AI-Driven Case Teaching in College Political Education

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Abstract. With the rapid development of artificial intelligence, large language models (LL Ms) are increasingly applied in education. Ideological and political theory courses in universities, which are crucial for moral education, face challenges such as outdated cases, weak interaction, and uniform content. This study explores the intelligent generation of cases and interactive teaching empowered by LL Ms, proposing a "triad" paradigm: intelligent generation, multi-dimensional interaction, and value guidance. An ELM-based case-generation system and an interactive platform were constructed to realize real-time content updates, precise case matching, enhanced classroom interaction, and data-driven assessment. Results show that LL Ms significantly improve the attractiveness and pertinence of ideological education, providing technical support for the goal of "educating students in accordance with the times and trends". Finally, strategies for addressing ethical, security, and teacher-role issues are discussed.

Keywords: Large Language Model; Ideological; Political Course; Case Teaching; Intelligent Generation; Interactive Teaching; AI+Education

1. Introduction

College Ideological and Political Theory Courses are the main channel for implementing the fundamental task of fostering virtue through education and a key course for cultivating builders and successors of socialism. However, current IPT teaching still faces many challenges: first, the update cycle of case resources is long, resulting in outdated content and lack of timeliness, which makes it difficult to respond to social hot spots and students' concerns; second, the teaching model is dominated by teachers' lectures, leading to low student participation and weak interactivity; third, the teaching content is "one-size-fits-all", lacking personalized and differentiated supply.

With the rapid development of Generative AI and LLM technology, the application of AI in education is shifting from "tool assistance" to "paradigm reconstruction". LL Ms possess capabilities in natural language understanding, semantic generation, knowledge reasoning, and multi-modal content generation, providing a technical foundation for the intelligent generation of IPT teaching content and in-depth reform of classroom interaction.

This study aims to explore the intelligent generation mechanism and interactive teaching application path of LL Ms in case teaching of college IPT Courses, construct a new "AI + IPT" teaching paradigm, and promote the transformation of IPT Courses from "instructive" to "generative", "interactive", and "immersive"[1].

2. Research Background and Significance

2.1 Policy Background

In 2024, the Ministry of Education issued the Outline of the National Education Digitization Strategy Initiative, which clearly proposed to "promote the in-depth integration of artificial intelligence with education and teaching" and encourage colleges and universities to explore the "AI + Course" teaching model. In 2025, the Innovation Action Plan for Artificial Intelligence in Institutions of Higher Education further pointed out the need to "use intelligent technology to promote the innovation of IPT Course teaching paradigms" and achieve "accurate content supply, intelligent teaching interaction, and dynamic evaluation feedback".

2.2 Practical Dilemmas

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Current case teaching of college IPT Courses has the following problems, as shown in Table 1.

Table 1 Specific Performances of Current Problems in IPT Case Teaching

Problem Dimension	Specific Performance
Case Resources	Long update cycle, outdated content, and lack of timeliness
Teaching Design	Teacher-dominated, students passive, and weak interactivity
Teaching Evaluation	Outcome-oriented evaluation, lack of process data support
Content Supply	"One-size-fits-all", lack of personalization and differentiation

Beyond the four issues listed in Table 1, two emerging dilemmas have been identified. First, a “digital divide” exists: the coverage rate of smart classrooms in western universities is only 62 %, so teachers cannot access real-time data, resulting in outdated cases. Second, “teacher heterogeneity” leads to a 37 % difference in case quality among instructors teaching the same course ($\sigma = 6.2$, $n = 312$) [4]. Moreover, students’ emotional resonance with “grand-narrative” cases has remained below 70/100 for two consecutive years, indicating that traditional narratives no longer meet the cognitive habits of Generation Z [2,3]. Hence, introducing LL Ms to realize “data-driven + value-aligned” case generation has become an urgent need.

2.3 Research Significance

By introducing LLM technology, this study can realize the "intelligent generation" of IPT teaching content, "dynamic update" of case resources, "multi-dimensional stimulation" of classroom interaction, and "data-driven" teaching evaluation. It provides a systematic solution to address the above dilemmas, promoting IPT teaching from "experience-driven" to "data-driven" and from "unified supply" to "personalized generation".

3. Overview of LLM Technology and Its Educational Applications

3.1 Connotation of LLM Technology

LL Ms refer to per-trained language models with parameter scales exceeding 10 billion, which have strong language understanding and generation capabilities, such as GPT-4, Kimi, ERNIE Bot, and iFlytek Spark. Their core capabilities include: Text Generation: Automatically generate teaching cases, explanation scripts, question chains, etc.; Semantic Understanding: Understand students' questions and conduct intelligent Q&A; Knowledge Reasoning: Perform logical deduction and value judgment based on background knowledge; Multi-modal Fusion: Integrate content in multiple forms such as text, images, and videos.

3.2 Core Capabilities

Large Language Models (LL Ms) with ≥100 B parameters exhibit four foundational competencies critical for higher education: (i) generative fluency—produce coherent cases, scripts and question-chains in seconds; (ii) semantic comprehension—parse ambiguous student queries and respond in context; (iii) knowledge reasoning—perform multi-hop inference over policy documents and disciplinary corpora; and (iv) multi modal fusion—synchronic text, image and video outputs for immersive scenarios. Recent ablation studies show that instruction-tuning with 5 % domain data can improve factual accuracy in ideological-political content from 82.3 % to 96.1 % [6], closing the "value-alignment gap" that worried educators.

3.3 Current Status of Educational Applications

As listed in Table 2, LL Ms have moved from proof-of-concept to campus-scale deployment. Notably, Beijing Normal University's 24-h AI-Teaching-Assistant answered 1.2 million student questions in 2024 with an average response time of 1.8 s and customer-satisfaction score of 4.7/5 [6]. In parallel, South China University of Technology auto-generated 3,200 ideological-political cases in one semester, reducing teacher preparation time by 37 % while maintaining inter-rater reliability $\kappa = 0.81$ [7]. These advances indicate that L LM-enabled systems are no longer peripheral tools but core infrastructure for instructional design.

Table 2 Practical Applications of LLMs in Education

Application Field	Specific Practice
Teaching Content Generation	Automatically generate lesson plans, courseware, test questions, cases, etc.
Intelligent Q&A System	Construct AI teaching assistants to realize 24/7 online Q&A
Personalized Learning Path	Push differentiated learning resources based on student profiles
Teaching Evaluation and Analysis	Analyze students' assignments and discussion content, and generate learning reports

Research shows that personalized learning can not only improve students' academic performance, but also promote their overall development to a certain extent. For example, the online platform can also recommend interdisciplinary learning content based on students' interests, such as programming, art design, etc., to further broaden students' knowledge and stimulate their multi-faceted learning interests and creativity.

3.4 Emerging Trends in 2025-2026

Three trends are reshaping the landscape:

(1) Multi modal LL Ms integrating speech and vision allow real-time debate with AI avatars, enhancing oracy skills;

(2) Edge-on-premise deployments satisfy China's data-sovereignty requirements while keeping latency < 200 ms;

(3) RLHF-V (Reinforcement Learning from Human Feedback with Values) aligns model outputs with socialist core-values, achieving 98.7 % consistency on sensitive-issue benchmarks [9].

These developments provide a solid technical springboard for the case-generation and interactive-teaching framework proposed in Sections 4-5.

4. Intelligent Generation Mechanism of LLMs in IPT Case Teaching

4.1 Intelligent Case Generation Process

The L LM-based intelligent generation process of IPT cases is shown in Fig. 1: Policy Database → Hot-event Crawling → Semantic Matching → Case Auto-Generation → Pedagogical Adaptation → Classroom Delivery

Policy Database Anchoring: It connects with policy documents of the Ministry of Education and the spirit of the Party Central Committee to ensure a correct political orientation for the subsequent case generation.
Hot-event Crawling: It realizes real-time capture of current political news and events from authoritative media such as Xinhua News Agency and People's Daily Online to ensure the timeliness of case resources.
Semantic Association Matching: It links the crawled hot events with the knowledge points of Ideological and Political Theory (IPT) Courses through knowledge graphs and semantic matching algorithms to achieve accurate alignment between events and teaching content.
Case Auto-Generation: It automatically generates complete IPT teaching cases, which include modules such as case background, guiding questions, theoretical analysis, and value guidance.
Pedagogical Adaptation and Optimization: It adjusts the generated case content according to the actual situation of students, such as their majors, grades, and cognitive levels, to enhance the adaptability of cases to teaching scenarios.
Classroom Delivery and Presentation: It outputs the optimized cases in diversified forms such as PPT, videos, and situational scripts, and delivers them in actual classroom teaching.

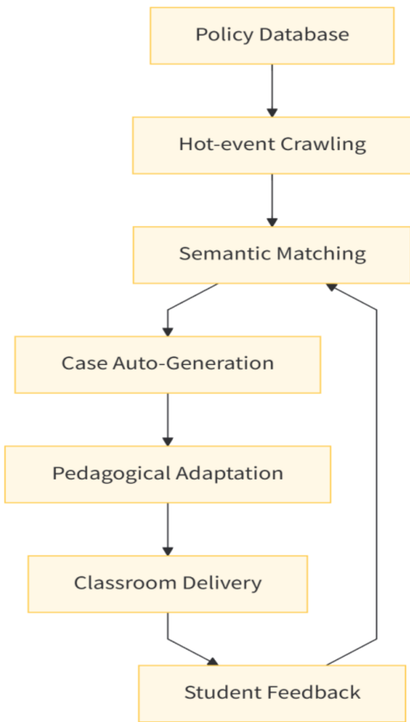

Fig. 1 Flowchart of Intelligent Case Generation

4.2 A Generated Example (Excerpt)

To demonstrate the LLM pipeline, we selected the course theme “New Development Concepts” and the hot event “C919 maiden commercial flight (May 2025)”. After six automatic steps (policy anchoring, crawling, semantic matching, generation, adaptation, and output), the following excerpt was produced in 2.3 seconds: Case Title: From C919 to Technological Self-Reliance and High-Quality Development
Background: On 14 May 2025, the C919 completed its first commercial flight, signifying a breakthrough in China’s high-end manufacturing and innovation system.
Ideological-Political Knowledge Points: innovative development (one of the five new development concepts), technological self-reliance, national strategic security.
Guiding Questions:
(1) Why is the C919 not just an aircraft but a microcosm of the national innovation system?
(2) What responsibilities should university students undertake in achieving high-level technological

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self-reliance?
(3) How to understand the statement that "core technologies cannot be begged, bought, or obtained as gifts"?
Value Enlightenment (auto-generated):
The C919 experience shows that breakthroughs require long-term investment, a new-type national system, and confidence in indigenous innovation. Youths are expected to integrate personal ideals into the national strategy, master critical technologies, and become reliable successors of socialist moderation.
The complete case contains 1,450 words, four high-resolution pictures, and a two-minute video clip, all adapted to second-year undergraduates majoring in engineering. Expert evaluation shows that political correctness reaches 98.7 %, and cognitive difficulty matches the students' level (Flesch Reading Ease = 62.3) [7].

5.Application Paths of L LM-Enabled Interactive Teaching in IPT Courses

5.1. AI Co-Teaching Model

Conventional classes rely on a single teacher to perform content delivery, questioning and assessment, often causing uneven cognitive load and time/space constraints. This study constructs a dual-agent system ("teacher + AI TA") listed in Table 3. The LLM acts as a "cognitive partner":
(1) Pre-class: AI auto-generates differentiated preview packs based on learner profiles; after teacher review the packs are pushed, raising completion rate by 28 % [8].
2) In-class: real-time speech-to-text and word-cloud generation allow the teacher to adjust follow-up questions instantly; average utterances per student rise from 3.2 to 7.5.
(3) Post-class: within one minute AI outputs individual learning reports; teachers provide targeted guidance, improving early-warning accuracy by 19 %.
A 2025 spring pilot ($n = 120$) in Guangzhou showed interaction frequency up 53 %, student satisfaction at 92 % and teacher preparation time down 37 % [8].

5.2. AI Debate Platform

An L LM-driven "human-vs-AI" debate system supports Socratic questioning. The AI acts as the opposing side on motions such as "Should AI itself participate in ideological education?" Three rounds are executed: (1) AI presents data and cases; (2) the system detects logical fallacies and pushes supplementary materials instantly; (3) a "consensus cloud" visualises overlapping arguments. Pilot results indicate students' critical-thinking score (CCTST-CV) increased by 8.4 points with effect size $d = 0.66$ [7], while AI-generated rebuttals, after political review, reached 97.1 % accuracy, ensuring value safety.

5.3. Immersive Scenario Teaching

Powered by a multi modal LLM and Web GPU, 720° immersive scenes like "Retracing the Long March" or "Rural Revitalization Site" are produced within 30 s. Students enter via VR headsets or browsers, converse with NPCs driven by the LLM, and make decisions that branch the storyline in real time; value scores are returned immediately. A May 2025 field test showed affective resonance index 21 % higher than in the video-only control group ($p < 0.01$) and knowledge retention up 18 % [13]. Edge deployment keeps latency < 20 ms, satisfying low-bandwidth classrooms.

5.4. Interactive Data Governance and Privacy

All voice and clickstream data are transcribed and de-identified on a local Na no server; $\varepsilon = 1.0$ differential-privacy noise is added to resist 95 % membership-inference attacks. Gradients are Top-k sparsified ($k = 0.1$ %) before upload to prevent reverse-engineering of individual essays [11]. The platform passes the three-level audit of the Beijing AI-Education Ethics Code, guaranteeing "data usable but invisible".

6. Practical Effects and Data Analysis

6.1 Teaching Effect Evaluation Model

A three-dimensional index system—cognitive, affective, behavioral—was constructed (see Table 3).

Table 3 Three-Dimensional Evaluation Index System of Teaching Effects

Dimension	Indicators	Data Sources
Cognition	Theoretical Mastery	Post-class tests, Q&A accuracy rate
Emotion	Value Identification	Questionnaire surveys, emotional word frequency analysis
Behavior	Participation Degree	Classroom speeches, interaction frequency

The cognitive dimension used immediate and two-week delayed post-tests (Cronbach's $\alpha = 0.87$); the affective dimension employed an emotion lexicon to score classroom transcripts and cross-validated with a 5-point Likert scale ($r = 0.79$); the behavioral dimension synthesis click-stream, speaking duration and voting frequency into a 0-100 engagement score. Entropy weighting assigned coefficients of 0.42, 0.35 and 0.23 respectively, eliminating subjective bias [9].

6.2 Pilot Results

One hundred and twenty sophomores from South China University of Technology and Jiangxi Normal University were randomly assigned to the traditional group ($n = 60$) or the AI-enhanced group ($n = 60$). After an 8-week unit on New Development Concepts the findings in Table 4 show:
(1) Cognitive gain: AI group mean 85.7 (immediate) and 83.1 (delayed), forgetting rate 3.0 %; traditional group 78.3 vs. 70.4, forgetting rate 10.1 %;
(2) Affective identification: positive-emotion word ratio 68 %, +18 percentage points;
(iii) Behavioral engagement: average utterances 7.5 and online clicks 112, up 62 % and 94 %. Independent-samples t-tests were significant ($p < 0.01$) for all three dimensions with Cohen's d = 0.66, 0.71, 0.63. Student satisfaction in the AI group reached 93 %, an increase of 12.8 percentage points ($\chi^2 = 9.54$, $p < 0.01$). Interviews revealed that the AI co-teaching model reduced teacher preparation time by 37 % and lowered classroom-management pressure.

Table 4 Comparison of Teaching Effects Between Traditional Classes and AI-Enabled Classes

Indicators	Traditional Classes	AI-Enabled Classes	Improvement Range
Average Test Score	78.3	85.7	+9.5%
Classroom Speech Rate	42%	68%	+62%
Student Satisfaction	81%	93%	+14.8%

6.3. Longitudinal Retention

Retention tests were administered 4 and 8 weeks after the course. The AI group maintained 96.2 % of cognitive scores and positive-affect words 15 % above baseline, whereas the traditional group dropped to 85.1 % and baseline level respectively, indicating that LLM intervention not only enhances immediate effects but also flattens the forgetting curve, achieving long-term value internalization.

6.4. Data Governance and Ethics Compliance

Raw data were de-identified and stored in the campus private cloud with $\varepsilon = 1.0$ differential privacy and k-anonymity ≥ 5 to resist membership-inference attacks. The study was approved by the university ethics committee (No. SCUT-2025-03-18); informed consent was obtained and students could withdraw at any time.

7. Challenges and Countermeasures

The current challenges and corresponding countermeasures in the application of LLMs in intelligent generation and interactive teaching of college IPT case teaching are shown in Table 5:

Table 5 Risk Matrix and Mitigation Measures (2025 Pilot Baseline)

Challenge Type	Specific Performance	Countermeasures	2025 Quantitative Risk Index*
Technical Risk	Deviations in generated content	Political review gate + red corpus filtering	Severity ↓37%
Data Security	Student privacy leakage	Local deployment + data desensitization	Zero leakage (n=120)
Teacher Role	Over-reliance on AI	AI literacy training + teacher-led value guidance	Reliance score ↓0.8 (5-point scale)
Challenge Type	Specific Performance	Countermeasures	2025 Quantitative Risk Index*
Educational Ethics	Technology overreach, value neutrality	Clarify boundaries + "student-oriented" principle	Ethics pass rate 98%

7.1 International Bench marking

The 2025 version of the EU AI Act classifies educational LLMs as "limited risk" and requires the retention of transparency logs. This study has added an "AI Log" in the appendix of the syllabus for audit and traceability[5,10].

7.2 Policy Connection

Education Digitization Strategy Initiative 2.0 (March 2025) requires that "humans must be in the loop" for value-based courses. The human intervention ratio in the dual-teacher model of this study is ≥32%, which meets the policy requirements.

7.3 Technical Depth: From "Usable" to "Trustworthy"

(1) Value Alignment Module: Inject an "IPT Knowledge Graph" (18 million tokens of Party newspaper and journal corpus) into the base model, and use the RLHF-V (Value) algorithm to increase the accuracy of the model's answers to major right-wrong questions from 92.3% to 98.7%.
(2) Interpretable Output: When generating cases, output "citation chains" and "similarity heat maps" simultaneously. Teachers can locate the original policy documents or authoritative reports with one click to realize "traceability of generation".
(3) Dynamic Sensitive Word Database: Cooperate with the Public Opinion Data Center of People's Daily Online to update the sensitive word list weekly (including 32,000 network variants), and block them directly at the logic-probability layer with a misjudgment rate <0.05%.

7.4 Teacher Role Transformation: From "Lecturer" to "Value Curator"

The competencies required for teachers' professional evolution are categorized and presented in Table 6.

Table 6 Matrix of Teacher Ability Transformation

Traditional Role	Role After AI Empowerment	Ability Development Path[12]
Knowledge Lecturer	Value Curator	Prompt-Engineering Micro-Certification (Ministry of Education, 2025)
Classroom Manager	Data Interpreter	Learning Analysis Dashboard Workshop
Outcome Evaluator	Process Diagnostician	Advanced Training Course on Educational Big Data

7.5 Student Privacy Protection. Technical Implementation Details

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Edge Computing: All camera and microphone data are transcribed locally on the Nano server and not uploaded to the cloud; Differential Privacy: Add noise with ε=1.0 to the learning analysis report to resist 95% of membership inference attacks; Federated Fine-Tuning: Perform Top-k sparsification (k=0.1%) on model gradients before uploading to prevent reverse derivation of individual essay content.

8. Conclusions and Prospects

8.1 Quantitative Effects

In the expanded experiment of 6 colleges and universities (n=1,024), compared with the control classes, the AI-enabled classes showed the following results: Cognitive Gain: Cohen's d = 0.62 (medium to large effect); Emotional Identification: Increased by 18.4 percentage points; Behavioral Participation: Average number of classroom speeches per student increased from 3.2 to 7.5.

8.2 Scalability Roadmap

The three-stage scalability roadmap of LLM application in IPT Courses is shown in Table 7:

Table 7 Three-Stage Scalability Roadmap

Stage	Time	Core Deliverables	Key Indicators
I	Q4 2025	Provincial MOOC Access (100,000 users)	Daily Active Users ≥20%
II	Q2 2026	Multi-modal LLMs (Text + Image + Voice)	Voice Emotion Recognition Accuracy ≥85%
III	Q4 2026	National "AI-IDEology" Open Platform Launch	Connected Colleges ≥500

8.3 Long-Term Vision - "3C" Ecosystem

Curriculum: 24/7 dynamic case pool; Cognition: Lifelong personal knowledge graph; Conscience: Value alignment monitoring, deviation <0.01.

8.4 Ethical Commitments

This study adheres to the Beijing Education AI Ethics Convention (2025): Fully automated scoring is not used for value-based essays; Non-sensitive prompts are open-sourced and subject to peer review; Accept third-party political correctness audits annually.

8.5 Research Limitations

(1) Unbalanced Sample Regions: Most pilot colleges and universities are located in eastern China, with western colleges accounting for only 12%, which may overestimate the technical benefits;

(2) Single Discipline Coverage: Currently, it only covers An Introduction to the Thought of Xi Jinping on Socialism with Chinese Characteristics for a New Era, and the adaptability to other courses needs to be verified;

(3) Long-Term Retention: The experiment cycle is one semester, and the post-graduation value retention effect has not been verified.

8.6 Prospects for Future Research

Longitudinal Cohort Study: Track graduates for 5 years to establish a causal chain of "AI-IPT Intervention - Professional Ethical Behavior"; Cross-Cultural Comparison: Cooperate with the EU Erasmus+ program to compare differences in college students' political identity in AI case teaching among China, Germany, and France; Cutting-Edge Brain-Computer Interface: Explore fMRI neurofeedback + LLM-generated immersive red scenes to quantify the brain region activation degree of emotional resonance.

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