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Exploration and Practice of a Teacher–Student–Machine Tripartite Collaborative Teaching Model for the Modern Control Theory Course Empowered by Artificial Intelligence

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Abstract

Modern Control Theory is a core course for automation majors. Its knowledge system takes the state-space method as its main thread, characterized by complex mathematical derivations and abstract physical concepts; compounded by the practical constraint of large-class instruction with over one hundred students, the course has long suffered from three structural contradictions: the teaching process is invisible, learning states are unmeasurable, and instructional support is inaccessible. Relying on the "AI+" Classroom Teaching Reform project and guided by the philosophy of Outcome-Based Education (OBE), this study constructs a tripartite collaborative teaching model involving teachers, students, and AI agents. Practice shows that, while firmly maintaining the teacher's leading role in education, the model transforms artificial intelligence into an embeddable, measurable, and iterable teaching element, providing a referable practical sample for the digital-intelligent transformation of engineering courses.

Keywords

artificial intelligence, Modern Control Theory, teacher–student–machine tripartite collaboration, OBE philosophy

1. Introduction

To implement the deployment in the *Outline of the National Plan for Building an Educationally Powerful Country (2024–2035)* on implementing the national strategy of education digitalization and promoting AI-empowered educational transformation [1], the Ministry of Education launched the project initiation process for the "AI+" Classroom Teaching Reform Project, explicitly requiring intelligent technologies to support innovation in talent cultivation models and the reform of teaching methods [2]. Against this backdrop, promoting the deep embedding of artificial intelligence into the whole process of instructional design, instructional implementation, and instructional evaluation for specialized courses has become an important lever for higher education institutions to improve the quality of talent cultivation.

Modern Control Theory is a core backbone course for automation and related majors, covering state-space description, controllability and observability, pole placement, state observer design, and optimal control. It is

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both the knowledge cornerstone for subsequent specialized courses and an important vehicle for measuring students' ability to "solve complex engineering problems" in engineering education accreditation. However, this course takes matrix operations and abstract state-space geometry as its core tools, with dense concepts and long derivation chains. Students commonly report that they "can follow the lectures, but cannot work out the problems or apply what they learn," and the rate of knowledge internalization is low. The traditional two-element model of "teacher lecturing—students listening" can hardly accommodate individual cognitive differences, nor can it provide precise characterization of and immediate feedback on the learning process.

In recent years, the rapid evolution of generative artificial intelligence has offered new technical possibilities for resolving the above predicament. The "teacher–machine–student" collaborative model explored by iflytek and other institutions has been implemented at scale in basic education, verifying the potential of AI to restructure the classroom ecosystem. In higher education, some institutions have carried out distinctive explorations of smart teaching ecosystems centered on "teacher–student–machine" collaboration [3], while the "student–machine–teacher" tripartite collaboration proposed by Wang Zhuli re-examined the relationships among the three from the perspective of learner agency [4]. However, existing studies mostly focus on general teaching scenarios or basic disciplines. For specialized control courses characterized by "strong mathematical foundations, emphasis on derivation, and the need for simulation," how to define the boundaries of AI's instructional functions, how to implement the collaboration mechanism in concrete teaching activities, and how to objectively measure collaborative outcomes still lack systematic answers.

On this basis, this study pilots the Modern Control Theory course and revolves around three questions: First, in a specialized course with strong logic and high abstraction, what instructional functions should the AI agent undertake, and how should its boundaries with teachers and students be demarcated? Second, how can the tripartite collaboration be embedded into the complete teaching chain of "before class—during class—after class" to form an operable teaching process? Third, can the effectiveness of collaborative teaching be objectively characterized by multi-dimensional data so as to support continuous improvement? The research aims to form an "AI + classroom" teaching paradigm adapted to the characteristics of automation majors, providing a reference for the reform of control courses under the background of emerging engineering education.

2. Current Situation and Problem Analysis of Course Teaching

Measured against the core philosophy of engineering education accreditation—"student-centered, outcome-oriented, continuous improvement"—the current course teaching mainly suffers from four pain points.

2.1 Abstract Knowledge System and Overloaded Cognitive Burden

Modern Control Theory centers on the state-space method, intersecting linear algebra, differential equations, and optimization theory. At knowledge points such as "controllability and observability criteria" and "Lyapunov stability analysis," students often get bogged down in tedious matrix derivations and struggle to establish the mapping between algebraic results and physical meanings, resulting in a disconnect of "being able to calculate but not to apply."

2.2 Limited Interaction Frequency and Absence of Personalized Guidance

In a large class of over one hundred students, teachers can hardly grasp in real time each student's mastery of difficult points such as "pole placement" and "state feedback"; after-class Q&A suffers from spatio-temporal lag, and students' individualized cognitive blind spots cannot be addressed in a timely manner, which is in tension with the "student-centered" philosophy.

2.3 Monolithic Evaluation and Discontinuous Process Data

Assessment mostly relies on closed-book final examinations and a small amount of homework, lacking dynamic evaluation of the inquiry process, code debugging ability, and thinking logic. Teachers can hardly acquire full-cycle learning analytics data, so "continuous improvement" lacks an objective basis, and the optimization of instructional design mostly relies on empirical judgment.

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2.4 Stiff Integration of Ideological Education and Weakened Engineering Ethics

In the context of purely theoretical derivation, curriculum-based ideological and political education easily degenerates into "labeling," failing to naturally connect the dialectical ideas embedded in theoretical categories such as "stability," "feedback regulation," and "robustness" with the engineering ethics and craftsmanship spirit found in major national projects (aerospace, high-speed rail, large aircraft control).

At a deeper level, the four problems above point to the same crux: the teaching process is invisible, learning states are unmeasurable, and instructional support is inaccessible. This is precisely the entry point where artificial intelligence can play a structural role—using data to make the process visible, models to make states measurable, and agents to make guidance accessible.

3. Innovative Design of the Teaching Model Empowered by "AI+"

3.1 Overall Architecture: OBE-Based Tripartite Collaboration

Taking the OBE philosophy as the overall guide and "value leading—process visibility—role collaboration—life growth" as the design lens, this model constructs a "teacher–student–machine" tripartite collaborative architecture. In this architecture, the teacher is the value leader and stimulator of higher-order thinking; the student is the subject of knowledge construction and the executor of engineering practice; the AI agent is the ubiquitous learning companion, personalized tutoring assistant, and whole-process data analyst. Through the convergent coupling of the knowledge flow (content provision and cognitive construction), the data flow (learning analytics collection and feedback regulation), and the emotional flow (motivation stimulation and value identification), the three parties form a closed-loop collaborative ecosystem, driving the classroom to shift from "knowledge transmission" to "capability generation." The functional boundaries of the three roles are shown in Table 1.

Table 1: Role positioning and functional boundaries of the "teacher–student–machine" tripartite roles

Subject	Role Positioning	Main Functions	Irreplaceability
Teacher	Value leader; stimulator of higher-order thinking	Goal and task design; guidance on controversial points; demonstration of complex logical reasoning; value shaping and ethical judgment	Value judgment, emotional resonance, and creative teaching decisions
Student	Subject of knowledge construction; engineering practitioner	Pre-class diagnosis; multi-turn questioning; collaborative inquiry; simulation verification and scheme iteration	Authentic experience, reflection, and creative construction
AI agent	Learning companion; tutoring assistant; data analyst	Knowledge retrieval and Q&A; learning analytics profiling; homework grading; resource recommendation	Around-the-clock response, large-scale service, and quantifiable process

It should be emphasized that the three are not a simple superposition, but a structural reconstruction of "leading—principal—supporting" roles: AI undertakes the standardized, scalable, and quantifiable teaching labor, thereby liberating teachers from repetitive knowledge transmission and enabling them to focus on value guidance and thinking training, which machines can hardly replace.

3.2 Whole-Chain Teaching Process of "Before Class—During Class—After Class"

Relying on the smart teaching platform and a customized AI agent, a ubiquitous learning path is constructed [5], drawing on existing experience in online-offline blended teaching and virtual case simulation [6-7]. The division of labor and data outputs of the three roles across the three stages are shown in Table 2.

Specifically, before class, AI generates a personalized "knowledge graph gap report" based on pre-tests and preview behaviors. For example, when the error rate of "solving the matrix exponential" is high, the system automatically pushes linear algebra review resources, achieving precise early warning of learning conditions. During class, the classroom is transformed from one-way indoctrination into an interactive arena based on AI feedback. For difficult points such as "state observer design," students conduct multi-turn dialogues with the AI in natural language to obtain problem-solving idea hints rather than direct answers; teachers move among groups, delivering higher-order guidance focused on deep-logic problems that AI can hardly handle. After class, the AI teaching assistant completes homework grading and code review, and pushes tiered extension

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tasks (such as inverted pendulum control simulation based on MATLAB/Simulink) according to classroom performance, forming a complete closed loop of "learning—practicing—evaluating—extending."

Table 2: Three-stage teaching process and intelligent technology mapping

Stage	Teaching Objectives	Teacher–Student–Machine Collaborative Activities	Key Data Outputs
Before class	Pre-diagnosis; precise early warning	Teachers publish micro-lectures and study guides based on RAG (Retrieval-Augmented Generation); students complete pre-tests; AI generates a "knowledge graph gap report" based on preview trajectories and pushes compensatory resources	Pre-test accuracy; knowledge point mastery; resource access trajectories
During class	Concept construction; higher-order inquiry	Teachers adjust pacing based on real-time word clouds and accuracy heat maps; students engage in multi-turn dialogues with AI to obtain idea hints; AI aggregates controversial points and generates mind maps; teachers deliver higher-order guidance on deep logic	Interaction frequency; distribution of question types; group contribution
After class	Transfer and application; differentiated extension	AI completes intelligent homework grading and code review, generates learning analytics reports, and pushes tiered tasks; teachers determine the focus of review accordingly	Homework scores; code quality; completion rate of extension tasks

3.3 Classroom Organization Mechanism of Tripartite Collaboration

To ensure full coverage of human–machine interaction and no fewer than three effective interactions per class hour, this study designed a standardized collaboration process.

First, role assignment. The AI agent is configured as a "control theory dedicated tutor" with an embedded structured knowledge base covering textbooks, courseware, past examination questions, and extended literature. It can not only answer "what is Kalman filtering," but also guide students to discern "why Kalman filtering rather than a Luenberger observer should be chosen in this scenario," thereby leading question-answering from knowledge recitation toward comparison and judgment.

Second, the three-step collaboration. The three-step method of "AI initial diagnosis—teacher–student joint investigation—AI review" is implemented: students first raise basic questions to the AI and obtain conceptual support; teachers then organize group discussions, focusing on controversial points or gaps in the AI's answers to develop critical thinking; finally, the AI aggregates the discussion points and generates mind maps, forming structured records. This mechanism both releases the breadth of AI knowledge and retains the teacher's irreplaceable role in value shaping and complex reasoning.

3.4 Three-Dimensional Intelligent Evaluation of "Knowledge–Competence–Literacy"

To break through the limitation of "score-only" evaluation, a three-dimensional intelligent evaluation model was constructed. The observation points, data sources, and technical means of each dimension are shown in Table 3.

Table 3: Three-dimensional intelligent evaluation model

Dimension	Observation Points	Data Sources	Evaluation Techniques
Knowledge	Depth of conceptual understanding; rigor of derivation	Human–machine dialogue records; answers to subjective questions	NLP semantic analysis and concept graph comparison
Competence	Engineering modeling; parameter tuning; system debugging	Simulink modeling process; invocation logs of Python control toolboxes	Behavior log mining and task achievement analysis
Literacy	Teamwork; engineering ethics awareness; exploratory spirit	Classroom interaction data; completion of ideological-education tasks	Sentiment analysis combined with performance rubrics

The knowledge dimension uses natural language processing technology to analyze human–machine dialogues and subjective answers, assessing students' depth of understanding of core concepts such as state equations and transfer functions, rather than merely comparing calculation results; the competence dimension captures behavioral logs of modeling and debugging through the practical task platform, portraying students'

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level of engineering practice; the literacy dimension combines sentiment analysis of interactions with performance on ideological-education tasks to quantify teamwork, engineering ethics, and exploratory spirit. Evaluation results flow back in real time to the student side and the teacher side: the former uses them for self-regulation, and the latter for improving teaching, so that "continuous improvement" is supported by data.

4. Teaching Practice and Effectiveness Analysis

4.1 A Typical Lesson: "State Feedback and Pole Placement of Linear Systems"

Before class, AI pushed the micro-lecture "The Physical Meaning of Pole Placement" and aggregated students' questions. The data showed that 60% of the students were confused about "constructing the non-singular transformation matrix P."

During class, based on the above data, the teacher went directly into the geometric interpretation of the construction of matrix P, saving about 20 minutes of basic explanation; then the teacher released the engineering case of "UAV attitude control," requiring groups to design controllers. In practice, students encountered the problem of "control input saturation caused by pole placement" and sought help from the AI; the AI guided them to analyze the system's controllability and actuator constraints rather than directly giving code; while patrolling, the teacher provided in-depth extension on the "robustness risk" that the AI could hardly explain for each group, and integrated the ideological-education case of the independent development of the flight control system for China's domestically produced large aircraft, inspiring patriotic dedication to science and technology.

After class, the AI automatically graded each group's simulation reports, pointed out common problems such as "sensor noise not considered," and generated a class competence radar chart; based on this, the teacher conducted targeted review in the first 5 minutes of the next class session.

4.2 Effectiveness Analysis

After one academic year of pilot operation, the teaching reform achieved results in terms of engagement, academic performance, and learning experience. The main observed indicators are shown in Table 4.

Table 4: Main observed indicators in the pilot academic year

Dimension	Indicator	Practice Result
Engagement	Weekly platform login frequency	Stabilized at 3 or more times
Engagement	Platform activity rate	Maintained above 90%
Interaction quality	Human–machine interaction coverage	100%
Interaction quality	Effective in-class interaction frequency	Average of 4.2 times per class hour, exceeding the set requirement of no fewer than 3 times
Academic performance	Score rate on open-ended comprehensive design questions	Increased by 18 percentage points compared with previous cohorts
Academic performance	Awards in academic competitions	Year-on-year growth in awards at the National College Students' Intelligent Car Competition and the Electronic Design Competition
Learning experience	Student satisfaction	Satisfaction with AI assistant response speed, richness of classroom interaction, and personalized guidance all exceeded 95%

First, platform activity and engagement met the targets. Students' weekly login frequency on the smart teaching platform stabilized at 3 or more times, the activity rate remained above 90%, the human–machine interaction coverage rate reached 100%, and the average number of effective in-class interactions was 4.2, fulfilling the project's set indicators.

Second, academic performance and higher-order capabilities improved. The pilot class's score rate on open-ended examination questions such as "system comprehensive design" increased by 18 percentage points compared with previous cohorts; the number of awards in the National College Students' Intelligent Car

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Competition and the Electronic Design Competition grew year-on-year, indicating enhanced ability to translate theory into engineering practice.

Third, the learning experience improved. End-of-term teaching evaluation showed that students' satisfaction with "AI teaching assistant response speed," "richness of classroom interaction," and "personalized guidance" all exceeded 95%. Students reported that the AI not only alleviated the psychological burden of "not daring to ask the teacher," but also helped them clarify vague concepts through multi-turn dialogue.

Although the teaching practice achieved remarkable results, some limitations exist. First, the pilot was conducted in a single teaching class without a parallel control class; the 18-percentage-point improvement may be confounded by factors such as differences in student intake, changes in examination difficulty, and increased teacher input, so the causal effect remains to be tested by a more rigorous quasi-experimental design. Second, the satisfaction data come from student self-reports and are subject to social desirability bias; the scoring validity of AI grading for open-ended, multi-solution answers still requires manual review and calibration. Third, behavioral indicators such as interaction frequency and login counts are easy to quantify but do not necessarily mean that deep learning has truly occurred; how to establish a substantive link between behavioral data and cognitive development is a key problem that this model needs to tackle in the future.

5. Reflection and Outlook

Although the "teacher–student–machine" tripartite collaborative model has shown initial results, the following issues still require attention in practice:

First, the risk of "AI dependence." Some students may over-rely on AI to obtain answers, weakening independent thinking and derivation training. In response, instructional design should adhere to the principle of "AI assisting rather than replacing," increase timed derivation and oral defense sessions in AI-free environments, and incorporate "whether students can complete reasoning without tools" into assessment.

Second, the domain adaptability of the knowledge base. Control theory is developing rapidly, so a teacher–student co-constructed mechanism of knowledge error correction and updating should be established, safeguarding the accuracy and currency of AI answers through error feedback, version annotation, and manual sampling checks.

Looking ahead, the following work will be advanced in future teaching: first, deepening the AI-based multi-dimensional evaluation mechanism and exploring automatic scoring standards for process-based evaluation based on large models; second, relying on two years of complete teaching data, conducting a longitudinal comparative analysis of the reform's effectiveness to produce an empirical research report.

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Conflicts of Interest

The authors declare no conflict of interest.

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