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Innovating Blended Teaching in Channel Management: Integrating AIGC and Curriculum Ideological-Political Education

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Abstract

Generative AI is changing Chinese business education at the same time that curriculum ideological-political education asks values to grow out of subject content rather than sit at the end of class. We report a Channel Management reform that brings the two together in a four-stage blended model built on AI-generated scenarios, problem-based learning, ideological micro-debates, and AI-supported feedback. Channel fairness organizes the ideological thread. The workflow uses commercial chatbots, the existing learning platform, and teacher review; no API or custom software is involved. A two-class pilot shows gains in participation, relevance, decision complexity, and value reflection. AI hallucination, uneven digital literacy, and approximate value measurement also emerged. The constraint is less technical than it looks: it lies in goal design, prompt quality, pacing, and the teacher's final judgment.

Keywords

AIGC; blended teaching; channel management; curriculum ideological-political education; marketing education.

1. Introduction

Channel Management is a core marketing course, yet many Chinese business schools still teach it with fixed slides, dated cases, and a closed-book exam. The problem is not simply format. Channel power, conflict, incentives, member selection, and control now intersect with platform monopolies, rural revitalization, green distribution, community group-buying, and common prosperity. A static diagram cannot show how a commission change moves through farmers, distributors, platforms, and local government. Students may memorize definitions and still struggle when several constraints press at once.

Generative AI changes part of that constraint. Teachers can generate locally grounded cases, data tables, and negotiation partners within seconds. AI can recalculate when assumptions change. Yet a tool by itself does not create learning value. Guha, Grewal, and Atlas argue that AI changes marketing education by redistributing what teachers and students do: teachers design reflection and evaluation, while students build judgment through critical use [1]. Chinese universities also report growing demand for AI-related curriculum support [2]. The question is no longer whether to use AI but how to use it well in a specific subject.

Curriculum ideological-political education (CIPE) adds another requirement: values education cannot sit outside professional content. Channel Management is well suited to this because fairness questions arise directly from distribution decisions. Surplus, market access, distributor squeeze, and green logistics costs are not side issues; they are part of channel analysis. Here we

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report a four-stage blended reform that links AIGC and CIPE through channel fairness and examines its first classroom implementation.

2. Literature Review

Research on AIGC in business education has moved beyond concepts toward design evidence. Existing work argues that AI should support critical evaluation, ethical reasoning, and creative application rather than simply speed up assignments [1]. Williams points out that privacy, bias, and academic integrity risks need classroom discussion and institutional policy together [3]. A scoping review finds that fluent AI text unsettles assessment models based on individual, traceable writing; assessment therefore needs to attend more closely to process, reflection, and human judgment [4]. Students also respond more actively when learning includes dialogue and feedback [5].

Blended learning offers a useful reference for course design. When online components support interaction, practice, and feedback, not just content delivery, learning outcomes are more stable; a meta-analysis of 133 studies reports an upper-medium positive effect [6]. Flipped classrooms vary more widely. Effective designs let students struggle productively, receive correction, and obtain feedback; moving lectures online alone is not enough [7]. Chinese literature likewise argues that intelligent technology should amplify human moral judgment, not replace it [8]. Human-machine precision teaching frameworks make the division clearer: machines handle data-intensive and rapidly updated tasks, while teachers retain goal setting, value interpretation, and formative judgment [9].

Gaps remain in practice. Most AI-education research discusses generic classrooms and seldom enters Channel Management, a course built around multi-party negotiation and dynamic tradeoffs. CIPE research supplies many ideas, but few cases integrate it deeply with AI-enabled teaching in one professional course. Many models also assume that teachers can code, access APIs, or build platforms; ordinary teaching-focused faculty cannot easily replicate them. This reform therefore takes a low-code, domain-specific, CIPE-embedded route and reports evidence from its first classroom trial.

The low-code choice is not a shortcut. It responds to the actual conditions in many teaching-focused universities. If integration depends on API access, procurement, or software development, adoption slows and may never reach ordinary classrooms. A copy-and-paste workflow is easier to test, revise, and borrow. It also makes failure visible: when a prompt produces a weak case, the teacher can rewrite it immediately rather than wait for a platform update.

The point is not to make every task automatic. It is to choose the parts where AI genuinely helps and leave the rest to the classroom.

3. Design

Four design principles guide the model. Low threshold: no custom software or API is needed, and AI tasks run through commercial chat interfaces and the existing learning platform. Dynamic scenario: cases are generated course by course from current events and local industry, not reused from a static case bank. Productive struggle: class time prioritizes decision, negotiation, and debate, with lecture compressed to about fifteen minutes. Visible values: ethical questions enter through voting and debate, not a closing remark. These principles come from constructivist learning theory and a judgment about human-machine division: AI supports data and feedback, while teachers retain value judgment and interpretation.

Each 45-minute session has four stages. In the scenario stage, students receive a new case, such as a county with 20,000 tonnes of yellow peaches, 15% group-buying penetration, a 12%

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platform commission, and an 8% distributor margin. In the problem-solving stage, teams represent manufacturers, distributors, platforms, or local government and negotiate a distribution arrangement. Teachers can adjust conditions, and AI recalculates margins immediately. In the ideological micro-debate stage, students vote and give reasons on questions such as whether raising commissions is consistent with common prosperity. In the feedback stage, AI summarizes notes and quiz answers into knowledge, ability, and value indicators; the teacher closes with a brief comment.

Each stage relies on a prompt library. Case prompts specify product, region, quantity, conflict, roles, data table, and diagram so that output is not generic. Role-play prompts give AI a manager identity and negotiation goal, requiring students to argue under pressure. Report prompts ask AI to score structural completeness, data credibility, green-channel consideration, and common-prosperity orientation. Teachers review all AI feedback before releasing it to students. This aligns with evidence that AI-supported feedback can improve quality without replacing human oversight [10].

A ten-node mapping matrix anchors CIPE integration. Course chapters, knowledge points, ideological themes, AI material, and classroom activities are matched item by item: channel power with anti-monopoly, channel structure with rural commerce, green distribution with dual-carbon goals, and platform commission with common prosperity. The matrix is not a fixed table; it changes each semester. What matters is not the number of nodes but that each ideological theme attaches to a knowledge point capable of supporting analysis, so values do not become a separate add-on.

What keeps values in the analysis is their attachment to decisions. Channel power is not just a concept; it becomes a debate about who can set terms. The teacher can ask whether a commission change shifts risk onto distributors with the least bargaining power. AI supplies evidence, but the classroom still has to decide what counts as fair. This is why the prompt library specifies not just the case but also the ideological question. Students must produce arguments, not slogans.

Assessment shifts from 70% closed-book exam to 30% AI-supported feedback, 10% peer assessment, 10% value commentary, and 60% final work. The final work includes an AI-assisted diagnostic report and an oral defence. Students may use AI, but they must explain data sources, reasoning, and how their channel design addresses a public-interest issue. The oral defence makes AI use auditable and moves attention from recall to judgment.

The assessment also changes what the teacher does. AI can score a draft quickly, but the teacher checks whether the evidence actually supports the recommendation. Peer assessment adds another view, while value commentary keeps ethics visible without turning it into a separate moral lecture. This is not a fully automated pipeline. It is a chain of checkpoints in which AI speeds up work and humans retain the final call.

4. Evidence

Two marketing classes of about 60 students each at the University of Science and Technology Liaoning piloted the reform. Attendance stayed above 95%, but behavioural participation changed more visibly. The share of students sitting in the front two rows rose from about 40% to 70%. Quiz response rates exceeded 90% in most sessions, and course evaluation rose from 92.3 to 95.1. The mean diagnostic report score was 82.4 and the mean oral defence score was 84.1. These marks cannot be compared directly with previous closed-book exam scores, but classroom observation found students more willing to connect channel concepts to concrete business situations.

A mid-semester survey (n=108; 90% response rate) showed that 83% thought AI cases made content closer to reality, 76% said debates led them to think harder about social effects, and

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68% found the radar chart useful for seeing gaps. At the same time, 22% felt there were too many digital tools, and 15% were unsure whether to trust AI information. Three observations stood out. Role-play generated policy options the teacher had not anticipated. Ideological debates produced real disagreement, not a single approved conclusion. After one student discovered an AI-fabricated regulatory story, the class moved into source verification and added a five-minute AI information check.

Classroom records also show why the four stages matter. The scenario creates urgency before theory appears. The negotiation stage turns abstract concepts into choices with consequences. The debate forces students to justify tradeoffs. The feedback stage converts these actions into something visible enough to discuss. When any stage is shortened, students tend to fall back into memorizing definitions.

The AI hallucination episode proved useful precisely because it was unexpected. Students had assumed that fluency meant accuracy. Once the fabricated regulatory story was exposed, the class discussed how to check sources, which authorities issue such notices, and how to distinguish a plausible narrative from evidence. The teacher did not ban AI; she built a routine around verification.

The evidence is still formative. There is no control group, so Hawthorne effects and teacher enthusiasm cannot be ruled out. Value identification is not a validated construct but a heuristic indicator. The sample comes from one course and one school, and long-term effects have not been measured. These results show that the model merits further trial, not causal proof.

5. Discussion and Conclusion

What makes the model useful is not technical sophistication. A low-code route shows that non-technical teachers can implement meaningful AI integration. Channel fairness gives AIGC and CIPE a shared point of contact, so values education enters analysis rather than a separate lecture. The AI-assisted report plus oral defence recognizes AI use while requiring students to explain their reasoning. The main difficulties are the rigidity of the four-stage structure, the gap between AI speed and the depth of carefully authored cases, approximate value measurement, and unequal digital resources. Paper alternatives, varied case formats, and lower weight on value scores can ease these issues but cannot remove them.

The next stage will test effects across classes, refine prompts and value observation, and extend the model to Retailing and Marketing Research. In practice, the lesson is simpler than the technology: AIGC does not need complex tools as much as clear goals, controlled prompts, classroom time for judgment, and teachers willing to treat AI errors as learning material rather than simply as mistakes to hide.

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