2024 Volume 2, Issue 2
Computer Simulation in Application
ISSN: 2630-4597 (Online)

Design of Innovative Computer System Experiments Based on General Large Language Models

Jin Zhang[1]*, Xiaoli Gong[1], Xiaopeng Gao[2], Feng Duan[3], Hongqi Xiong[4]
[1]College of Cyber Science, Nankai University, Tianjin 300071, China
[2]School of Computer Science and Engineering, Beihang University, Beijing 100191, China
[3]Tianjin Key Laboratory of Interventional Brain-Computer Interface and Intelligent Rehabilitation, Nankai University, Tianjin 300071, China
[4]School of Physics, Southeast University, Nanjing 211189, China

***Corresponding author:** Jin Zhang, zhangjin@nankai.edu.cn

Abstract:

Disruptive intelligent technologies, such as large language models, are driving the rapid development and formation of new forms of productivity, posing significant challenges to traditional knowledge-driven teaching models and introducing new demands for talent cultivation in higher education. This paper first analyzes the cultivation of students' novel innovative abilities through experimental teaching and proposes a framework for experimental course design characterized by "defined direction, diverse pathways, and flexible goals," as well as a comprehensive experimental design method to develop "intelligent collaborative innovation" capabilities. Then, using the computer organization principles course as an example, it details the design methodology for comprehensive innovation experiment cases. Finally, it evaluates the effectiveness of student ability development based on the implementation of the experimental courses.

Keywords:

Large language model
Experimental design
Computer system
Intelligent collaboration
System capacity

Online publication: December 27, 2024

1. Introduction

Artificial intelligence technology has had a significant impact on higher education. In 2018, the Ministry of Education proposed an action plan to integrate artificial intelligence into the development of the teaching workforce as part of its key work objectives. In the same year, the Ministry issued the "Innovation Action Plan for Artificial Intelligence in Higher Education," which aimed to optimize the scientific and technological innovation system and disciplinary structure in higher education institutions to align with the development of the new generation of artificial intelligence by 2020. The key tasks include promoting the transformation and demonstration of scientific and technological achievements in the field of artificial intelligence in higher education institutions. In 2018, the Ministry of Education decided to pilot the use of artificial intelligence to promote the development of the teaching workforce in Ningxia and Beijing Foreign Studies University, exploring new paths for artificial intelligence to optimize teacher management, reform teacher education, innovate teaching and learning, and support targeted poverty alleviation through education.

Since the emergence of generative intelligence represented by large language models in 2022, the overall productivity of society has been developing at an unprecedented speed with the empowerment of artificial intelligence. Since 2023, the training cost of artificial intelligence has decreased by 40,000 times, and its comprehensive capabilities have increased by 600,000 times. Various auxiliary systems integrating artificial intelligence have increased the work efficiency of knowledge-driven workers by nine times [1]. Similar to transformative technologies such as steam engines and electricity, large language models are profoundly changing the way humans produce and live. The dramatic changes of the times have placed higher demands on talent cultivation in higher education institutions.

The Ministry of Education attaches great importance to the development of new-generation artificial intelligence technologies such as large language models. Minister of Education Jinpeng Huai delivered a keynote speech titled "Working Together to Promote the Application, Sharing, and Innovation of Digital Education" at the World Digital Education Conference 2024, proposing to promote the deep integration of intelligent technology with education and teaching (AI for education), scientific research (AI for science), and society (AI for society). This integration aims to facilitate "intelligent assistance for learning, teaching, management, and research" and uphold the principle of "digital technology for good." In March 2024, the Ministry of Education launched the "LEAD Action (Artificial Intelligence Large Model Application Demonstration Action)" and promoted the creation of a dedicated large model for the education sector called "GEST" by teachers and students. In this acronym, G stands for Generative, E for Education, S for Special, and T for Transformer. In April 2024, the Ministry of Education announced the first batch of 18 typical cases of "Artificial Intelligence + Higher Education" application scenarios, serving as references for related exploration and practice.

Domestic researchers have conducted studies on the application of artificial intelligence in empowering higher education, ranging from macro-level prospects to specific implementation methods. Wang *et al.* presented a macro-level outlook and analysis based on the opportunities and challenges of artificial intelligence in the digitization of higher education [2]. Wang *et al.* proposed more specific visions and ideas in terms of the basic environment, operational mechanisms, and governance systems [3]. Zhang and Wang explored the potential values and risks that the process of intelligence may bring from the perspective of the relationship between technological change and higher education [4]. Kong *et al.* focused on "new business disciplines" to conduct research on digital and intelligent undergraduate courses [5]. Yao *et al.* attempted to use large language models to transform liberal arts experimental teaching methods [6]. Zhang *et al.* proposed reshaping experimental teaching ability goals in the context of large language models from the perspective of computer system ability training [7]. Zhai *et al.* tried to introduce large language models into teaching evaluation [8]. Xu *et al.* utilized artificial intelligence to construct an innovative practical teaching platform, helping students understand the progress of artificial intelligence technology applications through interdisciplinary integration [9]. Yao *et al.* introduced large language models into liberal arts teaching [6]. Su and Yang analyzed the impact and application of generative intelligence on education [10].

The development of generative intelligence technology and its impact on education are also highly concerning issues for foreign scholars [11,12]. Some scholars have contemplated the potential risks posed by generative intelligence [13], while others are exploring the integration of large language models into experimental teaching [14]. In the United States, six combination methods such as "new interactions" have been proposed for the enabling application of artificial intelligence technology in education and teaching, along with seven action suggestions including "trustworthiness and security" [15]. From the perspectives of teachers and educational technology experts, the UK has provided corresponding initiatives and discussions [16]. Focusing on the application of generative artificial intelligence technology in university teaching, Australia has released core principles and guiding statements covering six aspects: teaching and learning, human and social well-being, transparency, fairness, accountability, and continuous improvement [17].

This article explores the experimental practical ability requirements that students need to possess in the era of large language models, as well as the development ideas for corresponding training goals, based on the current technical characteristics and application methods of large language models.

2. Changes and challenges in capability development demands brought by large language models

2.1. Changes in industrial talent demand brought by artificial intelligence

Artificial intelligence technology has had a disruptive impact on various industries in society, and knowledge-driven work is facing significant shocks and challenges. According to the "Analysis Report on Computer Science and Technology Majors at Beijing University of Aeronautics and Astronautics" [12], there have been drastic changes in recent years in the demand for computer professionals' abilities by enterprises (**Table 1**). The demand for various job positions driven by knowledge

Table 1. Changes in partial skill requirements for computer science jobs (%)

Professional knowledge and skills	Average	2018	2022	Increase
Java language development	28.20	31.10	21.00	-10.10
Database application	34.50	37.40	28.10	-9.30
Web front-end technology	17.70	20.30	12.70	-7.50
Webpage production	15.00	17.60	10.10	-7.50
Java Web development technology	15.10	17.50	10.20	-7.30
Mobile Android application development	11.10	13.40	6.70	-6.70
Java Script development	13.50	15.80	9.20	-6.60
Mobile framework application	11.30	12.50	8.70	-3.80
Big data analysis and processing	10.20	11.10	7.30	-3.80
Distributed systems and cloud computing	10.20	11.00	7.30	-3.50
Statistical analysis	12.50	12.90	10.70	-2.30
Oracle database application	13.00	13.60	11.40	-2.20
Linux system development and application technology	20.70	21.40	19.30	-2.10
Professional scientific research	14.30	15.00	13.00	-2.00
Python language development	12.80	13.00	11.40	-1.60
Data visualization technology	13.80	13.90	12.40	-1.50
Algorithm design and analysis	12.60	13.20	11.70	-1.50
Computer vision application	3.83	3.43	5.01	1.58
C language development	23.88	23.37	27.79	4.42
Computer control technology	5.98	4.47	10.39	5.92
Embedded system development	6.71	5.15	11.48	6.33
Computer hardware development	9.01	6.87	15.32	8.45
Automation and automated line operation and maintenance	16.26	13.45	23.56	10.11

Note: The values represent the proportion of each skill appearing in 100 job descriptions.

and shallow experience has shown a significant decline, while the demand for positions emphasizing innovative abilities such as design has shown a clear upward trend.

Since the industrialization of generative intelligence tools such as large language models in 2023, the training and inference costs of artificial intelligence have dropped dramatically by 75% and 86% per year, respectively. The ARK Foundation predicts that by around 2030, artificial intelligence will automate most knowledge-driven jobs, thereby significantly increasing productivity [1]. Currently, the industry's demand for talent is undergoing drastic changes. Because large language models are essentially probabilistic computers trained on ultra-large-scale data, they can theoretically take over various jobs that can be represented in a data-driven manner through experience.

Driven by artificial intelligence technology, society's demand for industrial talent is undergoing profound changes. At the same time, general higher education institutions face significant challenges in their talent training programs, curriculum systems, and experimental teaching systems, which primarily focus on cultivating knowledge and shallow skills.

2.2. Changes in experimental ability training goals in universities in the era of large language models

Experimental teaching is a critical pathway for cultivating professional practical abilities, bearing the important responsibility of transforming theoretical knowledge into practical abilities. The industry's demand for talent requires individuals to have the ability to solve real and complex problems. Therefore, adjustments to talent training goals in universities must first originate from changes in experimental teaching. In the new era of productivity, experimental ability training goals should align with society's demand for talent abilities.

The emergence of generative intelligence, represented by large language models, has increasingly reduced the importance of knowledge and shallow experience. Consequently, it is necessary to adjust the relevant proportions in experimental teaching. In 2023, the Ministry of Education conducted a phased summary of national experimental teaching demonstration centers, classifying experiments into basic, professional, comprehensive, and innovative categories. Comprehensive and innovative experiments will become the main focus of future designs.

The new generation of artificial intelligence technologies, such as large language models, has redefined society's demand for talent. The important task for experimental teaching in universities is to re-explore and establish training objectives that align with these demands and design more comprehensive and innovative experiments to achieve ability cultivation by abstracting and restoring scenes of real and complex problems.

3. Comprehensive experimental design method for "smart collaborative innovation" ability cultivation

3.1. "Smart collaborative innovation" ability in the era of large language models

Large language models have automated most shallow skill-based work based on experience. Therefore, most work scenarios in various industries in the future will rely on human-machine collaboration to complete tasks, where intelligent agents with responsive capabilities cooperate with humans to accomplish work. Thus, how to better solve real problems with the assistance of artificial intelligence will become a key ability required in the future.

Large language models trained on big data still show inadequate performance in innovative activities in various scenarios. Large language models still struggle to complete innovative work that lacks large-scale data support, i.e., adopting new ideas, mechanisms, methods, or technologies to solve problems with high quality and efficiency. Innovation is not only the core talent ability requirement in the context of new productivity but also the most urgent ability demand for future industries.

Therefore, in the current talent training system, guiding students to learn how to collaborate with intelligent agents such as large language models to achieve innovation together becomes an extremely important ability training goal.

3.2. Design ideas based on the ability training goal of "smart collaborative innovation"

Whether in the process of professional establishment, curriculum construction, or experimental design, it is necessary to combine the ability of "smart collaborative innovation" with the characteristics of the profession and refine it into specific ability goals. In this process, the following five factors should be fully considered.

(1) Era change: Based on clarifying the current mission of higher education, refine and implement the ability training template by combining the development law of higher education with the requirements of the times. For example, the requirement of "integration of education, technology, and talent" should be reflected in the ability design, and the needs of "integration of science and education, and integration of production and education" should be fully considered.

(2) Industry foresight: The output of talent training should ultimately meet the needs of national development and the actual needs of the industry. With the rapid development of productivity, it is necessary to prospectively study the trend of technological development and fully consider the actual development status of the industry when students enter society. For example, it is not appropriate to use outdated software tools or platforms in computer teaching.

(3) Professional characteristics: The refinement of innovation ability should be integrated with subject and professional characteristics. Besides the common methodology, there needs to be a part that combines with the profession, such as debugging and transplantation of computer systems.

(4) Human-machine differences: It is necessary to fully understand the "incapabilities" of intelligent agents such as large language models, especially those determined by mechanisms. This is the most urgent demand for talent in society in the future. For example, the ability to design computer systems for a specific vertical application or brand-new demand.

(5) Scientific and technological ethics: Scientific and technological ethics are the values and behavioral norms that need to be followed in carrying out scientific research, technology development, and other scientific and technological activities. It is an important guarantee for promoting the healthy development of scientific and technological undertakings [18]. Technology for the better is a principle that needs to be adhered to and is an essential quality for students in the era of artificial intelligence.

3.3. Comprehensive innovative experimental design framework for real problems

To cultivate abilities required in the era of large language models, such as smart collaborative innovation, experimental teaching is bound to transform towards comprehensive innovative experiments facing real problems. From the perspective of the experimental process and results, teaching experiments can be roughly divided into four types as shown in **Table 2**.

To cultivate students' innovative abilities and restore the complex scenarios of real-world problems, propositional semi-open experiments and open experiments are preferred choices for conducting comprehensive and innovative experiments. This paper proposes a comprehensive innovative experimental

Table 2. Classification of teaching experiments

Experiment type	Experiment process (technical route)	Experiment results	Application scenario description
Deterministic experiment	Determinate	Determinate	Used to reproduce or verify existing conclusions
Propositional semi-open experiment	Uncertain	Determinate	Used to examine and train students' design and practical abilities
Practical semi-open experiment	Determinate	Uncertain	Suitable for examining and training students' practical operation skills
Open experiment	Uncertain	Uncertain	Suitable for students' innovative training projects

design framework of "established direction, multiple paths, and dynamic results," as shown in **Figure 1**. The left side of the figure represents the teacher's progressive research, judgment, and selection of design work, while the right side represents the supporting work carried out on intelligent agents such as large language models for verification.

Within the context of real-world problems, this framework sets a clear but flexible goal, encouraging students to explore solutions from different perspectives using diversified methods and approaches. This design not only tests students' innovative thinking but also strengthens their adaptability in the face of uncertainty and challenges. The dynamic result evaluation mechanism ensures the comprehensiveness and fairness of the experimental process, promoting further deep thinking and continuous improvement among students.

Before carrying out comprehensive experimental design, it is first necessary to clarify which abilities are planned to be trained and cultivated in this experiment. In principle, these abilities should be designed and specified in the professional or course plan.

(1) Selection of real problems: Experiments should originate from real industrial problems, scientific research problems, or engineering practice problems, and the design of experimental activities should be based on the solution of the core or key parts of these problems. The problems should have a certain timeliness, stimulating students' interest while cultivating their attention to the forefront of the industry. This is also an effective way to integrate ideological and political elements into the curriculum. In problem selection, on the one hand, it is necessary to ensure that the solution of the problem requires the integrated use of

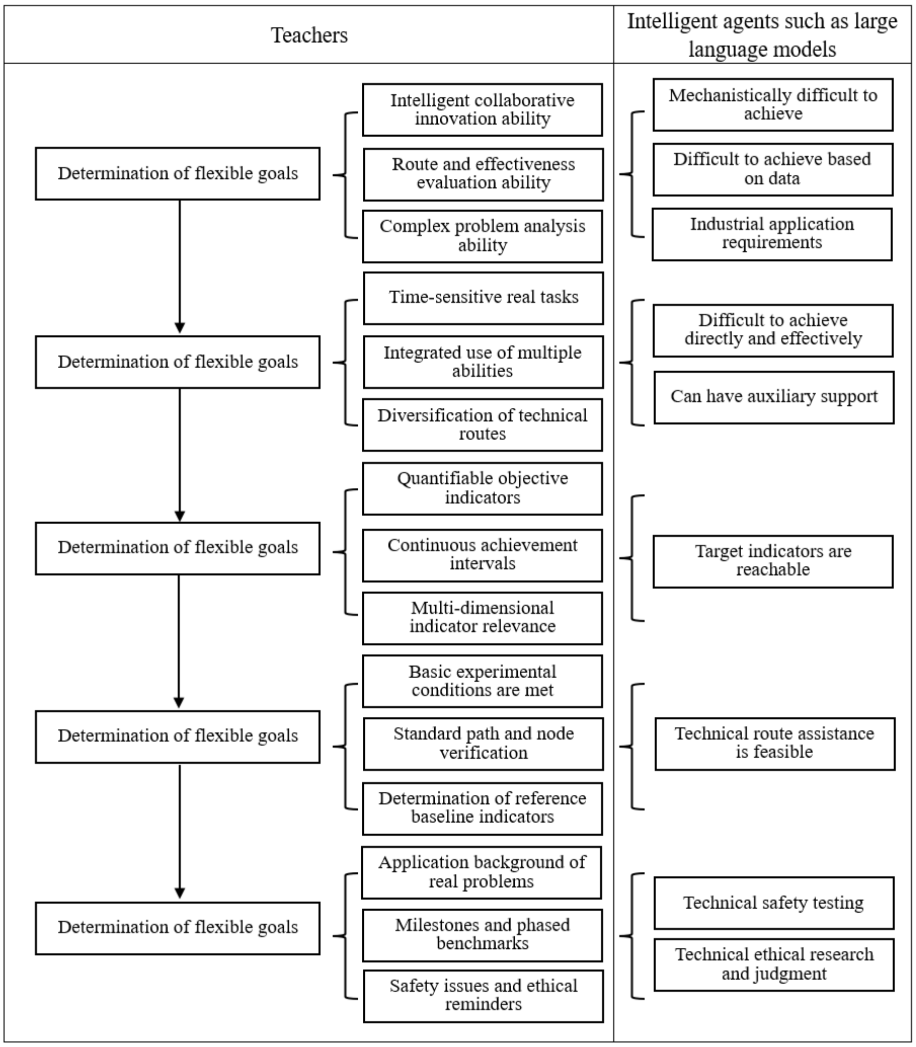


Figure 1. Experimental design framework

multiple abilities and knowledge from multiple fields; on the other hand, it is also necessary to ensure that multiple different technical routes can be adopted to complete related work, so as to train students' ability to analyze and solve problems. The designed experimental propositions should be tasks that are difficult for intelligent agents such as large language models to complete directly but can be assisted and accelerated through various auxiliary tasks.

(2) Determination of flexible goals: "Flexibility" refers to the fact that the final result goal is not a standard value but a reasonable range, which stimulates students' innovative spirit and challenge awareness, prompts them to continuously think and adjust their own solutions in pursuit of better results, and even set new records. The final indicators can be functional or technical, but they should all have quantifiable characteristics and continuous distribution features, that is, they should have comparable characteristics. If there are multiple dimensions of indicators, the correlation characteristics between the indicator dimensions, such as whether there is orthogonality, should be fully considered. At the same time, intelligent agents such as large language models can cooperate to complete the optimization of relevant indicators.

(3) Technical route verification: First, confirm that the basic environment can support the completion of the experiment, that is, relevant sites, equipment, consumables, and other conditions are available; secondly, design the standard path for experiment completion, fully consider the various technical routes that may exist in the experiment, and provide intermediate milestone nodes; at the same time, provide milestone node phased output delivery results to prevent accidents from causing the experiment to be unable to continue; finally, carry out verification experiments with the cooperation of intelligent agents such as large language models, and provide reference indicators for each node and the overall experiment.

(4) Writing of the experiment guide: Firstly, focus on the elaboration and explanation of the experimental scheme design background, strengthen the actual needs of engineering, industry, society, and other aspects, and help students develop the habit of caring about politics, industrial development, cutting-edge technology, and national economy and people's livelihood; secondly, while giving suggested routes, appropriately explain the division of each link of the task, especially the role and suggested indicators of milestone nodes; finally, fully study and judge the technical safety issues and ethical issues that may arise in the experiment, and explain them in the guide after verification through intelligent agents such as large language models.

4. Design and operation examples of comprehensive innovative experiments

4.1. Introduction to the course implementation

The Principles of Computer Organization is a landmark course in computer system courses. It is also one of the 12 core courses for computer science majors under the "101 Plan" of the Ministry of Education, occupying a pivotal position in the training system for computer professionals. It is included in the comprehensive examination outline for computer science majors in the national postgraduate entrance examination along with courses such as data structure, operating systems, and computer networks.

Nankai University offers a comprehensive innovative experiment course in Principles of Computer Organization for second-year undergraduates. This course is among the first batch of national first-class undergraduate courses (offline), a politically and morally oriented course demonstration in Tianjin universities, an innovation and entrepreneurship demonstration course in Tianjin, and a selected course for the Ministry of Education—Huawei Smart Base Project. The iterative construction cycle of this course is relatively long, and the construction foundation is sound. With "ability training" as the goal and "iterative design" as the guide, the course cultivates students' innovation ability, independent learning ability, and ability to solve real and complex problems through the study of computer

Table 3. Detailed table of abilities in computer system direction

Learning ability level	Computer system ability	Description
Analysis	Migration	Compare and analyze different systems to migrate existing tasks to other platforms
	Decomposition	Analyze the decomposition of existing systems or work into multiple subsystems
	Error correction	Analyze based on signs, feedback, and other information to find, locate, and correct errors
	Abstraction	Analyze complex systems and describe them in hierarchical and categorical ways
Evaluation	Assessment	Conduct quantitative evaluations of a system or task from multiple perspectives
	Selection	Choose from multiple routes or systems based on certain principles
	Reconstruction	Implement the original system using different methods or approaches
Innovation	Integration	Connect multiple systems to ensure smooth operation
	Optimization	Enhance the efficiency of existing systems by modifying them according to specific goals
	Design	Create new systems based on target requirements

system evaluation, instruction design, data path design, pipeline design, and storage system design. It has the implementation conditions for "intelligent collaboration" comprehensive innovative experiments.

4.2. Experiment design and approach

4.2.1. Design of ability training objectives

Computer system ability refers to the ability to apply the basic principles of computer systems to build application systems with computer technology as the core, and then solve practical problems. This is not only the design and expression in the International Computer Science Curriculum Guidelines (CS2013) but also the ability training direction strongly supported by the Computer Teaching Guidance Committee of the Ministry of Education. Combining educational psychologist Benjamin Bloom's six-level cognitive hierarchy thinking model (memory, understanding, application, analysis, evaluation, and innovation), in the Principles of Computer Organization course, "intelligent collaborative innovation ability" is defined as three levels of ability: analysis, evaluation, and innovation, which are broken down into 10 abilities as shown in **Table 3** [12].

4.2.2. Experimental topic design

Based on the principles and ideas of "established direction, multiple paths, and dynamic results," the core computational task of conventional large language models, namely the implementation and optimization of the "attention score" calculation task, was selected as the topic for this experiment. This topic bears significant characteristics of the times, aligns with the requirements of the "Four Orientations," and is likely to spark students' interest. To ensure a gradual progression, the overall task is divided into two parts: "implementation" and "optimization." The core objective of the "implementation" section is to cultivate students' abilities in "abstraction" and "decomposition," which involves quickly abstracting key technical aspects and core tasks from real-world problems. In this instance, the core task is identified as implementing tensor multiplication. The "optimization" section, on the other hand, is designed to exercise other abilities. Students can choose different hardware platforms and programming languages to construct various technical routes and select different optimization methods to ultimately achieve the optimization goals. This approach facilitates personalized teaching centered around learning and the student.

4.2.3. Flexible goal design

In line with the original design intent, the flexible goal for this experiment is set as the "time metric," specifically, the shortest execution time for the optimized program. The experimental guidelines emphasize the design requirement of "everything for time." Different routes, platforms, and methods yield varied results. This semi-open experimental approach, spanning platforms, languages, methods, and even curricular knowledge systems, greatly promotes students' autonomous learning abilities and their capacity to solve real and complex problems.

Similarly, space metrics can be chosen as optimization goals, such as spatio-temporal optimization in combination with FPGA design. Especially with appropriate hardware support, power consumption can also be considered an optimization target, and even cost factors can be incorporated into the optimization objectives.

4.2.4. Technical route design

To comprehensively cultivate the 10 target abilities, the experiment is divided into three parts: code generation (i.e., implementation), performance optimization, and task migration.

(1) Code generation: Students need to abstract the matrix multiplication task, particularly the specific tensor dimensions, based on the problem background provided in the experimental guidelines. This section focuses on developing students' abstraction skills. Here, large language models can be used to understand the problem's background knowledge and determine various parameters. Students must explain the reasons for abstraction, their thinking process, and the determination of quantitative parameters in a report document (**Figure 2**).

Based on the control experiment's standard requirements (i.e., various parameter configurations), students can write code manually or with the assistance of large language models. This code needs to be jointly evaluated by humans and large language models, focusing primarily on code standardization and interface checks. Additionally, students have the freedom to choose their programming language and hardware platform. The experiment provides x86, MIPS, and ARM hardware platforms, with ARM being the final target platform for migration.

(2) Performance optimization: In this experiment, time optimization is taken as an example to set optimization requirements. Students are required to design their own routes and methods for implementation, which can be based on optimizing the methods provided

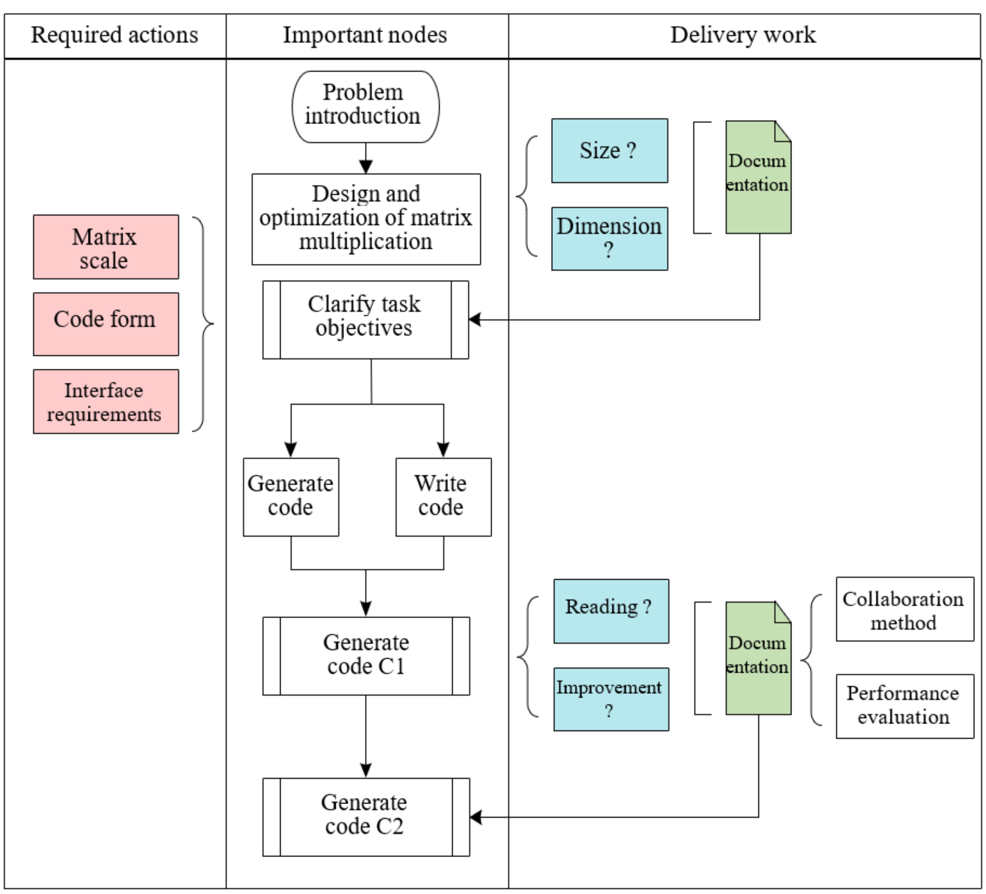


Figure 2. Schematic diagram of the technical route for code generation experiment. Note: The red part represents the content that will be given in the experiment guide; the blue part represents the work that can be done in collaboration with the large language model; and the green part represents the work documents that need to be delivered.

Figure 3. Schematic diagram of the technical route for performance optimization experiment. Note: The red part represents the content that will be given in the experiment guide; the blue part represents the work that can be done in collaboration with the large language model; and the green part represents the work documents that need to be delivered.

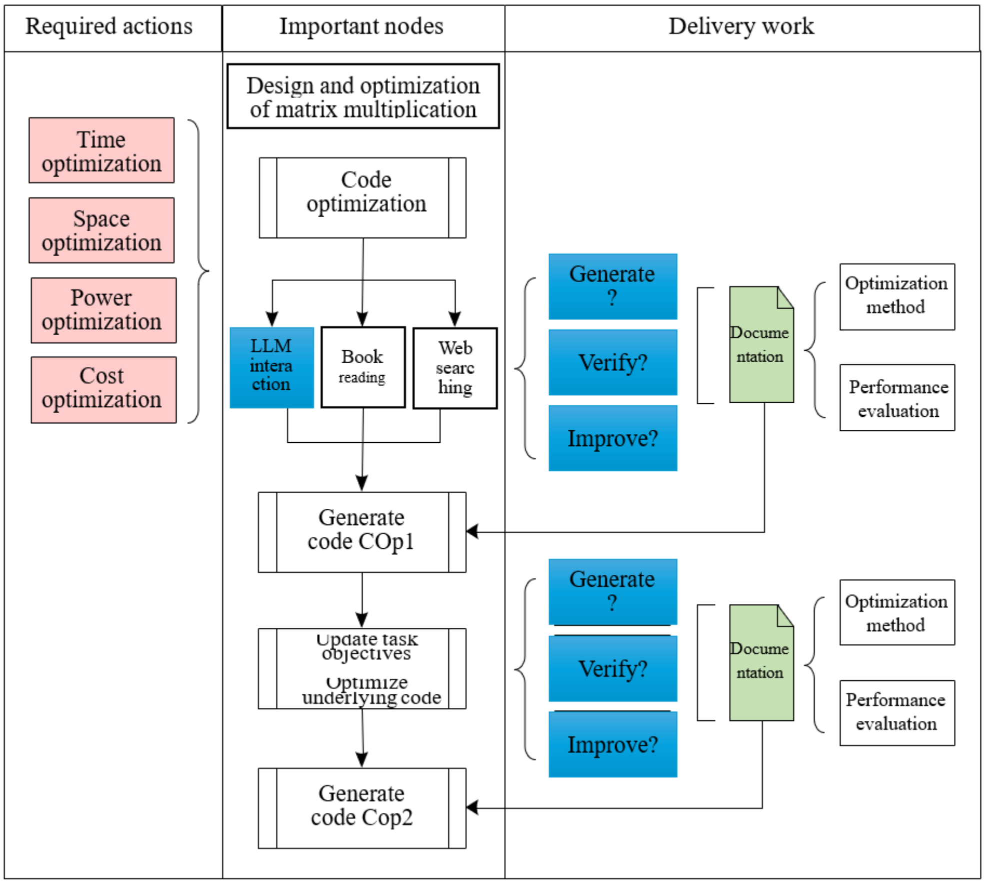
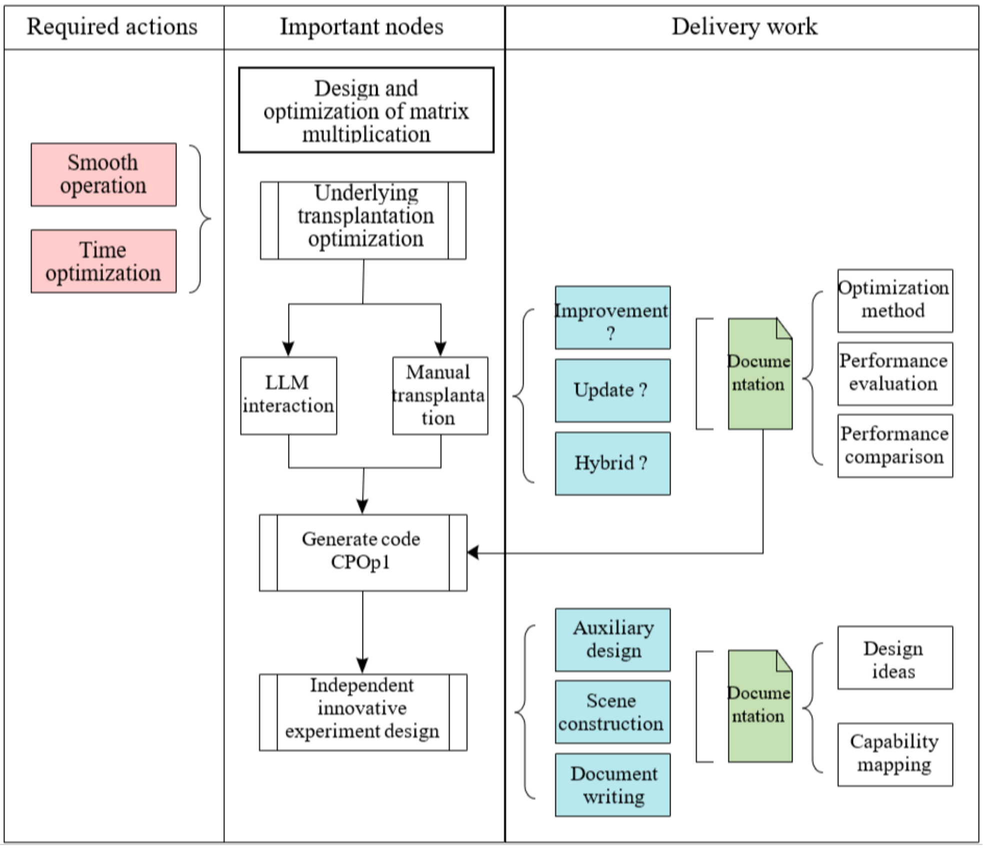


Figure 4. Schematic diagram of the technical route for task migration experiment. Note: The red part represents the content that will be given in the experiment guide; the blue part represents the work that can be done in collaboration with the large language model; and the green part represents the work documents that need to be delivered.



in the textbook, searching for relevant solutions through the internet or large language models, or even directly having the large language model assist in modifying the code to improve performance. However, before that, students need to collaborate with the large model to build a basic performance evaluation model and method, so as to evaluate the effectiveness of future improvements. At the same time, after completing the optimization at the high-level language level, students still need to optimize the code at the lower level such as assembly language, evaluate the corresponding results, and write relevant reports (**Figure 3**).

(3) Task migration: Students need to complete a transplantation task from the underlying code to the ARM platform, and collaborate with the large language model again after the transplantation to ensure that the transplanted code can operate smoothly and achieve optimal performance.

After the in-class experiment is completed, students are required to complete an independent and innovative experiment design based on this experiment to improve their own weaknesses. In the process of designing the experiment, they can use the large language model for assistance and collaboration to complete tasks such as scene construction and experiment guide writing (**Figure 4**).

4.2.5. Experiment guide design

This experiment does not involve technical safety-related content. Instead, it provides hints on the experimental environment, experimental conditions, experiment submission, and key node selection in the technical route.

In terms of the experimental environment, the guide introduces the use of virtual machine systems to support different hardware platforms and provides instructions on usage methods and permissions. Regarding experimental conditions, this experiment does not limit the use of large language model tools. The guide encourages students to select multiple large models for comparison or to work together in combination, aiming to cultivate and enhance their evaluation and selection abilities. As for experiment submission, the guide sets the format and location for submission.

4.2.6. Ability training design

In this comprehensive experiment, there are corresponding experimental sections and task designs for each of the 10 abilities derived from “intelligent collaborative innovation ability,” as detailed in **Table 4**.

5. Experiment implementation and effectiveness analysis

5.1. Experiment organization and operation

The experiment was conducted during the second semester of the 2023–2024 academic year in the “Computer Organization Principles” course at Nankai

Table 4. Correspondence table for experimental section design and abilities

Learning ability level	Computer system ability	Corresponding experimental section and design	Corresponding tasks
Analysis	Migration	Moving existing work to platforms like ARM	Task migration
	Decomposition	Exporting problems as tensor multiplication	Code generation
	Error correction	Experimental debugging	Various tasks
	Abstraction	Exporting problems as tensor multiplication	Code generation
Evaluation	Assessment	Establishing performance evaluation methods	Performance optimization
	Selection	Choosing optimization schemes based on large language model suggestions	Various tasks
	Reconstruction	Optimization for the target transplantation platform	Task migration
Innovation	Integration	Submitting interfaces and integrating code	Various tasks
	Optimization	Performance optimization, task migration	Various tasks
	Design	Independent and innovative experimental design	Task migration

University. The participants were all undergraduate students majoring in computer science and technology from the 2022 grade, totaling 141 students.

The experiment was divided into two parts: an independent 3-hour class experiment requiring students to complete code generation and performance optimization individually, and group work on task migration after class.

The experiment was conducted at the Computer Experimental Teaching Center of Nankai University, with experimental conditions including various open large models that can be directly accessed, as well as x86, MIPS, and ARM platforms. The MIPS platform was provided in the form of a virtual machine, while the ARM platform was supplied through a remote connection to a physical server.

5.2. Experimental data analysis

All 141 students participating in the experiment submitted experimental reports, and 135 of them completed the entire experimental process, with an overall completion rate of 95.7%. This indicates that the overall design of the experiment aligns with the students' ability requirements. During the experiment, most students chose "Tongyi Qianwen" and "Wenxin Yiyan" as their large language models, while three other large language models were also selected. This demonstrates the openness of the experiment and confirms that there are no significant differences among various large language models in assisting system optimization.

In terms of experimental platform selection, students mainly used computer platforms based on x86 and ARM architectures. Most students conducted experiments primarily using the C/C++ programming language, indicating that C/C++ is still excellent in terms of implementation efficiency and has gained students' recognition. At the same time, given Python's advantages in data processing and rapid development, some students chose to use Python.

The final experimental results were submitted in groups, and the specific distribution is shown in **Figure 5**. The figure shows that with the assistance of large models, 95.7% of the groups were able to successfully complete the migration and improvement of experimental tasks. Among them, nearly 75% of the groups could complete the algorithm within 25 seconds, and about 17% of the groups could further optimize the program to reduce the execution time to less than 10 seconds. The results basically show a bimodal distribution, which aligns with the original intention of the experimental design and achieves effective graded evaluation.

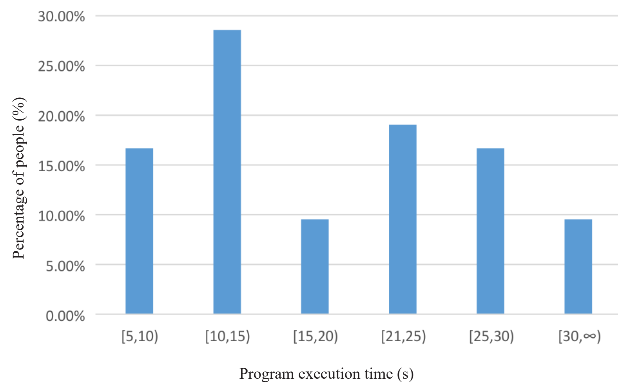


Figure 5. Distribution of experimental performance optimization time

5.3. Analysis of experimental results

Through analyzing the experimental reports, it was found that students encountered various programming challenges and performance bottlenecks during the process of writing and optimizing matrix multiplication code. With the assistance of large language models, they learned to address these issues in practice, which not only deepened their understanding of basic computer science knowledge but also provided them with a more profound comprehension and experience of "intelligent collaboration." By collaborating with intelligent systems, students felt the power of smart technology in learning and work, and gained a deeper insight into the application of large models in future technology.

Beyond meeting the basic experimental requirements, students achieved the fundamental teaching objectives of the course and demonstrated enthusiasm for knowledge exploration and a deep understanding of technical applications. Through independent and innovative experimental design, they further solidified their comprehension of intelligent collaboration capabilities. Based on the students' experimental performance, their independent innovations mainly fell into two categories:

The first category involved innovations in the experimental background. Referring to the experimental guidebook, students transferred the experimental context to different domains. For instance, some students selected architectural mechanisms such as cache and pipelines, and explored their performance and optimization strategies in various application scenarios using large models. Others focused on algorithmic levels, such as classic algorithms like Gaussian elimination and Fourier transform, experimenting to verify their efficiency and applicability, and even attempting to improve or optimize these algorithms.

The second category encompassed innovations in the experimental steps. Some students were not satisfied with the existing experimental framework and proposed additional steps to facilitate deeper learning and understanding. For example, students migrated the experiment to an FPGA (Field Programmable Gate Array), which required not only a profound knowledge of hardware programming but also mastery of implementing and optimizing algorithms at the hardware level.

China Education News reported on this work online [19]. Additionally, during the interview session after the experiment, all students mentioned the issue of learning pathways, specifically the shift from "learning from textbooks to learning from intelligence," which represents a significant direction in teaching reform: cultivating self-learning abilities in the era of large language models.

6. Conclusion

Artificial intelligence technologies, such as large language models, are disruptive and revolutionary, as mentioned in the discussion of new productive forces. They are triggering transformations in various industries and significantly impacting talent demand. In light of this, higher education reform must explore the application of AI technologies in various aspects, including assisting students, teachers, administrators, and researchers, while also emphasizing the cultivation of new talent abilities. This paper proposes the ability training goal of "intelligent collaborative innovation" and designs a comprehensive experimental teaching method based on it, applying it to practical teaching.

In the era of new productive forces, teaching reform research in higher education must be forward-looking, focusing on future industry trends, real business scenarios, and changes in ability requirements. Besides the emphasis on innovative ability training discussed in this paper, cultivating self-learning abilities is also a crucial task that aligns with the development needs of new productive forces and will become an important research direction in future experimental education and teaching reform.

Funding

Experimental Teaching and Teaching Laboratory Construction Research Project of the Department of Higher Education of the Ministry of Education (SYJX2024-025); Tianjin Higher Education Graduate Education Reform Research Program - Key Project (TJYGZ53); Tianjin General Higher Education Undergraduate Teaching Reform and Quality Construction Research Program (B231005505)

Disclosure statement

The authors declare no conflict of interest.

References

[1] ARK Investment Management LLC, 2024, Big Ideas 2024, viewed August 1, 2024, https://www.ark-invest.com/big-ideas-2024

[2] Wang F, Liu Y, Zhou T, 2024, Artificial Intelligence Leads the Digital Innovation and Development of Higher Education. China Higher Education, (Supplement 1): 9–12.

[3] Wang F, Wang F, 2024, Infinite Possibilities: World Higher Education Digital Development Report (2023). China Higher Education, (Supplement 1): 13–18.

[4] Zhang N, Wang X, 2023, The Interaction Path Between Technological Change and Higher Education and Its Reflection. Research in Higher Education of Engineering, 2023(4): 110–115.

[5] Kong X, Wang M, Chen X, 2022, Practice and Exploration of the Construction of "New Business" Digital Intelligence Undergraduate Courses in the Digital Economy. Teaching in China's Universities, 2022(8): 31–36.

[6] Yao C, Chen C, Chen M, 2024, AI Natural Language Generation Experiment and Teaching Design for Liberal Arts Students. Experimental Technology and Management, 41(4): 177–184.

[7] Zhang J, Gong X, Gao X, 2024, Intelligent Collaborative Teaching Experiment Design for Computer System Ability Training in the Era of Large Models. Laboratory Science, 27(2): 21–23.

[8] Zhai J, Li Y, Meng T, et al., 2023, Exploration and Practice of Personalized Computer Experiment Teaching Based on Decision Trees and Large Models. Experimental Technology and Management, 40(12): 8–15.

[9] Xu X, Mi J, Chen W, 2019, Engineering Training Platform for Collaborative Filtering Recommendation System from the Perspective of Artificial Intelligence. Experimental Technology and Management, 36(4): 109–113.

[10] Su J, Yang W, 2023, Unlocking the Power of ChatGPT: A Framework for Applying Generative AI in Education. ECNU Review of Education, 6(3): 355–366.

[11] Baidoo-Anu D, Ansah LO, 2023, Education in the Era of Generative Artificial Intelligence (AI): Understanding the Potential Benefits of ChatGPT in Promoting Teaching and Learning. Journal of AI, 7(1): 52–62.

[12] Geesje VDB, ElizE DP, 2023, ChatGPT and Generative AI: Possibilities for Its Contribution to Lesson Planning, Critical Thinking, and Openness in Teacher Education. Education Sciences, 13(10): 1–12.

[13] Jo A, 2023, The Promise and Peril of Generative AI. Nature, 614(1): 214–216.

[14] Singh H, Tayarani-Najaran MH, Yaqoob M, 2023, Exploring Computer Science Students' Perception of Chat GPT in Higher Education: A Descriptive and Correlation Study. Education Sciences, 13(9): 924.

[15] Office of Educational Technology, Department of Education, USA, 2023, Artificial Intelligence and the Future of Teaching and Learning: Insights and Recommendations, viewed August 1, 2024, https://tech.ed.gov/ai-future-of-teaching-and-learning/

[16] UK Government, 2023, Generative Artificial Intelligence (AI) in Education, viewed August 1, 2024, https://www.gov.uk/government/publications/generative-artificial-intelligence-in-education

[17] Department of Education, Australian Government, 2023, Australian Framework for Generative Artificial Intelligence (AI) in Schools, viewed August 1, 2024, https://www.education.gov.au/schooling/resources/australian-framework-generative-artificial-intelligence-ai-schools

[18] General Office of the Central Committee of the Communist Party of China, 2022, General Office of the Central Committee of the Communist Party of China and General Office of the State Council issued the "Opinions on Strengthening the Governance of Scientific and Technological Ethics," viewed August 1, 2024, https://www.gov.cn/zhengce/2022-03/20/content_5680105.htm

[19] Chen X, 2024, Nankai University: Students Conduct Experiments with Large Models, viewed August 1, 2024, http://www.jyb.cn/rmtzcg/xwy/wzxw/202407/t20240701_2111216592.html

Publisher's note

Whioce Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.