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AI-Empowered Reconstruction of Classroom Teaching in Vocational Undergraduate Education

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Abstract: Artificial intelligence offers opportunities to redesign vocational undergraduate teaching, yet its integration across instructional components remains a challenge. This study developed and evaluated an AI-supported classroom reconstruction model for Image Recognition Technology to address outdated course content, insufficient differentiation, and delayed assessment feedback. The model integrated instructional objectives, content, activities, and assessment through knowledge-graph-guided resource recommendation, learning diagnostics, timely feedback, and human-AI collaboration. A 16-week quasi-experimental study involved 186 second-year students from four intact classes at a vocational university, with 93 students in each condition. Compared with conventional instruction, the reconstructed model was associated with stronger core image-recognition skills, algorithm transfer, complex problem solving, classroom interaction, and vocational certification attainment. Image-classification accuracy was 88.6% versus 76.3%, transfer-task completion was 87.1% versus 64.5%, and vocational certification attainment was 97.8% versus 80.6%. These findings suggest that AI-supported integration of instructional objectives, content, activities, and assessment offers a promising approach to classroom teaching reconstruction in vocational undergraduate education.

1. Introduction

AI-enabled vocational education research has begun to address both teacher capacity and course-level instructional redesign. Work on intelligent manufacturing professional groups stresses the importance of building AI-capable teaching teams [1]. Course-specific research in control-system simulation likewise shows how AI can support intelligent teaching models in applied technical education [2]. Together, these studies indicate that technological adoption must be accompanied by changes in teaching organization and course design. Three problems are especially salient in the present context: standardized instruction that constrains differentiated development, one-dimensional assessment with delayed feedback, and course content that lags behind industrial practice. Because these problems are interdependent, isolated interventions are unlikely to produce sustained effects. This study therefore asks how artificial intelligence can be integrated across

instructional objectives, content, activities, and assessment rather than added as a separate technological layer.

AI-supported educational reform provides a broader institutional and pedagogical context for redesigning an image-recognition course. Integrated reform in teacher education has emphasized coordinated change across curriculum, instruction, and teacher development [3]. In vocational education, research on teacher role transformation and the Teacher-AI-Student collaborative model further indicates that technology should redistribute responsibilities among teachers, intelligent systems, and learners rather than function as an isolated tool [4]. Against this background, Image Recognition Technology is a core course in vocational undergraduate programs in Artificial Intelligence Technology Applications. The course covers image acquisition and preprocessing, feature extraction, convolutional neural networks, object detection, and model deployment. Its abstract concepts, substantial practical component, and rapid technological change make it an appropriate context in which to examine instructional reform. Existing research has progressed from conceptual arguments to practical pathways, but three gaps remain. First, most studies concern higher vocational colleges or general universities rather than vocational undergraduate programs. Second, studies often emphasize technical applications without examining the coordinated redesign of objectives, content, activities, and assessment. Third, process and outcome data are often insufficient to support a closed feedback loop.

This study develops a four-component reconstruction model and evaluates it through a one-semester quasi-experiment. Section 2 presents its rationale, implementation, and evaluation methods; Section 3 reports results; and Section 4 discusses implications and limitations.

2. Materials and Methods

2.1. Research Basis and Reconstruction Framework

AI-supported blended teaching in vocational education [5] and multidimensional accounts of higher-education reform [6] connect technology with instructional design. Ecosystem research extends this connection to organizational change and implementation [7]. Course-level studies identify complementary requirements: Hu et al. emphasize teacher capacity, resources, content, and diversified assessment in Geology [8], while Cai describes resource restructuring and scenario expansion in vocational nursing [9]. These studies offer design principles, although their disciplinary settings limit direct transfer to engineering courses.

Teacher competence and curriculum coherence are further prerequisites. AI-supported knowledge organization, resource recommendation, and lesson planning can assist novice teachers [10], while smart-manufacturing research links curriculum reconstruction with multimodal pedagogy [11]. Research on fundamental computer courses [12], systemic vocational-education transformation [13], and AI-supported PLC classrooms [14] likewise supports updating resources and connecting activities with feedback. These studies provide indirect foundations; the industrial image-recognition projects and integrated framework used here were developed for the present course.

The technical workflow, from data collection to system deployment, has clearly defined stages and produces observable outputs at each stage. This structure supports project-based learning because problems can be decomposed, diagnosed, and corrected. Working with imperfect real-world data is pedagogically valuable: it develops problem-solving ability while reinforcing engineering standards.

Image-recognition instruction combines knowledge development, iterative innovation, and critical reflection. Research on AI-empowered reform of fundamental computer-course content emphasizes updating curricula to reflect AI-enabled learning contexts [12]. In the present course,

that general rationale is operationalized through three interdependent requirements: students must work with image data and annotation knowledge, iteratively develop and refine models, and examine algorithmic bias, recognition error, and data ethics. The last requirement is easily neglected in instruction, although it is essential to responsible engineering practice.

The model connects objectives, content, activities, and assessment through data-informed decision making and human-AI collaboration. Objectives determine content and tasks; activity data provide assessment evidence; and assessment refines subsequent objectives and content. Industry-education integration connects technological adoption with institutional mechanisms and applied training [15], while engineering teachers' AI literacy supports responsible implementation [16]. Building on these complementary insights, the present study adapts the four-component framework to vocational undergraduate education.

The framework operates at three levels. Curriculum, tools, data, and activities define the elements to reconstruct. Teachers, intelligent systems, and students share explanation, diagnosis, practice, and reflection, consistent with the Teacher-AI-Student model [4]. Operationally, teacher competence, platforms, resources, and assessment are aligned with instructional stages. This three-level synthesis was developed in the present study rather than attributed solely to the cited source.

Task allocation depends on whether work is standardized, quantifiable, and repeatable. Systems handle routine training and assessment; teachers retain value-oriented guidance, difficult-case analysis, and project supervision.

2.2. Instructional Reconstruction and Implementation

Teaching objectives in vocational undergraduate education must reconcile undergraduate-level theoretical depth with a strong professional orientation. The present study divides its objectives into core skills, higher-order abilities, and professional competence, with separate achievement standards for each. Core skills include image acquisition and preprocessing, network architecture design, object detection, and image segmentation and can be assessed directly. Higher-order abilities focus on algorithm transfer and complex problem solving through projects and competitions. Professional competence is more difficult to measure. Because specialized instruments were unavailable, data ethics, recognition of algorithmic bias, awareness of engineering standards, and professional identity were represented indirectly through process and behavioral indicators and were not treated as directly validated outcomes.

Prior-semester grades in core major courses informed higher-, middle-, and lower-prior-achievement strata. Higher-achieving students emphasized optimization and innovative applications; the middle stratum completed the technical workflow and parameter tuning; and the lower stratum first secured correct module implementation and conceptual understanding. These differentiated standards sought to avoid underchallenging some students while overwhelming others.

The curriculum was structured around the technical workflow of data collection, model training, and system deployment and was organized into two complementary tracks. The modular track grouped content around image classification, object detection, and image segmentation to preserve conceptual coherence. The project-based track used applied scenarios, including industrial quality inspection and intelligent security, to connect technical principles with engineering practice. Both tracks drew on the same resource base. Because their time demands sometimes competed, the balance between them was adjusted according to the difficulty of each topic and the support required by each achievement stratum.

To organize the content, this study added a knowledge-graph layer above the conventional chapter sequence. The graph represented prerequisite relations, conceptual dependencies, and common errors, thereby converting a linear syllabus into a network that could guide learning paths

and support problem diagnosis. Resources were divided into principle-focused micro-lectures, datasets, baseline code, and hyperparameter-tuning examples and were delivered according to the knowledge graph and students' prior-achievement profiles. This arrangement allowed rapidly changing industrial applications to be updated without repeatedly reconstructing the stable conceptual core of the course.

Before class, the platform recommended resources on the basis of the knowledge graph and competency profiles and administered brief diagnostic tasks to assess baseline understanding. During class, students used a GPU cloud-training platform and virtual annotation environment to complete data collection, annotation, model training, and inference deployment, while the platform displayed loss curves and localized errors. When loss failed to decrease, students followed a diagnostic sequence: first checking the learning rate and then verifying annotation quality before changing the model. After class, students completed transfer tasks that applied the learned architecture to new problems. Successful transfer was treated as evidence of skill application rather than simple procedural reproduction.

The classroom division of labor distinguished routine, quantifiable tasks from tasks requiring professional judgment. The intelligent system supported diagnostic questions on convolutional neural network principles, routine training feedback, and personalized hyperparameter-tuning exercises. The instructor retained responsibility for analyzing difficult cases, supervising comprehensive projects, and providing career-oriented and professional-ethics guidance. By automating repetitive diagnostics and explanations, the design was intended to reduce routine workload and allow the instructor to concentrate on complex diagnosis and value-oriented guidance.

Assessment combined classification accuracy, mAP@0.5, first-attempt tuning success, dataset and annotation standards, complex problem solving, model transfer, classroom interaction, report quality, and certification. Two instructors independently scored performance using a common rubric. Platform records of learning paths, debugging, iterations, and interactions supported immediate error identification and tuning recommendations.

After each practical task, assessment evidence informed the next objectives, content emphasis, activities, and support. The components therefore operated concurrently, shortening the intended adjustment cycle from a semester to a task sequence. Implementation required integrated knowledge-graph, GPU-training, and annotation platforms, teachers able to interpret system output, and institutional rules for technology use, data practices, and student participation. Teacher competence required sustained development alongside platform investment.

2.3. Research Design and Participants

To evaluate the model in practice, this study used a one-semester quasi-experimental design in an authentic teaching setting. It examined whether students receiving the reconstructed model differed from those receiving conventional instruction in (1) core image-recognition skills, (2) algorithm transfer and complex problem-solving ability, and (3) assessment-related process outcomes, feedback, and engagement. Accordingly, H1 predicted higher core-skill performance in the experimental group; H2 predicted higher performance in algorithm transfer and complex problem solving; and H3 predicted stronger instructional interaction, formative-assessment outcomes, and vocational certification attainment. Because intact classes were retained, the design was not individually randomized. Both groups were taught by the same instructor and followed the same textbook and schedule.

Participants were 186 second-year students enrolled in Image Recognition Technology in an Artificial Intelligence Engineering Technology program at a vocational university in Henan Province. Students were classified into higher-, middle-, and lower-prior-achievement strata using

grades in Python Programming and Fundamentals of Machine Learning; the strata informed baseline description and differentiated instructional support. The experimental and control conditions each included 93 students drawn from four intact classes. The experimental group included 76 men and 17 women (mean age = 19.8 years, SD = 0.6), and the control group included 78 men and 15 women (mean age = 19.9 years, SD = 0.7). No statistically significant differences were detected in entrance-examination scores or prior-course grade-point averages ($p > 0.05$); this absence of significance was not treated as proof of baseline equivalence. The independent variable was the teaching model. Dependent variables comprised core skills (image-classification accuracy, object-detection mAP@0.5, and first-attempt model-tuning success), higher-order abilities (complex problem solving and model optimization and transfer), and process outcomes (classroom interaction, laboratory-report quality, and vocational certification). Instructor, course content, textbooks, contact hours, course progress, and laboratory configuration were held constant.

Data were obtained from three sources. First, two instructors independently assessed final practical work, first-attempt model success, and compliance with dataset-construction and annotation standards using a common rubric; the reported inter-rater reliability coefficient was 0.87. Second, the knowledge-graph system and GPU cloud-training environment recorded learning paths, debugging trajectories, iteration counts, and classroom interactions. Third, students completed the AI-Empowered Classroom Learning Experience Questionnaire, which measured perceived resource usefulness, interaction engagement, and learning satisfaction (Cronbach's alpha = 0.89). Items referring specifically to AI-supported resources were used descriptively for the experimental group rather than as between-group outcomes because the control group did not receive the same resources.

2.4. Experimental Procedure and Data Analysis

The experimental group followed the resource recommendation, diagnostic, cloud-training, annotation, and transfer sequence described above. Platform latency occasionally produced incomplete logs; only complete records entered log-based analyses. Control lessons used standardized presentations, board work, and common exercises. Students reproduced teacher demonstrations using standardized scripts, without individualized tuning support. Control assessment comprised a final theory examination (60%) and practical assessment (40%), without process-data collection or personalized feedback.

SPSS 26.0 was used for analysis. Categorical outcomes were compared with Pearson chi-square tests ($df = 1$), with Cramer's $V = \sqrt{(\chi^2/N)}$ for each 2×2 comparison. Following Levene's assessment of variance homogeneity, continuous outcomes were compared using independent-samples Student t tests ($df = 184$); Cohen's d used the pooled standard deviation. Significance was set at $\alpha = 0.05$, with d thresholds of 0.20, 0.50, and 0.80 indicating small, medium, and large differences. Multiple outcomes were interpreted as hypothesis-specific evidence rather than proof of a single causal mechanism.

3. Results and Discussion

3.1. Experimental Results

Table 1 presents a comparison of core image recognition skills between the experimental and control groups across multiple assessment indicators, providing a basis for interpreting observed group differences and examining learning outcomes associated with the reconstructed classroom teaching model.

Table 1. Comparison of Core Image Recognition Skills between Groups.

Measure	Experimental Group (n = 93)	Control Group (n = 93)	Statistical Value	p-Value	Effect Size
Image Classification Model Test Accuracy (%)	88.6 ± 6.4	76.3 ± 9.8	$t(184) = 10.13$	<0.001	Cohen's d = 1.49
mAP@0.5 (%)	84.2 ± 7.3	70.5 ± 11.2	$t(184) = 9.88$	<0.001	Cohen's d = 1.45
Model First-Pass Success Rate (%)	90.3% (84/93)	63.4% (59/93)	$\chi^2(1) = 18.91$	<0.001	Cramer's V = 0.32
Average Pass Rate for Core Competency Modules (%)	87.9 ± 5.8	69.4 ± 9.6	$t(184) = 15.91$	<0.001	Cohen's d = 2.33
Score for Dataset Creation and Annotation Standards (points)	91.3 ± 5.2	77.6 ± 8.9	$t(184) = 12.82$	<0.001	Cohen's d = 1.88

All core-skill outcomes favored the experimental group (Table 1), supporting H1; continuous-outcome effect sizes ranged from d = 1.45 to 2.33. Higher-order outcomes also favored reconstruction. Transfer-task completion was 87.1% (81/93) versus 64.5% (60/93), $\chi^2(1) = 12.93$, $p < 0.001$, Cramer's V = 0.26, and complex problem-solving scores were 90.7 ± 6.9 versus 75.4 ± 9.6, $t(184) = 12.48$, $p < 0.001$, $d = 1.83$, supporting H2. All 93 experimental students generated personalized learning paths. The experimental group received 2 national and 11 provincial competition awards, compared with 3 provincial awards in the control group; the small award counts were reported descriptively.

For process engagement and vocational competence, the Computer Vision Application Development Vocational Skills Certificate attainment rate was 97.8% (91/93) in the experimental group and 80.6% (75/93) in the control group, $\chi^2(1) = 14.34$, $p < 0.001$, Cramer's V = 0.28. The experimental group averaged 13.2 ± 3.4 classroom interactions per class period, compared with 5.6 ± 2.1 in the control group, $t(184) = 18.34$, $p < 0.001$, $d = 2.69$. Scores for code standardization and laboratory-report quality were 92.8 ± 5.1 and 80.3 ± 7.7, respectively, $t(184) = 13.05$, $p < 0.001$, $d = 1.91$. Within the experimental group, 82 of 93 students (88.2%) rated the micro-lectures on algorithmic principles and the cloud-based practical-training environment as very helpful or somewhat helpful. Because the control group did not receive the same resources, this questionnaire item was not used for a between-group hypothesis test. The inferential outcomes supported H3.

3.2. Discussion

The pattern across the three outcome groups is consistent with the coordinated-design rationale developed in Section 2. Personalized delivery may have focused practice, real-time feedback may have shortened error-correction cycles, and the division of labor between teachers and intelligent systems may have allowed teachers to concentrate on complex judgment. However, the intervention combined objectives, content, activities, assessment, and platform support as a package. The study therefore did not test mediation or identify the independent contribution of any single component. Alternative explanations, including intact-class allocation, classroom climate, and unmeasured baseline differences, cannot be excluded.

4. Conclusions, Limitations, and Future Directions

4.1. Key Research Findings

Results for all three hypotheses favored the reconstructed model over conventional instruction in core skills, higher-order abilities, and process outcomes. The findings are consistent with the proposition that objectives, content, activities, and assessment function as an interdependent system.

Because the components were implemented together, however, the study does not establish whether any single component would reproduce the observed differences.

The principal implication is that AI-enabled reform depends on alignment rather than tool accumulation. Objectives guide the organization of content and activities; process evidence supports assessment; and assessment results inform subsequent objectives, content emphasis, and instructional support. The present findings suggest that this feedback cycle is a plausible design mechanism, but causal claims about the mechanism require component-level or mediation studies.

Image Recognition Technology provided a suitable context for the model because it served both as course content and as a source of observable learning-process data. Embedding AI-supported resources and diagnostics within the technical workflow offered one route for connecting algorithmic principles with engineering implementation. The evidence supports this course-level application; it does not by itself establish that the same configuration will be effective in other disciplines.

Implementation is likely to depend on the coordinated development of platforms and resources, teachers' digital competence, and institutional arrangements. Teachers remain central because intelligent systems can generate data and recommendations but cannot independently convert them into context-sensitive instructional decisions. Investment in platforms should therefore be accompanied by sustained professional development and clear governance for instructional data.

4.2. Limitations of the Study

This study has several limitations. The sample comprised 186 students from four intact classes in one Artificial Intelligence Engineering Technology program at a single vocational university, limiting generalizability. The quasi-experimental design did not use individual randomization, and student-level analyses did not model class-level clustering; unmeasured baseline and classroom differences may therefore have contributed to the results. The analysis tested several outcomes without a familywise multiplicity adjustment, so the pattern and magnitude of effects should be considered alongside individual p values. The intervention lasted one semester and could not establish longer-term effects on occupational development or employment. Measurement was also limited: the questionnaire was not presented as an independently validated instrument, some constructs were represented by indirect indicators, and the number and distribution of incomplete platform logs were not documented. Finally, all components were implemented as a package, preventing estimation of the independent contribution of the platforms, differentiated objectives, activities, or feedback processes.

4.3. Future Research

Future research should use multicenter, cluster-aware designs, baseline adjustment, and prespecified primary outcomes. Validated measures of cognitive load, motivation, and learning experience and transparent missing-data reporting would strengthen inference. Factorial or dismantling studies could separate component contributions, while internship and employment follow-up could assess durability. Research should also test whether human-AI task allocation preserves teacher judgment and professional values as class sizes increase.

Objectives, content, activities, and assessment should be revised as a coordinated system. Because industrial technologies continue to change, model refinement should be treated as an ongoing process in which platform data are interpreted cautiously and translated into pedagogical decisions rather than collected as an end in themselves.

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