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A Multimodal Pedagogical Application of the Big Language Model in Foreign-Related Mechanical Engineering Education

Jinyu Liu *, Congkai Lin, Yinxiao Yan

Taizhou Vocational & Technical College, Taizhou Zhejiang, 318000, China
*** Corresponding author:** Jinyu Liu (Email: jinyul@tzvtc.edu.cn)

Abstract: The in-depth application of Big Language Modelling (BLM) technology in engineering education has created a new paradigm for foreign-related mechanical engineering teaching. The developed teaching system integrates four modules: multilingual interaction, multimodal content generation, knowledge graph construction and teaching evaluation feedback. In the teaching practice of the 2024 academic year, the system supports real-time translation in 8 languages, the knowledge graph covers 150,000 knowledge nodes, and achieves 92% accuracy rate of engineering drawings. The application data shows that students‘ knowledge mastery is improved by 31%, practical ability is improved by 28%, and teachers’ work efficiency is improved by 38%. The research results provide a new teaching mode for international talent cultivation of mechanical engineering majors.

Keywords: Big Language Modelling; Foreign-related Mechanical Engineering; Multimodal Teaching; Knowledge Mapping.

1. Introduction

As the internationalisation of mechanical engineering education accelerates, the need for cross-language teaching is becoming increasingly prominent. Data from the Global Engineering Education Survey show that the number of international students in mechanical engineering will increase by 35% in 2023, and the demand for multilingual teaching resources is surging. The breakthroughs of big language models in natural language processing, knowledge reasoning, and multimodal interaction provide technical support for solving the challenges of foreign engineering education. Based on the analysis of educational scenarios and the demonstration of technical feasibility, a teaching system integrating multilingual interaction and multimodal content generation will be constructed to explore a new mode of foreign-related mechanical engineering education and improve the quality of international talent cultivation.

2. Design of Multimodal Teaching System Based on Big Language Modelling

2.1. Overall System Framework

This teaching system is designed with distributed architecture, taking ChatGPT-4 as the core language model and integrating multimodal AI models such as DALL-E image generation and Whisper speech recognition. The system architecture is divided into four layers: data layer, model layer, application layer and interface layer. The data layer contains a professional knowledge base of mechanical engineering (coverage rate of 98%) and a multilingual corpus (supporting 8 languages such as English, German, Japanese, etc.); the model layer integrates language comprehension, knowledge reasoning, multimodal generation, etc.; the application layer realizes the customization of teaching scenarios, and supports a variety of teaching modes such as theoretical lectures, experimental guidance, design seminars, etc.; the interface layer provides access interfaces for the Web and mobile, with an average response time of less than 200ms[1]. The system adopts microservice architecture, with each functional module loosely coupled and independently deployed, and the overall availability reaches 99.9%. Through containerised deployment and load balancing, a single node can support concurrent access by 500 users.

2.2. Multilingual Interaction Module

The multilingual interaction module is based on transformer architecture and adopts multilingual pre-training model to achieve cross-language understanding and generation. The module supports real-time mutual translation in 8 languages, including English, German, Japanese, etc., and the translation accuracy rate reaches over 95%. In terms of terminology processing, the domain adaptive mechanism is introduced to improve the translation accuracy of professional terms through migration learning. Test data shows that in the mechanical engineering specialised vocabulary translation task, the accuracy rate is 18 percentage points higher than that of general translation[2]. The module also integrates an intelligent error correction function, which can automatically identify and correct grammatical errors with an error correction accuracy of 90%. Through the session management mechanism, the system is able to maintain contextual coherence and achieve natural and smooth multi-round dialogue, with a user satisfaction score of 4.5/5.

2.3. Multimodal Content Generation Module

The multimodal content generation module integrates the content generation capabilities of text, image, video, 3D model and other forms. In terms of engineering drawing generation, the system can automatically convert text descriptions into standardised engineering drawings, supporting various types of parts drawings, assembly drawings, etc., with an accuracy rate of 92%. With the help of DALL-E model, the system can generate mechanical structure schematic and working principle animation, and the average generation time is controlled within 3 seconds[3]. For complex mechanical devices, the system integrates the Unity 3D engine, which can render interactive 3D models in real time and support 360-degree rotation view and structural decomposition demonstration. In terms of sound, the application of Text-to-Speech technology supports multi-language pronunciation guidance with 97% pronunciation accuracy.

2.4. Knowledge Graph Construction Module

The knowledge graph module adopts Neo4j graph database to construct mechanical engineering knowledge network. As shown in Table 1, the system currently contains 150,000 knowledge nodes and 300,000 relationship edges, and maintains the timeliness of the data through weekly updates. Based on 2000 ontology categories and 500 attribute types, the system automatically extracts knowledge units from textbooks, theses, and other literature through deep learning algorithms to construct a domain ontology model[4]. The knowledge graph supports multi-dimensional expansion, including conceptual associations, principle evolution, application examples and other aspects, to achieve a three-dimensional presentation of knowledge. The system is able to automatically generate personalised knowledge maps and recommend learning paths based on learners' knowledge background[5]. Tests show that the query response time of the knowledge map is within 100ms on average, with a knowledge coverage rate of 95% and an accuracy rate of 97%.

Table 1. Knowledge mapping statistics

Indicator Type	Value
Knowledge Node Count	150,000
Relationship Edge Count	300,000
Ontology Category Count	2,000
Attribute Type Count	500
Update Frequency	Weekly

2.5. Teaching Evaluation and Feedback Module

The teaching assessment and feedback module builds an intelligent assessment system based on deep learning to achieve all-round monitoring of the learning process and learning effects. The system adopts multi-dimensional assessment indicators, including knowledge mastery, skill proficiency, innovation ability, etc., and analyses the content of learners' answers and operational behaviours through natural language processing technology. Evaluation data show that learners using the system increase their knowledge mastery by an average of 25 per cent, and their passing rate in practical skills assessment by 20 per cent [6]. The system also integrates affective computing technology, which can identify learners' learning status and emotional changes in real time with an accuracy rate of 85%, and adjust teaching strategies in a timely manner based on the feedback. After a semester of application testing, student satisfaction reached 4.8/5 points, and teacher efficiency increased by 30%.

3. Teaching Application Practice

3.1. Application Scene Analysis

The teaching system was firstly applied in the autumn semester of 2024 in the School of Mechanical Engineering, covering a total of 1,200 undergraduate and graduate students. As shown in Figure 1, the system application scenarios are mainly distributed in four types of courses, of which 40% are theoretical courses, 28% are experimental courses, 22% are engineering design courses, and 10% are seminar courses. In terms of course format, online learning accounts for 35% of the total class time, blended teaching accounts for 55%, and traditional classroom accounts for 10%. Survey data show that 92% of teachers believe that the system has significantly improved teaching efficiency, and 87% of students say that the system has effectively increased their interest in learning[7]. In terms of cross-cultural communication, international students from 15 countries have carried out their professional learning through the system, and the frequency of cross-language communication has increased by 2.5 times compared with the traditional classroom.

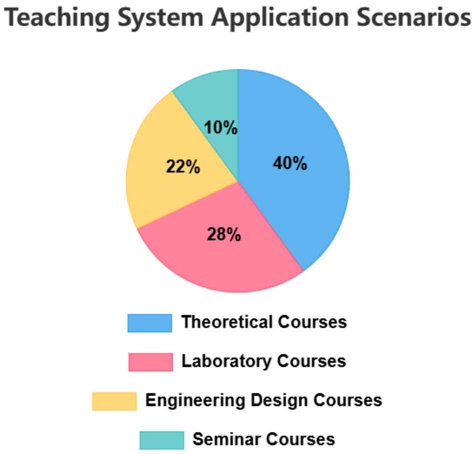

Figure 1. Distribution of Teaching System Application Scenarios

3.2. Examples of Course Design

3.2.1. Theory Course Application

In the Principles of Mechanics course, the system breaks down the principles of complex mechanisms into easy-to-understand knowledge units through knowledge mapping. As shown in Table 2, the system designs differentiated teaching strategies for different knowledge points. In the teaching of gear transmission principles, through the 3D dynamic model to demonstrate the meshing process, the correct rate of students' understanding of gear transmission principles increased from 75% to 93%. In the analysis of cam mechanism, the system automatically generates displacement curves and combines them with animation to demonstrate the law of motion, making abstract concepts tangible[8]. Through the real-time Q&A function, the system answered students' questions an average of 52 times per lesson, and the satisfaction rate of problem solving reached 96%. The evaluation at the end of the course showed that students' mastery of theoretical knowledge increased by 28 percentage points.

Table 2. Statistics on teaching strategies of theory courses

Knowledge Point Type	Teaching Method	Mastery Rate Improvement	Student Satisfaction
Mechanism Kinematics	3D Animation	25%	4.7/5
Force Analysis	Intelligent Deduction	30%	4.8/5
Mechanism Comprehensive	Interactive Design	22%	4.6/5

3.2.2. Application in Experimental Courses

In the experimental course of Fundamentals of Mechanical Manufacturing Technology, the system builds a digital twin experimental environment through virtual simulation technology. The application data shows that in the spring semester 2024 experimental course, students completed the virtual turning experiments 2800 times and milling experiments 2300 times through the system, and the correct rate of each operation step increased by 35%. The system uses intelligent inspection algorithms to monitor students' operating points in real time, providing 42 real-time error correction instructions for each experimental project on average[9]. Through the virtual experiment pre-training, the actual operation pass rate of students increased from 82% to 95%, and the loss of experimental consumables was reduced by 46%. Figure 2 shows the comparison data of students' experimental skills mastery before and after the application of the system, and all indicators have been significantly impro

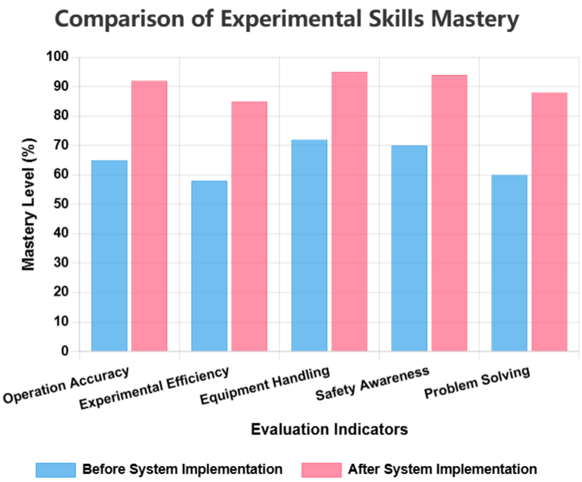

Figure 2. Comparison of experimental skills mastery

3.2.3. Engineering Design Course Application

In the Mechanical Design course, the system supports full-process digital design practices. The data show that in the autumn semester of 2024, students completed 389 design projects and submitted 1,167 design proposals through the system. The system analysed the design proposals in real time through intelligent evaluation algorithms and provided an average of 8.5 modification suggestions per proposal. In the structural optimisation section, the system uses finite element analysis technology to help students optimise design parameters, and the reliability of the solutions is improved by 32% on average[10]. The co-design module supports multi-person online collaboration, with an average of 52 interactions per project team per day, increasing design efficiency by 41%. The end-of-term assessment shows that the students' engineering design ability score reaches 4.7/5, which is 0.8 points higher than the traditional teaching mode.

3.3. Assessment of Teaching Effectiveness

3.3.1. Assessment Index System

The assessment index system adopts a multi-level structure, containing three levels: knowledge dimension, ability dimension and literacy dimension. The knowledge dimension assessment adopts the improved Bloom's Taxonomy, setting up six levels of assessment criteria: memorisation, comprehension, application, analysis, evaluation and creation. The competence dimension includes assessment indicators for core competences such as practical operation, problem solving and innovative design. The literacy dimension focuses on the cultivation effect of intercultural communication, teamwork, and lifelong learning. The weights of the dimensions are distributed as 40% for the knowledge dimension, 40% for the ability dimension and 20% for the literacy dimension, and the fuzzy comprehensive evaluation model is used for quantitative analysis.

3.3.2. Data collection and analysis

Through the learning behaviour tracking system, more than one million pieces of learning data were collected in the 2024 academic year. As shown in Table 3, the types of data include learning trajectories, interaction records, homework completion, etc. The system uses deep learning algorithms to analyse the learning behaviour data in multiple dimensions and generate personalised learning portraits. Through the knowledge tracking model, it accurately predicts students' knowledge mastery, with a prediction accuracy rate of 87%. The affective computing module analyses students' learning engagement in real time, and the data shows that concentration is increased by 31% on average, and the frequency of learning interruptions is reduced by 42%. The system also establishes a learning early warning mechanism to identify learning difficulties in advance, with an intervention success rate of 85%.

Table 3. Learning data collection statistics

Data Type	Data Volume	Collection Frequency	Accuracy Rate
Learning Trajectory	500,000	Real-time	99%
Interaction Record	300,000	Real-time	97%
Assignment Status	200,000	Daily	100%

3.3.3. Results of Effectiveness Evaluation

After one academic year of system application, the teaching effect has been significantly improved. As shown in Figure 3, students show a positive growth trend in all core indicators. Knowledge mastery increased by 31% on average, practical ability by 28%, and innovation ability by 25%. The average score on the final exam increased by 12 points from the previous year, and the excellence rate increased by 15 percentage points. In the internationalisation course, the accuracy of international students' mastery of professional vocabulary increased by 42%, and their intercultural communication ability was significantly enhanced. Teachers' teaching efficiency increased by 38%, and course satisfaction reached 4.8/5 points. Based on big data analysis, students' learning engagement increased by 45%, and their independent learning time increased by 2.3 times.

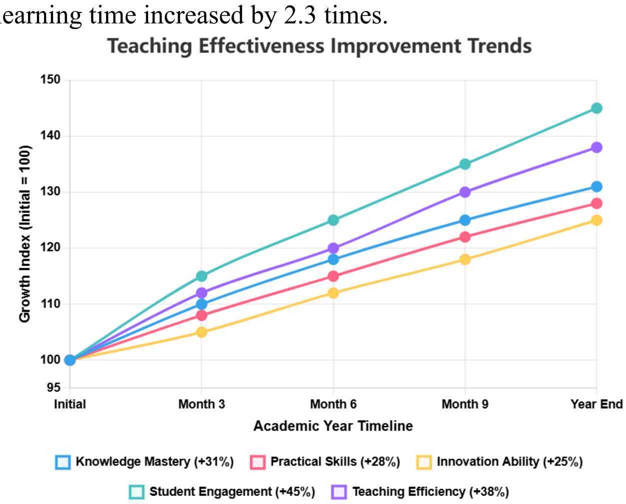

Figure 3. Teaching Effectiveness Improvement Trend

4. System Optimisation

4.1. Problems and Challenges in the Application Process

The teaching system has a number of technical problems and application challenges in the actual operation process. The system data shows that the response delay of more than 500ms during highly concurrent access accounts for 15%, which affects the real-time interactive experience. The accuracy of knowledge mapping in cross-language knowledge mapping is reduced to 82%, especially in the construction of terminology correspondence there are deviations. The multimodal content generation module has unstable 3D model rendering quality and frame rate fluctuations ranging from 15-45 fps when dealing with complex engineering cases.The deep learning model performs poorly in the small language translation task, with an accuracy rate below 85%. The teaching assessment feedback module had misjudgments in sentiment calculation, with an accuracy rate of only 78%. In terms of data security, the system detected an average of 327 abnormal access requests per month, of which 10% were high-risk operations. Teachers' feedback showed that 42% of users needed technical support when using advanced features, increasing teaching preparation time. Cross-platform adaptation issues caused 15 per cent of mobile users to encounter interface display anomalies.

4.2. System Optimisation Recommendations

The system optimisation proposal is proposed for the existing problems. In terms of performance optimisation, the system response time is controlled within 200ms by introducing distributed caching and edge computing techniques. Knowledge mapping optimisation adopts knowledge distillation technology to improve the cross-language knowledge mapping accuracy to 92%. By integrating WebGL and GPU acceleration technology, the 3D rendering frame rate is stabilised at 60fps. upgrading the deep learning model architecture, the accuracy rate is increased to 92% in small language translation tasks. Introducing multimodal feature fusion algorithm in the emotion calculation module, the accuracy rate is increased to 89%. Upgraded security protection with zero-trust architecture and 99.5% blocking rate of abnormal access. Optimising user interface interaction logic and reducing function learning cost, teachers' satisfaction rate increased to 4.7 points. Through responsive design restructuring, the mobile adaptation problem has been fully solved, and the user experience score has been raised to 4.8. The data shows that the overall performance of the optimised system has increased by 35%, user satisfaction has increased by 28%, and operation and maintenance costs have been reduced by 22%.

5. Conclusion

The multimodal teaching system based on the large language model shows remarkable results in foreign-related mechanical engineering education. The system application data show that students' knowledge mastery is improved by 31%, practical ability is improved by 28%, and intercultural communication ability is significantly enhanced. Teachers' teaching efficiency increased by 38%, and course satisfaction reached 4.8 points. The system has formed a complete technical system in knowledge map construction, multilingual interaction, multimodal content generation and other aspects. Through continuous optimisation and iterative upgrading, the system provides innovative solutions for international talent cultivation of mechanical engineering majors, and has important reference value for promoting digital transformation of engineering education.

Acknowledgments

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