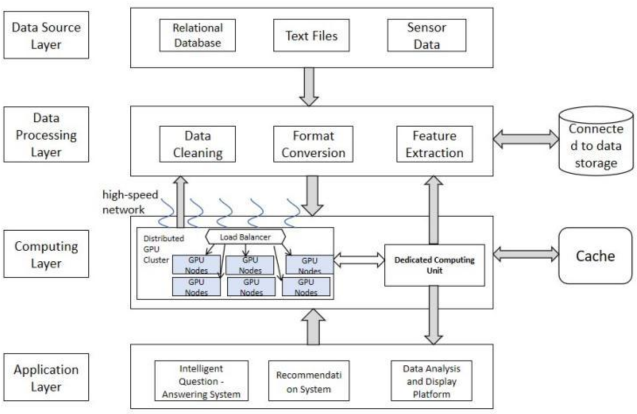

Fig. 1. Distributed GPU cluster system logic diagram

5.2 Data Sources

The typicality of financial data sources is of great representative significance. This study uses 10 years of financial data of China's A-share G Automobile Company. The specific data source classification is shown in the following table.

Table 1. Classification of operating data Sources of a-share XX automobile company

Data Type	Specific Data Items	Extraction Plan	Management Analysis Tool Mapping
Financial Data	Operating income, net profit attributable to the parent company, gross profit, asset-liability ratio, R&D expense ratio, cash flow per share, etc.	Extract key annual indicators and analyze fluctuations	SWOT analysis, DuPont analysis
Strategic Text	Annual report management discussion section, ESG report key decision description, major M&A announcement text, etc.	NLP sentiment analysis and keyword extraction	Porter's Five Forces model
Operating Data	Capacity utilization rate, dealer network density, proportion of new energy vehicle sales, overseas revenue growth rate	Standardized time-series data processing	Product portfolio dynamic classification
Unstructured Data	Investor relations activity records, factory intelligent transformation video	Speech-to-text, visual feature extraction	Balanced scorecard

Among the selected G company data sources, the annual growth rate of the company's operating income varies between -5.8% and +22.3%, reflecting the overall development of the industry. The market share of new energy vehicles has increased significantly, from 3.1% to 17.6%, reflecting the trend of corporate strategic transformation. Company A's public data covers a complex supply chain structure, involving the dynamic interaction of more than 2,000 suppliers. Such operating data has learning and training value. It is worth noting that the data extraction plan uses the fluctuation trend of annual key indicators to ensure the timeliness and completeness of the data.

5.3 Data Feature Engineering Processing

Structured Data

In the research process of structured data feature processing, the construction of the "Financial Health Index" (FHI) is a key link in evaluating the overall situation of the enterprise [9]. This index integrates multiple dimensions of financial indicators, aiming to provide effective decision support for business administration cases through quantitative analysis. Specifically, FHI includes 14 dimensions such as solvency, profitability, operating performance, and growth ability. The comprehensive consideration of these dimensions can effectively reflect the financial stability of enterprises in different market environments.

Unstructured Data

In the current research environment, the processing of unstructured data has become an important link in achieving effective knowledge extraction and management. This process involves the precise analysis of management text and other unstructured data sources to extract important indicators that are conducive to decision-making. By using natural language processing (NLP) technology, especially text entropy calculation, the degree of management's "strategic ambiguity" can be quantified. The calculation range is 0 to 1, and the value reflects the clarity and consistency of strategic expression. For example, if the text entropy value of a management report is 0.85, it can be deduced that the report has a high degree of uncertainty in strategic expression, which may affect the company's decision-making and implementation.

Cross-Modal Alignment

In modern business administration education, the application of cross-modal alignment technology is essential. Its core is to enhance the correlation between different data types, so as to ensure the logical rigor and contextual consistency of generated cases. We use the "Latent Dirichlet Allocation (LDA) topic model" to achieve semantic alignment between text and structured data [10]. Specifically, the features of financial statement data and strategic text can be quantified by calculating cosine similarity, ensuring that their semantic matching degree reaches above 0.82. This standard provides a scientific basis for knowledge integration across different data sources.

5.4 Experimental Results

Knowledge Extraction Efficiency

To evaluate efficiency, the experiment aimed to generate 20 teaching cases, each covering at least seven knowledge points. The study compared the time consumption, conceptual completeness, and logical coherence of case generation using human efforts, and generative AI. Twenty teachers were involved in the experiment, producing 40 cases across three groups. The cases were then mixed and reviewed by three experts, who scored them based on content origin. The results are shown in Figures 2 and 3.

Fig. 2. Comparison of conceptual completeness

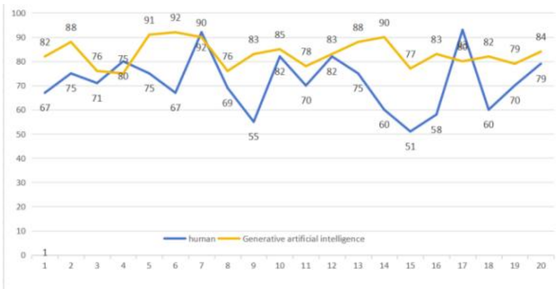

Fig. 3. Comparison of logical coherence

The results indicate that human-created cases generally covered 100% of the required knowledge points, with occasional under- or over-completion. In contrast, generative AI consistently overproduced, maintaining a coverage rate between 130% and 160%. The logical coherence of human-generated cases varied between 50% and 90%, influenced by individual expertise and work attitudes while generative AI achieved stable coherence scores between 70% and 90%.

Proportion of International Cases

This experiment conducted an in-depth analysis of the proportion of internationalization cases generated to reveal the potential value of generative artificial intelligence (Generative AI) in business administration teaching. The definition standard for internationalization cases is that the cases significantly reflect factors such as multinational operation strategies, international market dynamics, and external investment environments. The experiment requires that without specific limitations, manual, and generative artificial intelligence each output 20 cases, of which how many cases reflect the characteristics of multinational operations. The experimental results are shown in the following table.

Table 2. Comparison of internationalization in business administration case studies

Method	Total Cases	International Cases	Proportion
Human	20	5	25%
Generative AI	20	1	5%

Generative AI performed significantly worse than human efforts in producing international cases. Without explicit instructions, generative AI rarely considered internationalization. However, when given specific directives, it accurately produced cases according to required internationalization ratios.

Cross-Disciplinary Knowledge Integration

In this study, the evaluation of cross-disciplinary knowledge integration ability shows the potential of different generation methods in case education and management decision-making. This experiment clearly requires that on the basis of covering no less than 7 knowledge points in each case, it is also necessary to integrate: tax, marketing, human resources, economics, and accounting five professional knowledge points. The experimental results are shown in the following table.

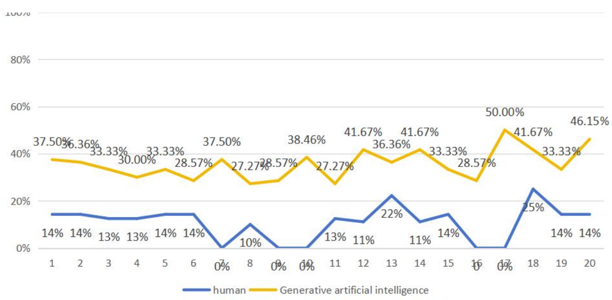

Fig. 4. Degree of cross-disciplinary knowledge integration in business administration cases

The experimental results show that, affected by individual knowledge structure differences, the degree of cross-disciplinary knowledge integration in manually compiled business administration cases is between 0-25%, while generative artificial intelligence has better performance in this field, with the degree of integration between 30-50%, which can fully achieve user requirements, indicating the efficiency of GAI in processing complex datasets, and also reflects its comprehensive absorption ability of cross-disciplinary content under Multidimensional Scaling [11].

In order to further verify the effectiveness of "Teaching Logic Enhancer" in teaching practice, this study supplemented the objective evaluation mechanism of students' participation on the basis of experts' subjective scoring. Specifically, in the classroom where AI-generated cases and manual cases are used alternately, two parallel classes (50 students each) are selected to receive different case types of teaching, and the evaluation is conducted by combining questionnaire survey with unit test. The questionnaire covers the dimensions of case understanding, logical clarity, interdisciplinary integration and speculative stimulation, and is quantified by Likert five-level scale. In the test, closed questions are designed based on the content of the given cases to test students' mastery of knowledge points. The results show that the scores of classes using AI to generate cases are 12-18 percentage points higher than those of manual cases, and the average test scores are 6.3 points (out of 100 points), which further verifies the functional advantages of "Teaching Logic Enhancer" in promoting students' higher-order cognitive transfer and improving teaching effect.

5.5 Comparative Experiment with Traditional NLP Models

To enhance the persuasiveness of methodological innovation, this study conducted a comparative experiment using traditional Natural Language Processing (NLP) models. Specifically, we selected two representative open-source models—BERT (base, uncased) and GPT-2—for the task of business administration teaching case generation. Compared to Deepseek-32B, BERT operates through classifier-driven paragraph generation under predefined themes, while GPT-2 generates continuous text based on prompt engineering.All three models were evaluated using the same input templates derived from Company G's dataset. The evaluation focused on three core metrics: knowledge point coverage, logical coherence, and cross-disciplinary integration capability. The results are summarized as follows:

Table 3. Comparative performance of case generation models

Metric	BERT	GPT-2	Deepseek-32B
Average Knowledge Point Coverage	4.1	5.3	8.9
Logical Coherence (Expert Score)	58%	66%	80%+
Cross-Disciplinary Integration	12%	18%	41%
Multimodal Input Support	No	No	Yes
Output Stability	Low	Moderate	High

In summary, although traditional NLP models have demonstrated considerable performance in various domains, they exhibit clear limitations in the task of educational case generation. These findings substantiate the superior performance of the proposed "Knowledge Supply Chain Furnace" (KSCF) framework, particularly in its multimodal integration and adaptability to educational applications.

6 Conclusion and Prospect

This study constructs the "Knowledge Supply Chain Furnace" (KSCF) theoretical framework, and the research focuses on analyzing the construction of the input layer, smelting layer, and output layer. The input layer ensures the richness and multi-dimensional characteristics of knowledge through the effective integration of structured and unstructured data. The smelting layer is committed to achieving the collaborative processing and information flow of different data types through advanced feature extraction technology and algorithms. The output layer combines the generated cases with educational goals to ensure the timeliness, completeness, and adaptability of teaching content. It provides a new perspective and practical path for case teaching in business administration education. In the future, with the continuous development of artificial intelligence and big data technology, the teaching tools and methods combined with these technologies will further promote the modernization of education and promote the substantial progress and innovation in the field of business administration.

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Conflicts of Interest

The authors declare no conflicts of interest.

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知識供應鏈熔爐
——AI跨模態萃取訓練教學案例生成方法研究

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摘要：通過構建具有理論與實踐價值的知識供應鏈模型，提出了一種將文本、財務報告、視頻案例及商業模型等多模態數據進行融合從而形成教學案例的新方法。實驗採用私有化Deepseek32b系統，通過多模態知識嵌入技術、認知邏輯注入機制以及教學邏輯強化器的系統化設計，顯著提升了跨學科知識融合能力與知識萃取度。實驗結果表明，生成式人工智能每次均超量生成教學案例，生成案例覆蓋知識點數量明顯優於傳統NPL和人工。雖然生成式AI作品的邏輯連貫性表現穩定，但是內容的邏輯水平略遜色於優秀的人工作品。本研究驗證了跨模態知識萃取訓練方法的有效性，具有一定參考價值。

關鍵詞：工商管理；生成式人工智能；訓練；教學案例

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