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DEVELOPMENT AND EMPIRICAL EVALUATION OF AN ONLINE COURSE ON INTELLIGENT VEHICLE ENVIRONMENT PERCEPTION

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Abstract: Intelligent vehicle environment perception is a core component of automotive engineering education, yet traditional teaching is constrained by costly perception hardware, rapidly changing algorithms, limited simulation time and fragmented learning resources. This study develops an online course for Intelligent Vehicle Environment Perception Technology using the ADDIE instructional design model. The course integrates learner and industry demand analysis, modular digital resources, CARLA-based simulation experiments, multi-sensor fusion cases and hierarchical assessment. Teaching effectiveness was evaluated over 16 weeks across four intact course sections (n=120) using theoretical scores, experiment scores, course completion and student satisfaction. The proposed mixed online-offline course achieved an average theoretical score of 84.6, an experiment score of 82.9 and a completion rate of 95.3%, compared with 72.3, 65.1 and 76.4%, respectively, for pure offline teaching. In the ablation analysis, removing the simulation module reduced experiment performance and satisfaction more than removing the industrial-case module. The findings indicate that systematic digital resources and virtual simulation can complement physical laboratory teaching and support practical learning under hardware constraints. Further replication across institutions and cohorts is required to establish generalisability.
Keywords: Intelligent vehicle; Environment perception technology; Online course development; ADDIE model; Mixed teaching; Autonomous driving simulation

1 INTRODUCTION

With the large-scale commercial application of intelligent vehicles and the rapid iteration of autonomous driving perception algorithms, compound talents mastering multi-sensor perception, deep learning detection and vehicle simulation testing are in short supply in the automotive industry [1-3]. As the core precondition of autonomous driving decision-making and control, intelligent vehicle environment perception technology covers camera, LiDAR, millimeter-wave radar and multi-modal fusion algorithms, which have become core teaching topics of vehicle engineering, intelligent transportation and automotive artificial intelligence majors [1-4]. Among many teaching difficulties, insufficient experimental equipment and disconnection between classroom content and industrial frontier technologies are two key factors restricting the cultivation of students' engineering practical ability [5-6]. High-cost LiDAR test vehicles, limited offline training time and slow iteration of textbooks make it difficult for traditional offline teaching to support full-process perceptual algorithm practice for all students. Developing systematic online courses with simulation experiment resources has become an urgent demand for higher automotive engineering education.

To address these challenges, a large number of studies on online automotive courses have been carried out. For online course construction, mainstream theories include ADDIE systematic instructional design, backward design and competency-based curriculum development [5-6]. For intelligent vehicle perception teaching, existing studies have explored CARLA simulation-assisted offline teaching and scattered short-video algorithm tutorials [7-8]. Although these methods have achieved partial teaching optimisation, they still have obvious limitations. On the one hand, most existing digital teaching resources are fragmented algorithm sharing materials without complete hierarchical curriculum logic and standardised assessment system. On the other hand, few studies integrate industrial post competency standards into the whole-process online course development framework, lacking closed-loop optimisation links from resource development to teaching evaluation. Prior instructional-design literature provides systematic frameworks for course development, but limited evidence is available on their application to intelligent-vehicle perception courses together with comparative teaching evaluation and module-level ablation [5-6]. In recent years, MOOC platforms, cloud simulation laboratories and micro-video teaching have provided mature technical support for the construction of systematic online engineering courses, which brings new solutions to break the hardware and time-space limitations of traditional perception teaching [9].

Motivated by this, this paper investigates the whole-process development method of an online course targeting Intelligent Vehicle Environment Perception Technology based on the ADDIE model. Specifically, the course construction process is divided into five closed-loop stages: Analysis, Design, Development, Implementation and Evaluation, and the core elements including learner demand analysis, modular knowledge framework, multi-type digital teaching resources and diversified evaluation mechanism are systematically constructed. On this basis, a complete online teaching resource library covering theory, virtual simulation, industrial cases and after-class assessment is developed and deployed on the university MOOC platform. Finally, comparative teaching experiments, questionnaires and module ablation analysis are conducted to evaluate the course teaching effect. This work aims to provide a standardised development template for online courses of intelligent vehicle core technologies, narrow the gap between campus teaching and enterprise engineering demands, and improve the autonomous learning efficiency and practical ability of vehicle major students.

2 MATERIALS AND METHODS

To this end, this paper models the online course construction as an iterative closed-loop process based on the ADDIE instructional design model. At each optimisation stage of course construction, developers adjust curriculum modules, supplement teaching resources and optimise assessment rules according to learning feedback, so as to continuously improve the overall teaching effect. More specifically, the analysis stage extracts core information related to curriculum positioning, including learner knowledge reserve, enterprise post competency requirements, offline teaching bottlenecks and platform resource constraints. The design stage determines hierarchical teaching objectives, modular knowledge framework, mixed online-offline teaching activities and comprehensive evaluation rules. The development stage completes the production of micro-videos, electronic courseware, simulation experimental packages and question banks. The implementation stage realizes course release, online learning management and teacher-student interactive discussion on the MOOC platform. The evaluation stage collects learning data, questionnaire feedback and teaching effect indicators to iterate and optimise course resources. The optimisation objective of the whole course construction is to maximize the comprehensive teaching gain within the existing teaching resource constraints, which can be expressed as maximizing the cumulative teaching effectiveness of all modules:

$$[\max J = \Sigma(m=1 \text{ to } M)\ [\alpha K_m + (1 - \alpha)P_m] \tag{1}$$

where J denotes the overall teaching effectiveness, M is the total number of curriculum modules, α ($0 \leq \alpha \leq 1$) is the weight factor balancing basic knowledge learning and advanced practical ability training, K_m represents the knowledge-learning gain of the m-th curriculum module, and P_m represents the practical ability gain of the m-th curriculum module.

2.1 ADDIE-based Online Course Development Framework

To achieve systematic construction and closed-loop optimisation of the environment perception online course, this paper develops an ADDIE-driven online teaching construction framework. The central idea of the framework is to view automotive engineering online teaching as a closed-loop optimisation process consisting of demand analysis, curriculum design, resource development, platform delivery and feedback-driven course iteration, so that course designers can continuously refine teaching resources through interaction with real student learning data. Unlike traditional teaching modes that depend on fixed textbooks and static offline labs, the proposed framework is able to adaptively learn, from student learning feedback, which teaching modules and virtual simulation resources are more likely to improve knowledge mastery and practical operation ability under limited hardware budgets. In this way, theoretical knowledge learning and simulation practice training are no longer treated as isolated tasks; instead, they are modeled as two closely related components under a shared competency training objective, both contributing to the overall improvement of teaching effectiveness.

Within this framework, the current teaching demand is first characterised by a demand analysis module, which encodes relevant information such as students' pre-course knowledge reserve, enterprise engineer competency standards, offline hardware shortages and MOOC platform function limits. Based on this demand information, curriculum designers formulate the complete course architecture. For the theoretical learning task, resources include sensor principal animations, algorithm micro-videos and electronic courseware. For the practical training task, resources correspond to CARLA simulation packages, open-source driving datasets and step-by-step experimental operation guides. After students finish online learning tasks, the MOOC platform returns feedback signals, such as chapter completion rate, test scores, experiment submission quality and questionnaire satisfaction. The framework then quantifies teaching gain and updates module resource allocation accordingly. Through this interaction mechanism, the course gradually approaches a more effective teaching structure by continuously learning from student trial and feedback.

Figure 1 illustrates the course homepage built on the MOOC platform. The interface integrates a video player with speed control and timestamped note-taking, a chapter navigation sidebar for quick access to all 32 lessons, and a course information panel displaying key metadata such as total duration, enrollment count, and instructor information. This layout is designed to minimize cognitive load, allowing students to watch lectures, take notes, and navigate between chapters without leaving the page.

From a procedural perspective, the framework can be summarized into five main stages. The first stage is learner & industry demand modeling, whose goal is to extract decision-relevant information from talent cultivation schemes and enterprise recruitment standards and transform it into clear course positioning suitable for undergraduate learners. The second stage is curriculum design, in which designers divide progressive modules, set three-dimensional teaching objectives and design mixed online-offline teaching activities, thereby learning how to arrange theoretical knowledge and practical training reasonably.

Figure 2 presents the course catalog, which organises the curriculum into five chapters and 32 lessons. Each lesson is labelled with a type icon — video, document, lab, or quiz — and a progress indicator showing one of three states:

completed, in-progress, or pending. The top statistics bar aggregates total study hours, completed lessons, and overall progress, giving students a clear overview of their learning trajectory.

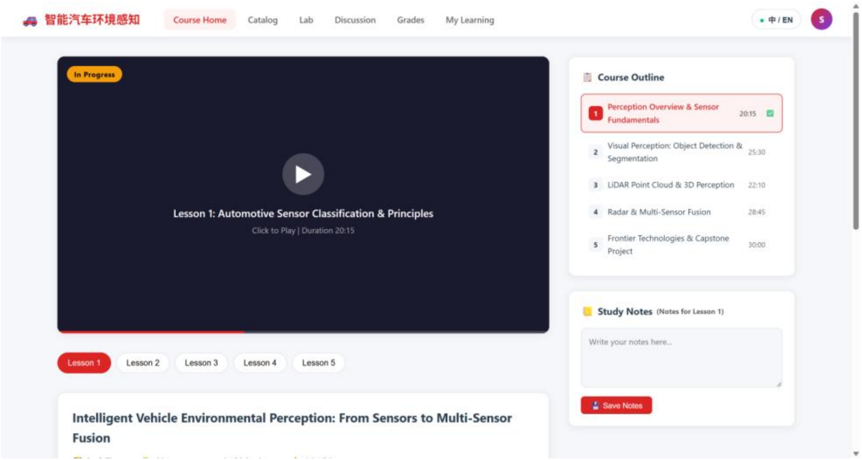

Figure 1 MOOC Course Homepage

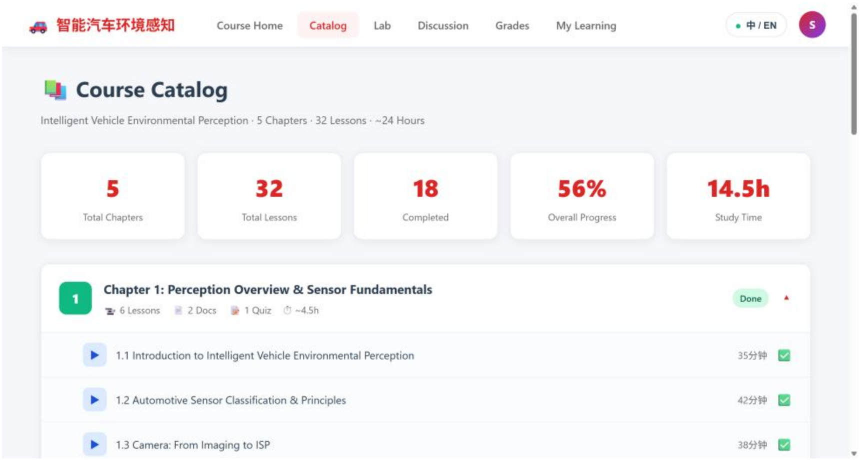

Figure 2 Course Catalogue Structure

The third stage is diversified teaching resource development, where all digital materials are produced to support autonomous learning and remote simulation operation.

Figure 3 illustrates the virtual simulation experiment platform, a core innovation of this course. The interface consists of three panels: an experiment list on the left showing five experiments from YOLOv8 object detection to multi-sensor fusion system integration, a code editor with Python syntax highlighting in the center, and a real-time visualization output panel on the right. A bottom status bar displays the simulated runtime environment (PyTorch 2.0, CUDA 11.8) and GPU memory usage. Students can run, stop, reset, and export experimental results entirely in the browser, eliminating the need for local GPU hardware.

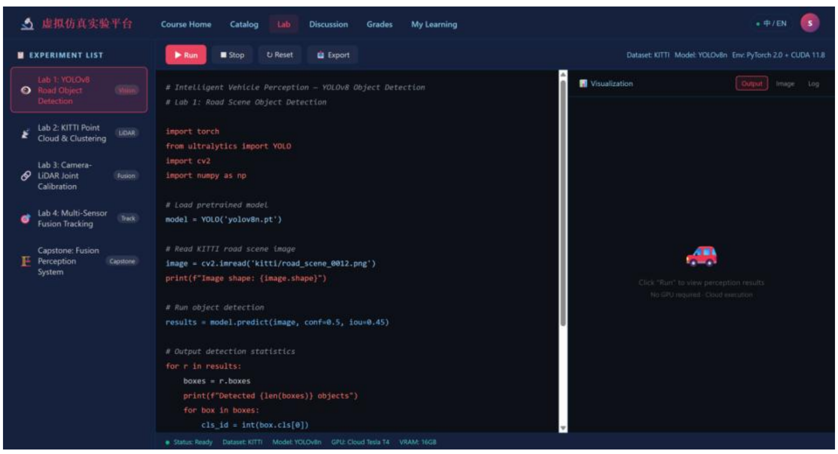

Figure 3 CARLA Simulation Platform

The fourth stage is online course deployment and teaching implementation, where the course is launched on MOOC platforms and daily online teaching management is carried out.
Figure 4 shows two additional platform modules that support interaction and assessment. The discussion forum allows students to post questions filtered by category — technical discussion, lab Q&A, resource sharing, and general topics — with pinned announcements and engagement metrics. The grade center provides a chapter-wise score breakdown with progress bars, grade badges, and a weighted overall grade composition, enabling students to track their performance across all assessment components.
The fifth stage is teaching effect evaluation and course iteration, where all learning data and student feedback are analysed to optimise module content and resource proportion. Under this framework, theoretical micro-video resources are treated as the front-end process for knowledge input, while cloud simulation experimental resources are regarded as the back-end process for improving students' practical engineering ability. Together, they form a unified feedback-driven online teaching optimisation mechanism.

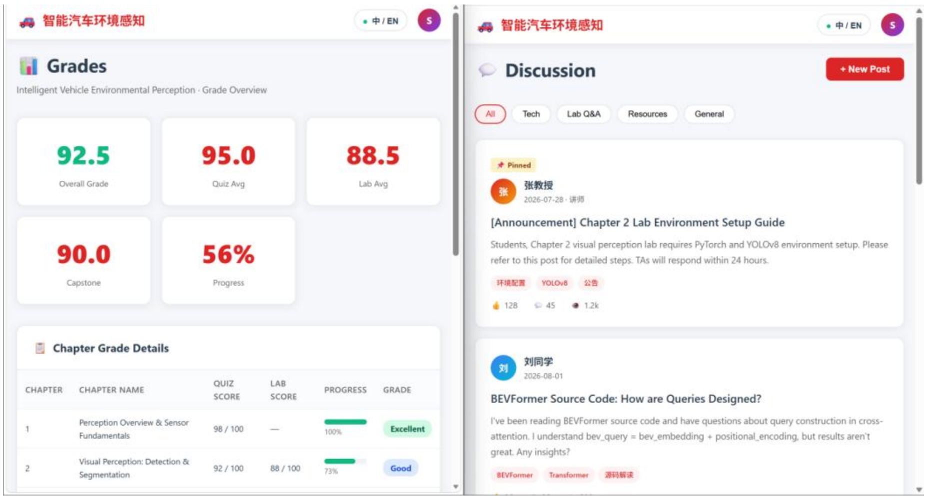

Figure 4 Forum and Grade Center

2.2 Experimental Design and Evaluation

To evaluate the effectiveness of the proposed ADDIE-based online course construction scheme, experiments were conducted from two perspectives: overall teaching performance and core module contribution ablation test. The evaluation focused on three research questions. First, does the proposed online course yield higher observed theoretical scores and simulation experiment performance than pure offline teaching? Second, can it effectively solve the problem of insufficient offline perception experimental hardware and improve student learning satisfaction? Third, do the simulation experiment module and industrial case module make a substantial contribution to the overall teaching quality improvement? To answer these questions, several representative baseline teaching modes were considered, including pure offline traditional teaching, offline teaching with scattered network short videos, and offline teaching with only static electronic courseware. The proposed full mixed online-offline course was then compared against these baselines in terms of theoretical test score, experiment score, overall course completion rate and student satisfaction.
In the experimental design, the overall teaching effect comparison was evaluated first, followed by an ablation study to investigate the impact of core resource modules on teaching quality. For the overall teaching evaluation task, the main metrics included average theoretical score, average experiment score and course completion rate. For the ablation test, the analysis focused on theoretical scores, experiment scores and comprehensive satisfaction under different module combinations. All groups were tested under the same 16-week teaching cycle, unified instructor and consistent textbook difficulty in order to ensure a fair and consistent comparison.

2.3 Participants and Teaching Conditions

Participants: approximately 120 students in total (n=120), drawn from 4 parallel sections of the course of Interdisciplinary Automotive Artificial Intelligence at National Advanced school of Engineering during the 3rd-semester offering in September 2025. Each teaching mode was assigned to one intact section of approximately 35 students (n_1=35 for Pure Offline, n_2=27 for Offline + Scattered Videos, n_3=28 for Offline + Courseware, n_4=30 for the Proposed Course).
Operational definition of conditions: Pure Offline Teaching consisted of in-person lectures and physical lab sessions only, with no digital course resources provided; the two intermediate conditions added, respectively, unstructured third-party video links or static electronic slide decks alongside the same offline lectures; the "Proposed Course" replaced/supplemented these with the full ADDIE-developed resource set (sensor animations, CARLA simulation packages, industrial case materials, and hierarchical question banks).

2.4 Measures and Analysis

The primary outcome measures were average theoretical score, average experiment score, course completion rate and student satisfaction. The ablation analysis used average theoretical score, average experiment score and satisfaction score. Because the manuscript provides group means but not standard deviations, confidence intervals or inferential test results, the present analysis is reported descriptively; no statistical significance is claimed.

3 RESULTS

3.1 Overall Teaching Effectiveness

Table 1 presents the comparison results of different teaching modes in terms of theoretical mastery and practical ability. As shown in the table, the proposed full online-offline mixed course showed the highest observed values across all reported metrics.

Table 1 Comparison of Comprehensive Teaching Performance of Different Modes

Teaching Mode	Average Theoretical Score (100 pts)	Average Experiment Score (100 pts)	Course Completion Rate (%)
Pure Offline Teaching	72.3	65.1	76.4
Offline + Scattered Network Videos	76.8	70.5	81.2
Offline + Electronic Courseware Only	75.4	68.7	79.6
Proposed Full Mixed Online-offline Course	84.6	82.9	95.3

The results in Table 1 show that pure offline teaching, although easy to organise, shows lower observed performance in both theoretical understanding and practical operation, limited by expensive and insufficient perception experimental equipment. The two auxiliary online resource modes slightly improve learning indicators, but lack systematic progressive curriculum logic and complete cloud simulation experiment packages. In contrast, the proposed ADDIE-based online course is associated with a higher average theoretical score to 84.6, average experiment score to 82.9, and the course completion rate to 95.3. These improvements suggest that modular hierarchical resources and remote simulation experiments can make more effective use of after-class learning time and continuously guide students to explore complex vehicle perception algorithms and road scenarios.

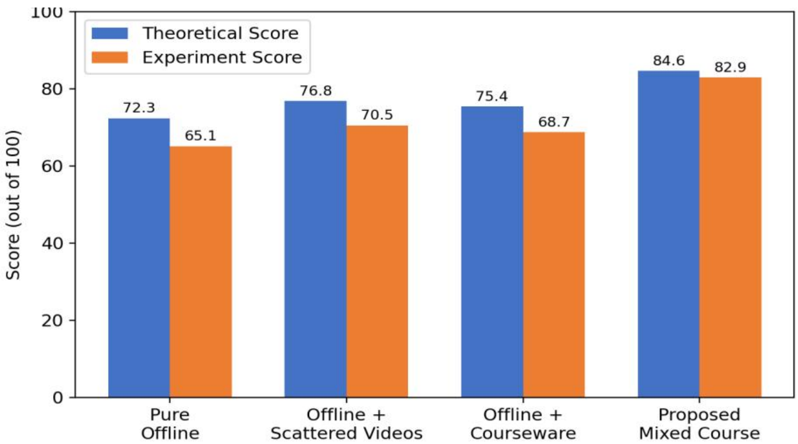

Figure 5 Learning Score Comparison of Four Teaching Modes

To provide a more intuitive view of the learning performance gap, Figure 5 illustrates the comparison of theoretical scores and experiment scores across different teaching modes. It can be clearly observed that the proposed course maintains a consistent advantage on both metrics. This suggests that the mixed teaching mode may improve the breadth of students' knowledge coverage but also strengthens hands-on training of multi-sensor fusion cases. Such an advantage is particularly important for cultivating engineering thinking for intelligent vehicle majors, and it also supports the rationale of modeling online course construction as a feedback-driven closed-loop optimisation task.

3.2 Student Learning Satisfaction

In addition to academic performance, the proposed course was further evaluated on student learning satisfaction. Table 2 reports the comparison results of different teaching modes in terms of average satisfaction score, high satisfaction ratio and the proportion of students who think hardware shortage is solved.

As shown in Table 2, pure offline teaching yields the weakest satisfaction performance, with an average satisfaction score of only 3.12 (full score 5), indicating that offline labs cannot provide enough independent practice opportunities for all students. Offline teaching with scattered videos and simple courseware achieve average satisfaction scores of 3.65 and 3.48 respectively, demonstrating that fragmented digital resources can slightly enrich learning materials but cannot fundamentally resolve hardware constraints. However, the proposed full online course reaches an average satisfaction score of 4.57, showing the highest observed value among the tested conditions. Moreover, 89.2% of students recognize that cloud simulation experiments effectively make up for offline equipment shortages, whereas only 11.5% of students under pure offline teaching hold this opinion. This result suggests that the multi-level simulation resource system in the ADDIE-based framework can integrate theoretical learning and virtual practice to build a student-friendly autonomous learning environment.

Table 2 Comparison of Student Learning Satisfaction

Teaching Mode	Average Satisfaction Score (5-point)	Satisfaction Rate (Score ≥4)	Students Who Think Hardware Shortage Is Solved (%)
Pure Offline Teaching	3.12	42.7	11.5
Offline + Scattered Network Videos	3.65	58.4	36.2
Offline + Electronic Courseware Only	3.48	53.1	24.8
Proposed Full Mixed Online-offline Course	4.57	93.6	89.2

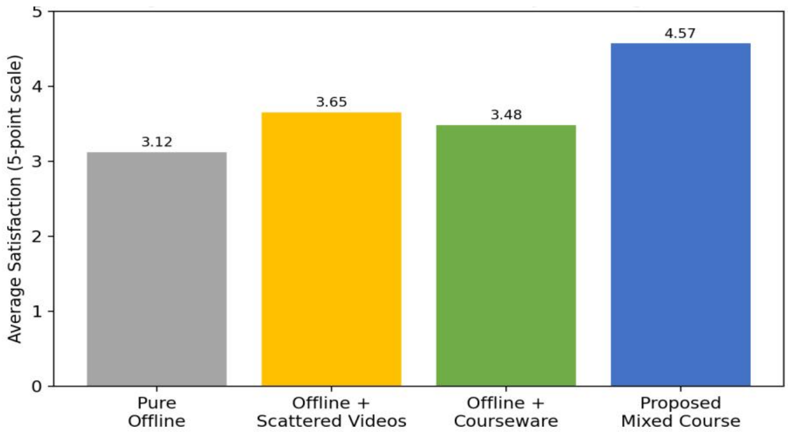

Figure 6 Student Satisfaction Score Comparison

Figure 6 further visualises the average satisfaction score of different teaching modes. The proposed approach has the highest observed score among the tested schemes, indicating its ability to provide sufficient simulation practice resources and systematic industrial cases for students. This advantage is especially valuable for undergraduate vehicle engineering majors, where experimental hardware investment is often limited in many universities. In addition, the proposed course also shows obvious advantages in learning completion rate, indicating that the improvement of teaching experience is not achieved at the cost of heavy learning burden. Instead, it reflects a better balance between knowledge input and hands-on training.

3.3 Ablation Analysis

To further examine the contribution of different core resource modules in the proposed framework, an ablation study was conducted on two key teaching components: cloud simulation experiment module and industrial case expansion module. Specifically, the simulation module and industrial case module were removed one at a time, and the resulting two simplified course variants were compared with the full version course. The results are shown in Table 3.

Table 3 Ablation Study of Core Course Modules

Course Setting	Average Theoretical Score	Average Experiment Score	Overall Satisfaction Score
w/o Simulation Experiment Module	79.5	69.2	3.71
w/o Industrial Case Module	82.1	78.6	4.13
Full Version Online Course	84.6	82.9	4.57

As Table 3 shows, removing the simulation experiment module leads to a noticeable decrease in experiment scores and satisfaction, indicating that cloud simulation resources play a substantial contribution in improving students' practical operation ability and learning experience. When the industrial case module is removed, the model still maintains moderate theoretical performance, but the experiment score and satisfaction drop moderately. This suggests that industrial case materials are crucial for connecting textbook knowledge with real intelligent vehicle engineering scenarios. By contrast, when both modules are retained in the full course, all evaluation indicators reach the optimal level. This indicates that only relying on theoretical micro-videos cannot maximize overall teaching utility, and the collaborative matching of simulation experiments and industrial cases helps the course learn a more practically meaningful teaching structure.

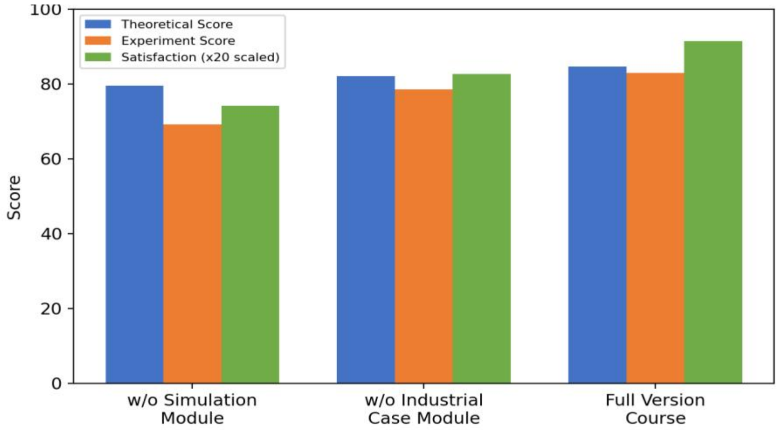

Figure 7 Ablation Study of Core Course Modules Across Metrics

Figure 7 visualises the average comprehensive scores under different ablation settings. The full model consistently achieves the best result, further demonstrating the effectiveness of the proposed multi-component collaborative resource design. Overall, this finding highlights two important characteristics of the ADDIE course construction framework. First, teaching quality should not be driven by theoretical resources alone; instead, theoretical learning, simulation practice and industrial case expansion should be considered jointly. Second, the advantage of the proposed online course comes not only from the ADDIE design process itself, but also from the multi-level digital resource system well aligned with the practical training objectives of intelligent vehicle majors.

Taken together, the above results indicate that the proposed ADDIE-based online course development framework is effective in both theoretical knowledge teaching and practical ability training. Compared with pure offline teaching and fragmented auxiliary online resources, the proposed scheme appears to make better use of post-class autonomous learning time and shows higher observed performance in academic scores, experiment completion quality and student satisfaction. The ablation study further confirms that the simulation experiment module and industrial case module are key complementary components behind the observed teaching improvement. Overall, the proposed method provides an adaptive and extensible solution for digital teaching reform of intelligent vehicle engineering majors.

4 DISCUSSION

4.1 Limitations

• Single-institution setting: all data were collected from one university and, potentially, a single instructor team, which limits generalisability to other institutions, student populations, or curricular contexts.

• Short observation window: outcomes were measured within a single 16-week cycle; no data were collected on longer-term knowledge retention, transfer to subsequent courses, or actual job/internship performance.

• Possible novelty effect: students in the newly introduced mixed online-offline format may have shown elevated engagement and satisfaction partly due to the novelty of the format rather than its instructional design alone; a second-cohort replication would help rule this out.

Taken together, the above results indicate that the proposed ADDIE-based online course development framework is associated with improvements in both theoretical knowledge teaching and practical ability training relative to the baselines tested here. Compared with pure offline teaching and fragmented auxiliary online resources, the proposed scheme appears to make better use of post-class autonomous learning time and achieves higher observed performance in academic scores, experiment completion quality and student satisfaction. The ablation study further indicates that the simulation experiment module and industrial case module are complementary components behind the observed teaching improvement, though replication across additional cohorts and institutions is needed to confirm generalisability.

5 CONCLUSIONS

This paper investigated the teaching dilemma of intelligent vehicle environment perception courses and proposed a unified online course construction framework based on the ADDIE systematic instructional design model. Unlike traditional teaching modes that separate theoretical teaching and practical training and lack standardised digital teaching resources, the proposed method formulates the whole course construction as a five-stage closed-loop optimisation process aimed at maximizing comprehensive teaching effectiveness. A corresponding complete resource system was constructed through demand analysis, modular curriculum design, diversified resource development, MOOC platform deployment and multi-dimensional teaching evaluation. On this basis, a feedback-driven online teaching system was developed, enabling the course to dynamically adjust module proportion and resource richness according to students' learning data and satisfaction feedback, thereby continuously optimizing the mixed online-offline teaching process.

Experimental results demonstrated that the proposed online-offline mixed teaching scheme is effective in both theoretical knowledge learning and simulation practice training. For theoretical learning, the course helps students systematically master multi-sensor principles and perception algorithms, outperforming representative baseline teaching modes such as pure offline teaching and fragmented video-assisted teaching in terms of theoretical test scores and course completion rate. For practical training, the cloud simulation experiment resources realize low-cost full-student hands-on operation under limited hardware budgets and obtain superior results on key indicators such as experiment scores and student satisfaction. In addition, the ablation study showed that simulation experiment resources and industrial case resources play complementary roles in improving overall teaching quality, indicating that multi-component collaborative resource design is a critical factor in maximizing the teaching benefit of the online course. Overall, the findings of this study suggest that the ADDIE model provides an adaptive and unified solution for the whole-process construction of intelligent vehicle specialized online courses.

Although encouraging teaching effects have been obtained, there remains considerable room for further improvement. Future work may proceed in several directions. First, the course module difficulty can be stratified to develop differentiated learning versions for higher vocational students, undergraduates and enterprise on-the-job engineers. Second, large language model intelligent tutoring modules can be embedded into the MOOC platform to realize personalized learning path recommendation and automatic correction of simulation experiment codes. Third, real vehicle road perception data collected by domestic intelligent vehicle enterprises can be introduced to replace part of open-source simulation datasets, further enhancing the engineering practicability of course experiments. Finally, it would also be promising to build Chinese-English bilingual course resources to meet the online learning demands of international students majoring in intelligent transportation and autonomous driving.

Advancing along these directions may not only further improve the richness and practicability of intelligent vehicle online teaching resources, but also promote the deep integration of autonomous driving engineering education and digital online teaching technology.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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