Generative AI in Political Economy Teaching: A Classroom Practice Study

Na Qu [1*], Qinghui Wang [2], Fang Cui [3]

[1] College of Digital Economy, Taishan University, Taian, Shandong, China, quna@tsu.edu.cn,

[2] College of Art, Taishan University, Taian, Shandong, China, wanghui@tsu.edu.cn,

[3] College of Business, Taishan University, Taian, Shandong, China, cuifang2022@gmail.com,

Abstract. The Political Economy course is a theoretical economics course characterized by high levels of abstraction and complex logical chains of reasoning. In large-class teaching environments, students often struggle to maintain effective engagement throughout the high-density, continuous theoretical lectures. Based on this, this paper focuses on undergraduate political economy courses to explore suitable methods for integrating generative artificial intelligence into classroom teaching and its pedagogical effectiveness. In instructional design, generative AI is not merely used as a simple content-generation tool but rather as a scaffolding aid in the teaching process. It is mainly reflected in generating numerical case studies, guiding theoretical reasoning through structured questions, and providing real-time exercises and mind-map summaries. During the explanation of key concepts, guiding questions and simplified or biased interpretations are introduced to help students identify logical gaps and refine the derivation process, thereby achieving a shift from passive reception to active construction.

This study selected two parallel classes with essentially identical teaching conditions for comparative analysis. One class served as the experimental group, in which generative AI was integrated as a teaching aid, while the other served as the control group and followed conventional lecture-based instruction. The results showed that students in the experimental group demonstrated higher engagement in classroom discussions, along with improved completion rates and accuracy in chapter exercises. Furthermore, the grade distribution in the experimental group was more concentrated, with a lower proportion of students receiving low grades and no instances of failing the course.

Overall, when generative AI aligns with the intrinsic logic of theoretical instruction and is embedded within a structured instructional design, it can serve as a cognitive scaffold to promote student engagement and reinforce the depth and stability of their understanding of theoretical logic, thereby playing a positive role in large-class theoretical course instruction.

Keywords: Generative AI; Political Economy; Large-Class Instruction; Student Engagement

C. V. Garcés et al. (eds.), *Proceedings of the 6th International Conference on Internet, Education and Information Technology (IEIT 2026)*, Atlantis Highlights in Social Sciences, Education and Humanities 53,
https://doi.org/10.2991/978-94-6239-733-0_4

1 Introduction

In foundational theory courses for first-year undergraduates, the practice of combining classes to conduct large-class instruction remains relatively common. Taking the Class of 2025 in the Economics major that I teach as an example, the combined class size reached approximately 80 students, far exceeding the ideal teaching capacity. As a theory-intensive discipline, Marxist political economy features an interlinked conceptual framework. For instance, the derivation process from the dual nature of commodities to the theory of surplus value requires students to possess the ability to follow a continuous logical sequence. However, Generation Z students are more accustomed to fragmented, short-video-style learning, which tends to reduce their ability to maintain sustained attention in long theoretical lectures. In large-class settings, opportunities for instructors to provide immediate answers or personalized feedback are also relatively limited. Consequently, maintaining student engagement and fostering conceptual understanding remain persistent challenges in teaching practice.

In recent years, generative artificial intelligence has attracted growing attention in higher education. Existing studies on large language models suggest that these tools support learning through structured explanations, examples, and guided inquiry [1]-[3]. At the same time, empirical research shows that AI-assisted learning can shape how students approach learning tasks by scaffolding their reasoning processes, while also raising concerns about potential overreliance on such tools [4]. From a broader pedagogical perspective, scholars have examined how generative AI reshapes classroom interaction patterns and teaching organization [5], and have further pointed out that its effective classroom integration is contingent upon factors such as teacher preparedness and students' AI literacy [6]. Furthermore, research on large-class teaching consistently indicates that meaningful classroom participation depends more on well-designed, structured learning tasks and guided discussion than on the mere adoption of technology [7]. Taken together, the educational value of generative AI lies in its alignment with coherent instructional design and practice.

Based on this, this study explores the integration and application of generative AI in large-class undergraduate political economy courses. The study incorporates AI-assisted activities into multiple stages of instruction, including the generation of contextualized industry case studies, guided questioning during theoretical discussions, and structured exercises. By observing two parallel courses with similar teaching conditions (the core difference being the extent to which generative AI was used to support instructional design), this study conducted a comparative analysis of students' classroom participation patterns, performance on chapter exercises, and final assessment results. Through this classroom-based analysis, the study aims to investigate how generative AI-assisted instructional guidance can help enhance student engagement and conceptual learning outcomes in large-class theoretical instruction.

2 Integration of Generative AI into Instructional Design

2.1 Framework and Implementation of AI Integration

Based on constructivist learning theory, this study has developed a pedagogical framework for integrating generative artificial intelligence into large-class political economy courses. This framework moves beyond the traditional model of treating technology as a mere tool; instead, it positions generative AI as a cognitive scaffold. By dynamically adapting to the teaching process, it achieves a deep integration of technological empowerment and knowledge construction. Specifically, the framework functions across three key phases: it reinforces the structured presentation of knowledge during the course preparation phase, fosters the development of students' critical thinking during classroom interactions, and provides personalized feedback during the assessment phase, thereby forming a complete closed-loop system of instructional support.

The lesson preparation phase employs a human-machine collaborative knowledge modeling approach. Teachers lead the definition of core concepts and use GPT-4 to assist in constructing a political economy concept map (covering core nodes such as commodities, value, and capital). During classroom implementation, based on Vygotsky's Zone of Proximal Development theory, AI is used to generate cognitive conflict-based problem chains (such as the quantification dilemma of abstract labor in the digital platform economy) to guide students in structured debates. In the assessment phase, AI-generated differentiated exercises of varying difficulty levels (memorization-based, analytical, and creative) are used to identify typical cognitive biases in student responses, such as the misconception of equating average profit with equilibrium price.

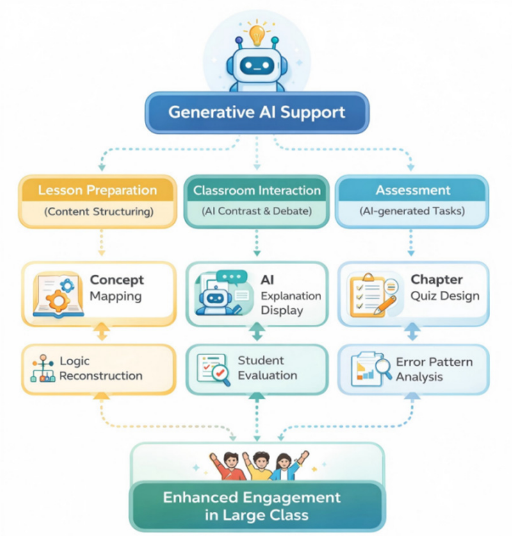

Fig. 1. Generative AI-Supported Framework for Large-Class Political Economy Teaching.

As shown in Figure 1, this framework achieves a spiral deepening of theoretical knowledge through a three-stage design: pre-class concept activation, in-class reasoning construction, and post-class transfer and consolidation. In experimental classes of approximately 80 students, an AI-assisted group discussion system (virtual communities of 8 students per group) increased the average effective classroom interaction time per student from about 3 minutes in traditional models to about 8 minutes (based on classroom video statistics from the Spring 2025 semester), while maintaining the logical rigor of the political economy conceptual framework (such as the complete chain of reasoning from the dual nature of commodities to the production of surplus value, and then to the transformation of surplus value).

Furthermore, to mitigate the inherent limitations of generative AI—particularly the risk of misleading guidance in long-chain reasoning—all AI-generated examples and prompts intended for classroom use undergo rigorous review by instructors. In classroom discussions, these outputs are not presented as authoritative conclusions but rather as provisional materials requiring further verification and refinement. In certain contexts, we intentionally introduce simplified or partially contradictory interpretations to guide students in identifying logical flaws and clarifying underlying assumptions, thereby helping to ensure that the application of AI supports rather than undermines the rigor of theoretical reasoning.

2.2 AI-Supported Instructional Design in the "Transformation of Surplus Value" Unit

To illustrate the implementation of the aforementioned teaching framework in actual classroom practice, this study selects the unit on the transformation of surplus value as an example. This topic typically poses a challenge to students' understanding because it involves a series of interrelated conceptual transformations that link the formation of surplus value, profit, and the average rate of profit ($\overline{p}$). Students must not only focus on the final conclusions but also understand how differences in the organic composition of capital (c/v) lead to variations in initial profit rates, and how competition among different sectors gradually drives profit rates toward equality.

The teaching process unfolds in three stages: numerical evolution, theoretical deconstruction, and critical reconstruction. In the course introduction, capital composition cases for three sectors—machinery (90c+10v), textiles (80c+20v), and food (70c+30v)—are presented (with a rate of surplus value m' = 100%). Students are guided to calculate the surplus value (m = 10, 20,30) and profit rates (p' = 10%, 20%, 30%) for each sector. Through data comparison, students intuitively develop a preliminary understanding of the inverse relationship between the organic composition of capital (c/v) and the profit rate (p′).

During the theoretical derivation phase, we implement a dual-track prompting method. At critical junctures (such as the intermediate step where profit is converted into average profit), we simultaneously present two sets of materials: one is a simplified explanation generated by GPT-4 (e.g., the formulaic expression that average profit rate = total surplus value / total capital), and the other is the classic exposition from Chapter 9 of Volume III of *Capital*. We also designed cognitive conflict questions at three levels: the foundational level focuses on data relationships (e.g., why the food sector has the highest surplus value but the lowest organic composition of capital); the advanced level explores conversion mechanisms (e.g., how sectoral competition evens out profit rate differences caused by varying capital compositions); and the innovative level extends to real-world applications (e.g., what are the unique characteristics of average profit formation in the digital platform economy). After 2–3 minutes of independent thinking, students engage in group debates. The teacher identifies common misunderstandings by analyzing student comments (such as confusing the equalization of profit rates with the equalization of profit amounts) and provides further corrections and logical explanations.

For example, students are asked to analyze the following statements: Does an increase in the rate of surplus value necessarily lead to a rise in the rate of profit? Can sectors with different capital compositions achieve equal returns? The teacher does not directly correct these statements but encourages students to examine the underlying assumptions and identify the conditions under which these conclusions might not hold.

As shown in Figure 2, the teaching process integrates three core elements: first, dynamic numerical deduction (a complete calculation chain from sectoral profit rate differences to the formation of production prices); second, mutual verification of theoretical texts (comparative analysis of AI-generated explanations and original texts); and third, critical discussion design (exposing cognitive blind spots through the error-prompting method). This structured design transforms students' conceptual reconstruction process from passive reception to active inquiry. In the end-of-semester conceptual transfer test, the experimental class achieved a 78.5% accuracy rate in applying the law of the average rate of profit, a significant improvement over the control class (52.3%) (independent samples t-test, $p < 0.01$).

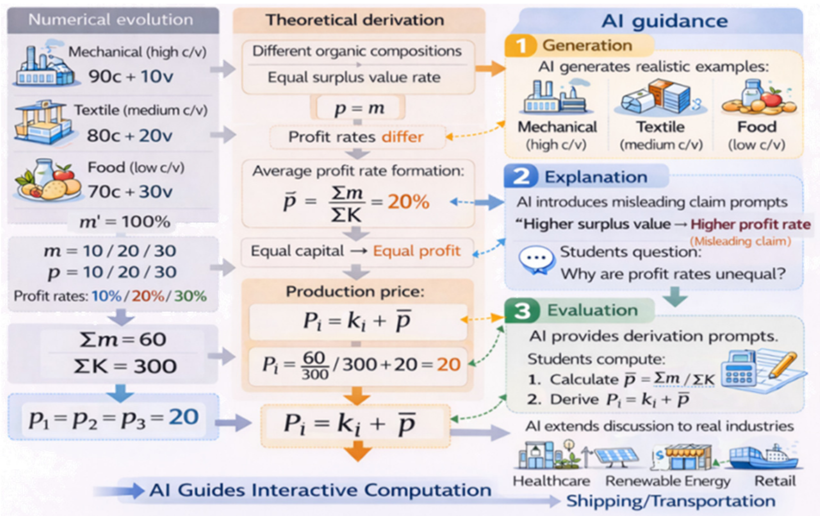

Fig. 2. AI-Supported Derivation Framework for the "Transformation of Surplus Value" Unit.

3 Experimental Design and Data Analysis

To systematically evaluate the effectiveness of the innovative teaching intervention in theory-intensive teaching units, this study adopted a quasi-experimental design with pre- and post-tests in unequal groups, selecting two undergraduate courses offered in parallel during the same semester as the research subjects. The experimental group consisted of 75 students, and the control group of 79 students. Both groups were taught by the same instructor and used the same textbook, teaching schedule, and assessment criteria to ensure that extraneous variables other than the experimental treatment were strictly controlled. Students in both groups took the same final exam. Since the classes were randomly formed by the Academic Affairs Office, an independent samples t-test confirmed that there were no statistically significant differences in the previous semester's core course grades ($p > 0.05$), indicating baseline comparability.

In the unit on the transformation of surplus value, the experimental group received generative AI-assisted instruction, specifically including: a dynamic industry case repository (covering capital composition data for typical sectors such as machinery, textiles, and food); a three-tier cognitive conflict prompting system (basic/advanced/innovative problem chains); guided derivation worksheets; and a critical discussion framework. The control group followed a traditional lecture-based model, primarily consisting of teacher-led theoretical explanations and blackboard derivations. This teaching unit encompassed a complete logical chain from surplus value → profit → average rate of profit → production price, requiring the completion of five core conceptual transformations and three sets of mathematical derivations, thereby meeting the experimental requirements for assessing complex cognitive skills.

To evaluate teaching effectiveness, the study examined both process-based and outcome-based indicators. Process-based indicators included classroom participation rate, frequency of discussion contributions, completion rate of in-class formative exercises, and accuracy rate on chapter exercises. These indicators reflected students' level of engagement in classroom interactions. Outcome-based indicators included chapter assessment scores, final exam scores related to the target unit, and grade distribution characteristics (including mean, standard deviation, and pass rate). The analysis focused on comparing patterns of differences between the two groups to investigate variations in engagement and learning stability within the classroom environment.

4 Results and Discussion

Intergroup comparisons indicate that the instructional intervention produced significant differences between the two groups in both participation patterns and academic performance, particularly evident in the delayed final exams administered several weeks after the intervention. These longitudinal data suggest that the deepening of conceptual understanding extends beyond immediate classroom interactions and demonstrates a retention effect over time. Although the mean difference represents a moderate effect size (Cohen's d = 0.28), the score distribution characteristics reveal substantial differences in learning stability and the degree of conceptual consolidation.

As shown in Table 1, the experimental group demonstrated a systematic advantage across three dimensions: daily performance (M = 90 vs. 89), homework scores (M = 85 vs. 83), and final exams (M = 74.44 vs. 71.41). Results from an independent samples t-test indicate that the difference in final exam scores was statistically significant ($t = 2.14$, $df = 152$, $p = 0.034$). A more pedagogically significant finding is that the standard deviation of the experimental group's score distribution was significantly lower (SD = 8.53 vs. 12.60), suggesting that the instructional intervention effectively enhanced the stability of learning outcomes.

Table 1. Comparison of Overall Academic Performance.

Indicator	Experimental Group (n=75)	Comparison Group (n=79)
Daily Performance (Mean)	90	89
Assignment Score (Mean)	85	83
Final Examination (Mean)	74.44	71.41
Standard Deviation (Final Exam)	8.53	12.60
Pass Rate (%)	100%	97.47%
Fail Count	0	2

Further frequency distribution analysis revealed a more detailed pattern of score differentiation (Table 2). In the experimental group, 41.33% of students scored in the 70–79 range, an increase of 12.22 percentage points compared to the control group (29.11%); the high-score segment (≥80) accounted for 34.67%, slightly higher than the control group's 31.64%. In contrast, the control group showed a concentrated distribution in the 60–69 score range (36.71%) and a failure rate of 2.53%, while the experimental group achieved a 100% pass rate. These distribution characteristics confirm the positive impact of the instructional intervention on the equity of academic performance.

Table 2. Distribution of Final Exam Scores (%).

Score Range	Experimental Group (%)	Comparison Group (%)
90–100	6.67	5.06
80–89	28.00	26.58
70–79	41.33	29.11
60–69	24.00	36.71
Below 60	0.00	2.53

Structured observations of classroom participation revealed that the experimental group participated significantly more frequently than the control group during the theoretical derivation phase. The guiding questions designed in the instructional intervention (such as the contradictory proposition that a high rate of surplus value does not necessarily lead to a high rate of profit) effectively stimulated in-depth discussions aimed at clarifying these issues. Students demonstrated a cognitive shift from passive acceptance to active questioning, specifically manifested in an enhanced ability to independently reconstruct the theoretical chain of surplus value → profit → average rate of profit → production price.

A comprehensive analysis indicates that the core value of the instructional intervention lies not in raising average scores, but in the group-level equalization of conceptual understanding. The dispersion of scores in the experimental group decreased significantly, indicating that the intervention effectively reduced individual differences. This structural improvement manifested specifically in: enhanced logical coherence in theoretical expressions, a decrease in the proportion of students in the low-scoring segment, and an overall improvement in conceptual transfer abilities.

These findings should be interpreted with caution. The realization of instructional effectiveness does not depend on the application of a single tool, but rather on the compatibility between the design of cognitive scaffolding and theoretical logic. Of particular note is the risk of cognitive dependency: through a strategy of partial information presentation combined with logical discontinuities, this study required students to critically reconstruct instructional materials (e.g., identifying the implicit assumption of the organic composition of capital in simplified models). This metacognitive training effectively prevented a tendency toward passive acceptance.

Crucial validation evidence comes from academic performance under unsupported conditions: both chapter quizzes and final exams were completed in an environment without external tool support, yet the experimental group maintained its advantage, indicating that students had internalized key reasoning steps rather than relying on immediate assistance. This corroborates the core hypothesis of cognitive scaffolding theory—that structured interventions, serving as temporary support, ultimately foster the development of independent cognitive abilities. The findings of this study suggest that, in large-class political economy courses, guided derivation strategies based on cognitive conflict can effectively enhance engagement depth, optimize the stability of grade distributions, and promote conceptual restructuring; however, teaching plans must be continuously optimized through a design-validation-iteration cycle.

5 Conclusion

This study explored pathways for the adaptive application of generative artificial intelligence in the teaching of the "Transformation of Surplus Value" module within undergraduate political economy courses. Through a quasi-experimental comparison of two parallel classes, it systematically examined the mechanisms by which intelligent-assisted teaching models influence learning outcomes and classroom engagement.

The results indicate that, although there was no significant difference in average grades, the instructional intervention produced notable structural improvements: the experimental group exhibited a more concentrated grade distribution, with no failing grades, and demonstrated greater completeness in the logical progression from surplus value (m) to profit (p) to average rate of profit ($\overline{p}$). This indicates that when intelligent assistive tools are integrated into structured derivation processes, they can effectively support students in actively constructing theoretical reasoning, rather than simply providing standardized answers.

The study also confirms that the effectiveness of instructional tools depends on the alignment between instructional design and theoretical logic; their core value lies in serving as cognitive scaffolding to support conceptual learning, rather than replacing teacher-led theoretical explanations. Through guided question design and interactive reasoning training, this instructional model enhances the depth of student engagement while ensuring the academic rigor of theoretical instruction.

This study has three limitations: First, it did not directly measure students' ability to apply higher-order reasoning and theoretical knowledge across different contexts without the use of assistive tools, making it impossible to completely rule out individual differences in reliance on instructional scaffolding. Second, the observation period was limited to a single semester, leaving the long-term retention of theoretical knowledge and the ability to transfer and apply it to be verified. Third, although the quality of the assistive materials was strictly controlled, a dynamic supervision mechanism involving student feedback and teacher calibration must be established during instructional application to avoid potential biases. Future research could further refine the validation framework through controlled experimental designs and extended follow-up periods.

In summary, generative AI holds significant practical value in theory-oriented courses. Its effectiveness hinges on achieving deep integration with the intrinsic logical structure of disciplinary theories, promoting substantial development of students' cognitive abilities through structured interventions, and providing a replicable practical model for the intelligent reform of theoretical course instruction.

Acknowledgement

This work was supported by the Ministry of Education of China under the Industry–University Cooperative Education Program (Project No. 231007061082220 & Project No. 240703009235658).

References

1. Lo, C. K. (2023). What Is the Impact of ChatGPT on Education? A Rapid Review of the Literature. Education Sciences, 13(4), 410. https://doi.org/10.3390/educsci13040410
2. Munaye, Y. Y., Admass, W., Belayneh, Y., Molla, A., & Asmare, M. (2025). ChatGPT in Education: A Systematic Review on Opportunities, Challenges, and Future Directions. Algorithms, 18(6), 352. https://doi.org/10.3390/a18060352

3. Deng, R., Jiang, M., Yu, X., Lu, Y., & Liu, S. (2025). Does ChatGPT enhance student learning? A systematic review and meta-analysis of experimental studies. Computers & Education, 227, 105224. https://doi.org/10.1016/j.compedu.2024.105224.
4. Darvishi, A., Khosravi, H., Sadiq, S., Gašević, D., & Siemens, G. (2024). Impact of AI assistance on student agency. Computers & Education, 210, 104967. https://doi.org/10.1016/j.compedu.2023.104967
5. Ning, D., & Wei, T. (2026). Coupling mechanism, risk review, and promotion pathways of generative artificial intelligence empowering higher education classroom teaching reform. China University Teaching, (01), 77–83 (in Chinese).
6. Ng, D. T. K., Chan, E. K. C., & Lo, C. K. (2025). Opportunities, challenges and school strategies for integrating generative AI in education. Computers and Education: Artificial Intelligence, 8, 100373.https://doi.org/10.1016/j.caeai.2025.100373
7. Ma, H., Han, X., & Wang, X. (2025). Teaching design of large-class management courses based on active learning. University, (26), 164–167 (in Chinese).