Research on Applied Talent Training Path Based on the In-depth Integration of Artificial Intelligence and Mathematical Modeling Competitions

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Abstract: With the explosive development of artificial intelligence (AI) technologies, traditional modes of learning and working are being transformed. The cultivation of traditional, application-oriented talent requires students to have an extremely solid foundation of knowledge, self-discipline, and learning ability. This results in a persistent shortage of such talent. Mathematical modeling competitions are widely adopted as one of the platforms for training application-oriented talents; nevertheless, many students are deterred from participating in these contests. As a vital bridge linking theory to practice, mathematical modeling competitions are undergoing a paradigm shift from "traditional modeling" to "AI-driven modeling". This paper mainly aims to construct an educational theoretical framework featuring the in-depth integration of "AI + mathematical modeling" by integrating constructivist learning theory, psychological theories and mathematical modeling methodologies. Meanwhile, a multi-dimensional evaluation system is designed for the dynamic process of competency acquisition, so as to address long-standing difficulties in cultivating application-oriented talents and provide theoretical support for the teaching reform of higher education.

Keywords: Artificial Intelligence; Mathematical Modeling; Application-Oriented Talents; Constructivism; Talent Cultivation System

1 Introduction

1.1 Research Background

1.1.1 Ai-based mathematical modeling talents as the core of global scientific and technological competition

The world is currently at the intersection of a new scientific and technological revolution and an industrial transformation. Artificial intelligence (AI) is a strategic technology that will lead the future and has already made a significant impact on key fields such as financial risk control, intelligent manufacturing, medical diagnosis and smart cities. Mathematical modelling serves as the core support for the industrial application of AI technologies, acting as a bridge connecting mathematical theories and practical real-world problems. Competence in mathematical modelling is essential for the mathematical derivation of machine learning algorithms, model construction in big data analysis and the design of schemes for optimising complex systems. However, the concept of mathematical modelling has undergone profound changes in the AI era. AI-based mathematical modelling is no longer confined to formulaic deduction; it has evolved into a systematic engineering discipline centred on computing power, algorithms, and data.

Firstly, the AI-based modelling paradigm has greatly expanded the scope for solving complex problems. Traditional, mechanism-driven modelling is often limited by variable dimensions and non-linear complexity, which makes it difficult to describe highly complex real-world systems accurately. In contrast, AI-based modelling approaches can automatically extract features from large amounts of unstructured data to accurately characterise highly dimensional, dynamic and strongly coupled systems.

Secondly, the adoption of AI tools has significantly lowered the technical barrier to modelling and improved its efficiency. Conventional mathematical modelling is limited by modellers' mathematical theoretical foundation and coding capabilities [1]. With the help of artificial intelligence, automated machine learning (AutoML) and large language model (LLM)-aided code generation, as well as intelligent simulation technologies, modelers can now complete the entire workflow, from model validation to parameter optimization, much more quickly. This human-machine collaborative modelling capability has become standard practice in modern scientific research and engineering applications.

According to the Global Artificial Intelligence Development Report (2025), China's core artificial intelligence industry exceeded a value of 900 billion yuan in 2024, and this figure is expected to exceed 1.2 trillion yuan by 2025. Under China's strategy of fostering new quality productive forces, there has been a shift in corporate demand for talent from mere algorithm implementation to comprehensive modelling capabilities for solving complex real-world scenarios based on AI. There is an urgent need for interdisciplinary, application-oriented talent with a solid grasp of fundamental mathematical logic and proficiency in using AI tools for data cleaning, feature engineering, and model deployment.

Meanwhile, mathematical modelling contests have evolved into a core vehicle for talent cultivation in universities worldwide, providing a vital platform for examining and improving students' modelling capabilities. Such contests also provide an important opportunity for institutions to nurture innovative, application-oriented talent [2]. For instance, the number of teams participating in the China Undergraduate Mathematical Contest in Modelling (CUMCM) exceeded 60,000 in 2025, representing over 1,200 universities nationwide. However, many teams reduce mathematical modelling to "verbal modelling" during the competition, focusing solely on writing papers rather than solving practical problems. This is primarily due to the high entry barrier of mathematical modelling, which leaves many students unable to solve contest problems. Artificial Intelligence (AI) can support these students by providing tangible assistance with problem-solving methodologies and code writing [3].

1.1.2 Breaking the gap between theory and practice for the cultivation of application-oriented talents

In recent years, the reform of higher education in China has explicitly focused on cultivating application-oriented talent. Nevertheless, multiple obstacles still hinder the integration of mathematical modelling and AI education in practical teaching.

First, the curriculum system is fragmented. In most universities, mathematical modelling courses are separate from artificial intelligence, machine learning, and other relevant courses, and are administered by different departments. This results in disjointed teaching content. Mathematical modelling courses focus on theoretical deduction and traditional models, such as differential equations and linear programming, while AI courses focus on algorithm application and code implementation. Consequently, students fail to develop a systematic approach to solving mathematical modelling problems using AI tools.

Secondly, practical teaching is merely formalistic. Due to a lack of teachers, equipment and other resources, practical sessions mostly consist of simulated exercises that are not aligned with real industrial problems [4].

1.2 Research Significance

Exploring the integration of artificial intelligence and mathematical modelling in competitions can improve students' performance in competitions and, more importantly, cultivate their ability to perform mathematical abstraction, implement algorithms and verify results using AI tools in a quasi-real scenario. This has substantial practical significance for the development of emerging engineering education and the advancement of the quality improvement project of higher education.

1.2.1 Enriching the theoretical framework of application-oriented talent training

This paper presents a theoretical framework for the integrated approach of 'AI + Mathematical Modelling Contest'. Taking a multidisciplinary approach that includes pedagogy (constructivist learning theory), psychology (situated cognition theory), mathematics (the methodology of mathematical modelling) and computer science (the principles of AI technology), the paper analyses the internal logic behind the integration of artificial intelligence and mathematical modelling contests.

AI provides high-efficiency computing tools and intelligent optimisation approaches for mathematical modelling, while mathematical modelling contests offer real-world application scenarios and problem-driven use cases for AI technologies. Together, they form a collaborative, closed-loop educational system centred on 'technology-scenario-competency'. This integration represents more than a simple superposition at the instrumental level; it signifies a theoretical advancement in the transition from traditional knowledge-based education to competency-based education. By redefining the relationship between students and intelligent tools, this integration overcomes the theoretical limitations of conventional, single-discipline talent development and provides new theoretical support and philosophical paradigms for the interdisciplinary training of application-oriented talent.

1.2.2 Addressing practical predicaments of application-oriented talent training

The practical obstacles to cultivating application-oriented talent lie mainly in three areas: (1) the rapid acquisition of interdisciplinary knowledge; (2) the selection of appropriate mathematical knowledge for analysis and the construction of mathematical models; and (3) the solution of problems via computer programming.

Through the in-depth integration of the 'AI + Mathematical Modelling Contest', students can develop the following three core competencies:

Firstly, they will develop the ability to rapidly acquire knowledge. Existing AI tools, such as Doubao, DeepSeek and ChatGPT, support real-time Q&A and enable personalised learning.

Secondly, they can develop mathematical modelling capability. Students can use multiple AI tools to analyse contest topics, build models, identify problem categories and determine relevant mathematical theories and algorithms, thus broadening their thinking horizons effectively.

Thirdly, programming proficiency. Within the "AI + Mathematical Modelling Contest" framework, students only need to specify functional requirements and direct AI to generate the corresponding code. This competency enables students to address high-dimensional, non-linear and unstructured data challenges that traditional mathematical methods find difficult to handle [5], facilitating the transition from idealised modelling to industrial-grade modelling.

2. Logical Analysis of "AI + Mathematical Modeling" from a Multidisciplinary Perspective

2.1 Pedagogical Perspective: Constructivist View of Learning Activities

Constructivism holds that knowledge is not acquired through instruction from teachers. Instead, learners construct meaning and gain knowledge in specific contexts with the help of others and essential learning materials [6].

In the context of 'AI + Mathematical Modelling', AI can generate authentic industrial problems to strengthen students' sense of meaningful learning. Large language models and industry-specific AI tools can import raw data and business backgrounds from sectors including economics, environmental science, logistics, and healthcare to create unsimplified, open-ended modelling tasks. Examples include urban shared bicycle scheduling, river water pollution prediction, and campus power load optimisation. Unlike standardised textbook examples, these real-world problems feature missing data, mixed variables, and conflicting constraints, aligning with practical modelling work and enhancing the meaningfulness of learning tasks.

Acting as a personalised learning assistant, AI provides timely support. When students encounter obstacles in data pre-processing, model solving or error analysis, AI avoids providing standard answers directly and instead asks guiding questions such as "Your dataset contains outliers. What data cleaning methods could you use?" and "The fitting error of your linear model is excessively large. Would you consider introducing nonlinear terms?' These heuristic dialogues encourage independent thinking, replacing traditional lecturing. For students with weak foundations, AI offers step-by-step hints on how to think; for advanced learners, it presents more complex research directions, including multi-objective optimisation and integrated modelling with machine learning, thus enabling differentiated knowledge construction.

2.2 Psychological Perspective: Negative Correlation between Learning Anxiety and Academic Performance

When an individual suffers from learning anxiety, the brain allocates a large amount of working memory resources to process negative emotions such as tension, fear and self-denial. As a result, the remaining cognitive resources available for logical deduction, model calculation and problem construction are limited. Taking mathematical modeling learning as an example, students may experience anxiety triggered by complicated formulas, massive datasets and programming difficulties. Their attention is occupied by negative predictions like “I cannot work out the solution” or “I will make mistakes in model construction”, making it hard for them to carry out high-order thinking activities including variable analysis and iterative optimization, which directly reduces task completion quality and academic performance. Research conducted by Wang and Che [7] demonstrates a negative correlation between learning anxiety and academic achievement. In traditional learning environments, mistakes are often accompanied by negative feedback such as teachers’ criticism, peer comparison and low scores. Learners equate failure to solve problems with insufficient personal competence, which gives rise to persistent learning anxiety.

AI boasts psychological strengths including neutrality, absence of subjective judgment and instant feedback, offering learners a cost-free space for trial and error. During mathematical modeling practice, students are allowed to repeatedly switch models, tune parameters and revise datasets. AI rapidly conducts massive computations and simulations, and displays updated results immediately. This enables students to gain multiple rewarding experiences of independently revising and optimizing models within a short period. Continuous positive task feedback reshapes learners’ negative perception that “I am incapable of solving difficult problems”, reduces feelings of fear and nervousness, lowers the level of learning anxiety, and weakens the negative correlation between anxiety and academic performance.

2.3 Mathematical Modeling and Artificial Intelligence

The underlying core of all algorithms is constructed from mathematical models. Whether traditional numerical algorithms or artificial intelligence algorithms such as deep learning and machine learning, they are essentially encapsulated mathematical mapping, optimization and fitting models. This determines that mathematical modeling is the foundation and core soul for the existence and practical application of AI. Restricted by analytical solving capabilities, traditional mathematical modeling struggles with complex systems in industry, meteorology, biology and other fields characterized by high dimensionality, strong coupling, severe nonlinearity and multivariate interaction. For such systems, it is difficult to derive mechanism equations, and analytical solutions are nearly unattainable. By contrast, relying on the capabilities of machine learning and deep learning including numerical iteration, gradient optimization and data fitting, AI provides a numerical solution approach that does not require complete mechanism equations, greatly lowering the solving threshold for modeling complex systems.

Sun et al. [8] pointed out that mathematical modeling can be categorized into three types: pure mechanism-driven modeling, pure data-driven modeling, and hybrid mechanism-data modeling. As a core branch of AI, machine learning runs through the whole process of all three modeling categories.

In addition to providing data analysis and mathematical modelling methods, AI can also be used to write and refine mathematical modelling papers [9]. Han et al. analysed the advantages of AI as a mathematical modelling tool in the literature, while also pointing out potential problems arising from over-reliance on AI and corresponding solutions.

3. Establishment of the In-depth Integration Evaluation System

A sound talent evaluation system contributes to the improvement of talent cultivation quality. Traditional evaluation of application-oriented talents generally takes “award levels” as the sole assessment indicator. Tong and Li [10] argued that the evaluation system for undergraduate application-oriented talent cultivation should cover three primary indicators: knowledge, ability, and literacy. Zhao et al. [11] proposed that the classified evaluation indicators for innovative scientific and technological talents consist of six primary dimensions, including innovative knowledge, innovative skills, influence, innovative competence, innovative motivation, and management capability. Combined with the characteristics of mathematical modeling competitions, this study establishes four primary indicators—knowledge, ability, motivation, and quality—as well as a series of corresponding secondary indicators, as detailed in the following table 1.

Table 1: Indicators of Talent Evaluation System

	Secondary Indicator	Weight of Secondary Indicator	Weight of Primary Indicator
Knowledge (A_1)	Award Level (B_{11})	0.6	0.25
	Professional Knowledge (B_{12})	0.4	
Competence (A_2)	Learning Competence (B_{21})	0.6	0.25
	Management Competence (B_{22})	0.4	
Motivation (A_3)	Learning Motivation (B_{31})	0.5	0.3
	Life Motivation (B_{32})	0.5	
Quality (A_4)	Teamwork (B_{41})	0.4	0.25
	Time Management (B_{42})	0.6	

The evaluation score of each secondary indicator is denoted as x, which takes values of 1, 2, 3 and 4. A higher score represents a better performance in the corresponding indicator.

Let the comprehensive evaluation score be defined as S:

$$S = \sum_{i=1}^{4}\sum_{j=1}^{2} w_{ij} x_{ij} \tag{1}$$

Where x_{ij} and w_{ij} denote the evaluation score and weight of the corresponding secondary indicator B_{ij}, respectively, i=1,2,3,4; j=1,2.

4 Conclusions and Prospects

The popularization of artificial intelligence lowers the threshold of knowledge learning and understanding, and effectively improves learners' comprehensive ability to apply knowledge to solve practical problems. Personalized teaching, which was previously difficult to implement due to the limitations of teacher resources and teaching energy, can be fully realized relying on artificial intelligence technology. Serving as a scaffolding tool throughout the learning process, AI assists students in quickly getting started with unfamiliar disciplines and constructing knowledge frameworks. The in-depth integration of artificial intelligence and mathematical modeling also enhances the feasibility and implementability of the innovative talent training mode based on mathematical modeling competitions.

Meanwhile, further exploration and in-depth research are still required to fully release the empowering value of artificial intelligence while avoiding excessive technological dominance that may weaken students' independent thinking capabilities.

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