AI-Empowered Real-Time Classroom Assessment in Industry–Education Integration: Practical Explorations and Implications for Loose-Leaf Teaching Material Optimization

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Abstract: The evaluation of industry-education integration within classroom settings typically encounters challenges such as delays, pronounced subjectivity, and the inability to provide real-time feedback on pedagogical issues. This study utilises the Mechanical Drawing course from a specific vocational college as a case study, introducing a lightweight AI classroom analysis tool. It collects and analyses real-time evaluation data, including AI-generated metrics on classroom participation, the frequency of interactions between educators and students, and heat maps of knowledge mastery across four practical training classes focused on industry-education integration. Experience has demonstrated that AI tools can produce visual evaluation reports within five minutes of class completion, thereby objectively highlighting the weaknesses present in the classroom and assisting teachers in promptly adjusting their teaching strategies. This method markedly enhances evaluation efficiency in comparison to traditional approaches that rely on listening to and assessing classes. Furthermore, AI evaluation has revealed limitations in the recognition of deeper competencies, including the standardisation of skill operations and adherence to professional ethics. This study proposes a hybrid evaluation model comprising "AI real-time evaluation, key point assessment by enterprise mentors, and self-evaluation by students". Furthermore, it explores the viable pathway for utilising AI evaluation data as a foundation for the dynamic revision of loose-leaf textbooks. Practical verification indicates that this approach significantly improves the timeliness and accuracy of classroom assessments within the context of industry-education integration, all without imposing additional burdens on teachers. Consequently, it offers a replicable and streamlined solution for similar courses.

Keywords: AI Classroom Analysis Tools; Industry–Education Integration; Real-Time Assessment; Loose-Leaf Teaching Materials; Vocational Colleges

1. Introduction

The integration of industry and education represents a crucial focus for contemporary teaching reform in vocational colleges. A primary strategy for addressing the structural mismatch between talent supply and industrial demand is to emphasise the close alignment of teaching content with the job requirements of enterprises [1,2]. In the practical implementation of industry-education integration classrooms, a persistent two-skin dilemma exists within the classroom evaluation process. On one hand, enterprise mentors are constrained by their working hours, which hampers their ability to engage meaningfully in daily classroom assessments. On the other hand, while teachers within the school possess a strong understanding of pedagogical practices, they often lack practical experience in industry settings, rendering them unable to accurately comprehend the genuine job standards upheld by enterprises. This disconnect frequently results in the issue of inaccurate assessment [3,4]. Traditional evaluation methods frequently fail to keep pace with the teaching process. By the time the evaluation results are available, the optimal opportunity for instructional adjustment has often been lost [5]. This discrepancy is especially evident in the Mechanical Drawing course, which necessitates that students possess robust spatial imagination and standardised drawing skills. Each drawing exercise conducted in class requires prompt and precise feedback. If errors are not identified and rectified in a timely manner, further complications are likely to arise in subsequent learning.

Traditional classroom observation and evaluation methods expose three major deficiencies when confronted with the aforementioned challenges. First, there is a temporal lag: evaluation reports typically require several days to compile after the lesson, making it impossible to provide real-time feedback during the instructional process [5]. Second, subjectivity is pervasive, as assessment outcomes are heavily dependent on the personal experience of the observing teachers, and different evaluators may assign considerably divergent scores to the same lesson [6]. Third, coverage is limited: a single observation session tends to focus on only a few students, failing to capture the learning status of the entire class. These issues are particularly acute during the hands-on sessions of the Mechanical Drawing course—instructors find it difficult to simultaneously monitor the drafting process of all students, and it is only when reviewing assignments after class that numerous common errors are discovered, by which time students have already completed the entire drawing with those mistakes embedded.

In recent years, the rapid advancement of artificial intelligence has offered novel solutions for classroom evaluation. Lightweight AI tools, typified by the Chaoxing AI Teaching Assistant and classroom intelligent feedback systems, are capable of automatically capturing process-oriented data—including attendance records, response accuracy rates, interaction frequencies, and student engagement curves—during class sessions without imposing additional workload on instructors, and can generate visualized evaluation reports within five minutes after the lesson . The deployment of such tools renders it feasible for classroom assessment to shift from a post-hoc summary approach to real-time feedback [7].

This study takes the Mechanical Drawing course as a case example to investigate the application effects of AI-powered classroom analytics tools in real-time assessment within industry–education integrated classrooms, with a focus on two primary aspects. First, whether AI tools can effectively enhance the timeliness, objectivity, and comprehensiveness of classroom assessment. Second, how the process-oriented data generated by AI-based assessment can inform the dynamic optimization of loose-leaf teaching materials [8,9].Through practical exploration and outcome analysis, this study aims to offer an actionable lightweight evaluation framework that can be readily replicated in analogous course contexts.

2. Current Status and Logic of AI-Powered Classroom Analytics Tools in Empowering Assessment for Industry–Education Integration

With the rapid advancement of artificial intelligence technologies, classroom assessment is undergoing a profound transformation from experience-based judgment to data-driven approaches [6,7]. In the context of industry–education integration, the question of how to leverage AI tools to achieve immediacy, objectivity, and comprehensiveness in classroom assessment has emerged as a central concern in vocational education research.

2.1 Development Trajectory

The evolution of AI-powered classroom analytics tools can be broadly delineated into three phases. The first phase is the basic data collection stage. During this period, learning management systems (LMS) such as Moodle and Blackboard were predominantly employed to record structured data—including attendance, assignment submissions, and quiz scores—thereby enabling fundamental behavioral statistics. Nevertheless, assessment at this stage remained largely post-hoc, characterized by insufficient timeliness [10]. The second phase is the multimodal perception stage. With the maturation of computer vision and speech recognition technologies, classrooms began to integrate cameras and microphones to capture unstructured data, such as students' head-up rates, facial expressions, and verbal interactions. Typical applications included engagement curves and speaking time statistics. While this phase achieved real-time acquisition of classroom process data, the resulting reports still necessitated manual interpretation [10]. The third phase is the intelligent diagnosis and instant feedback stage. Breakthroughs in generative AI and deep learning have enabled AI tools to autonomously generate visualized evaluation reports and provide instructional improvement recommendations. Current mainstream classroom intelligent feedback systems are already capable of producing comprehensive reports—encompassing knowledge mastery heatmaps, interaction heatmaps, and lists of students requiring additional attention—within five minutes after the lesson concludes [6,7].

2.2 Typical Tools

Currently, three main categories of AI classroom analytics tools are commonly employed in vocational colleges. Table 1 presents a comparative overview of representative AI classroom analytics tools. In this study, we adopt the Chaoxing Learning Platform AI Teaching Assistant, which additionally covers the recording of the drafting process during practical training sessions.

Table 1. Comparison of Representative AI Classroom Analytics Tools

Tool Name	Core Functions	Data Collection Methods	Applicable Scenarios
Chaoxing Learning Platform AI Teaching Assistant	Attendance statistics, response analysis, engagement curve	Mobile app &in- classroom cameras	Theoretical courses; theory- practice integrated courses
Rain Classroom AI Analysis	Interaction frequency, identification of knowledge weak points	WeChat interface & PowerPoint plugin	Large- scale theoretical courses
Classroom Intelligent Feedback System	Multimodal integration, real- time report generation	In- classroom multisensors	Industry- education integration practical training courses

2.3 Application Modes

AI tools' involvement in classroom evaluation can be categorised into three application models based on their depth of integration. The first model is the auxiliary recording type, wherein AI is tasked solely with the collection of raw data, such as attendance rates and answer accuracy rates. In this model, evaluation reports are prepared manually by teachers. Although this approach presents a low technical barrier, the enhancement in evaluation efficiency remains constrained. The second category is the automatic diagnostic type. In this mode, AI generates visual reports autonomously, enabling teachers to reflect on their teaching practices based on these reports. This approach represents the prevailing application in the field, and this study utilises this mode. The third category is the intelligent intervention type. Artificial intelligence can detect learning difficulties in real time within the classroom and provide personalised prompts to either students or teachers. This model necessitates advanced technology and substantial computing power, and it remains in the exploratory phase within vocational education [11]. The fourth category is the collaborative evaluation type. The evaluation criteria must align with the enterprise's job requirements and facilitate the asynchronous participation of enterprise mentors. For example, the evaluation dimensions for the Mechanical Drawing course should be established in accordance with the enterprise's drawing standards. Enterprise mentors need not be physically present in the classroom; instead, they can log into the platform after class to access the AI-generated evaluation report and remotely assess key skill points. This approach offers a technical solution to the two-skin dilemma, in which enterprise mentors lack the time to evaluate, and on-campus teachers struggle to evaluate accurately.

3. Program Design for AI-Empowered Classroom Assessment in Industry–Education Integration

3.1 Course Selection

This study focuses on the Mechanical Drawing course within the Mechanical Design and Manufacturing programme at a specific vocational college. The selection of this course is informed by several considerations. Firstly, it serves as a core foundational course, encompassing a broad student demographic and yielding representative practical outcomes. Secondly, the course incorporates numerous practical drawing sessions, during which students frequently encounter common issues, such as incorrect views and non-standard line types. These problems are often challenging to identify and address promptly through traditional evaluation methods. Lastly, the course has been systematically managed via the Chaoxing Learning Pass platform, providing the essential conditions for the implementation of AI-based evaluation.

3.2 Tool Selection

Taking into account functional compatibility, operational convenience, and deployment cost, this study adopts the Chaoxing Learning Platform AI Teaching Assistant as the core tool [7]. This tool offers the following three functions: (1) attendance and classroom participation statistics; (2) real-time analysis of response accuracy; (3) automatic generation of classroom evaluation reports within five minutes after class, which include interaction heatmaps and annotations of knowledge weak points. The aforementioned functions adequately meet the data collection requirements for process-oriented assessment in industry–education integrated classrooms.

3.3 Implementation Procedure

The implementation procedure comprises three phases: pre-class, in-class, and post-class. In the pre-class phase, teachers upload loose-leaf materials (drawing task sheets and enterprise case drawings) and release a pre-class quiz via the Chaoxing platform. During in-class sessions, students check in via QR code with attendance automatically recorded by AI; throughout lectures and practical drafting, teachers intersperse questions, and students respond, compete, or vote through the platform while AI logs participation counts and accuracy rates for each interaction. After class, students complete a 5–10 minute self-assessment covering task completion, major difficulties, and use of learning resources, followed by peer assessment in which each student anonymously rates three randomly assigned drawings against enterprise standards—both self-assessment and peer-assessment data are automatically aggregated into the AI report as supplementary process-oriented dimensions. The system subsequently generates and transmits the visual evaluation report to the teacher. The teacher then downloads and records the essential data for reflective teaching practices. Concurrently, the teacher shares the report with the enterprise mentor. Attendance at the entire class is not required for enterprise mentors; they can complete the critical scoring within a mere 10 to 15 minutes, thereby addressing the practical challenge of limited time for daily evaluations. The results of this review are concurrently entered into the platform, contributing to the students' process evaluation.

4. Application Effects and Discussion of AI-Empowered Classroom Assessment in Industry–Education Integration

This research was practically applied in four training sessions of the Mechanical Drawing course, collecting process data from a total of 42 students. According to the comparison table of AI tool evaluation and traditional class observation and evaluation in Table 2, it can be seen that there are several improvements compared with the traditional method. First, the evaluation efficiency has been significantly enhanced. The AI tool automatically generates a report within 30 minutes after class, while traditional listening and evaluation classes take 2 to 3 days, significantly improving the evaluation efficiency. Second, the evaluation coverage is wide. The traditional approach can only focus on 5 to 8 students at a time, while the AI evaluation covers 42 students in the entire class and can generate a list of students to be followed. The third is the visualization of weak points in knowledge. According to the statistics of the in-class test accuracy rate, the AI heat map clearly shows that the accuracy rate of the "sectional view drawing method" is only 58%, and the accuracy rate of the "dimensioning" is only 62%. Based on this, the teacher strengthened the explanation in subsequent classes, and the relevant correct rates in the third class increased to 75% and 80% respectively. Fourth, promote immediate adjustments in teaching. The AI report of the first class showed that the participation rate of answering questions decreased from the 70th to the 80th minute. In the second class, the teacher inserted a group discussion session during this period, and the participation rate rebounded from 65% to 82%.

However, AI evaluation also has obvious limitations. First, it is impossible to evaluate the standardization of skill operations. For instance, when students draw, it is difficult for AI to automatically determine whether the line types are standardized and the steps are reasonable. The second issue is the inability to identify deep learning attitudes, such as plagiarizing answers and group discussions being merely formalistic. Thirdly, it relies on student terminal devices. The malfunction of individual students' mobile phones can affect the integrity of data collection. Fourth, the characteristics of integrating industry and education are not fully reflected. The AI evaluation in this practice is mainly based on general classroom behavior data (sign-in, answering questions, discussion), and has not yet been fully integrated with the enterprise job standards. For instance, in the Mechanical Drawing course, the core professional quality of "drawing standardization" cannot be automatically judged by AI and still relies on manual review by enterprise mentors. The fifth issue is the insufficient cultivation of students' self-awareness and reflection abilities. Relying solely on AI evaluation and review by enterprise mentors, students passively accept feedback and lack the opportunity for active reflection. After the introduction of student self-evaluation, students need to assess their own works against enterprise standards, which is conducive to cultivating their professional self-awareness ability. This confirms the two-skin predicament proposed in the introduction: relying solely on AI evaluation cannot fully address the evaluation pain points in the industry-education integration classroom, so a hybrid evaluation model involving AI, enterprise mentors, and students is necessary.

Table 2. Comparison Table of AI Tool Evaluation and Traditional Class Observation and Evaluation

Dimension of Comparison	Traditional lesson observation and evaluation	AI Tool Evaluation
Report generation time	2–3 days	5 minutes
Data coverage	Sampled 5–8 students	Entire class of 42 students
Subjective/Objective	Strong subjectivity	mainly objective data
Identification of knowledge weaknesses	Rely on teachers' experience to automatically label	based on test data
Extra burden on teachers	Notes need to be organized	Automatically generated, no burden required

5. Pathways for Optimizing Loose-Leaf Teaching Materials Driven by AI Evaluation Data

Through empirical practice, it has been demonstrated that AI evaluation can effectively identify deficiencies in knowledge and time-intensive skill tasks. This processed data offers an objective foundation for the dynamic revision of loose-leaf textbooks.

- Content supplementation based on weak points in knowledge. Knowledge points marked with an accuracy rate lower than 60% by the AI heat map indicate that there may be problems with the presentation of relevant content in the textbook. Take "Sectional View Drawing Method" as an example. The original loose-leaf textbook only provides textual descriptions and static legends. Based on AI feedback, three additional contents can be added to the loose-leaf textbook: The first is the decomposition diagram of the steps for drawing sectional views (3-4 steps); The second is a comparison table of typical error cases (for comparison of right and wrong); The third step is to insert a QR code link to the sectional view to draw a micro-lesson video.
- Difficulty breakdown based on task time consumption. The AI report shows that the average time students spent on completing the "Three-view Drawing of the combined Body" task exceeded the planned time by 30%. The analysis suggests that the difficulty range of the original task is too wide. Based on this, the original task is split into two sub-tasks: sub-task one is "Drawing Three Views of Simple Combinations", and sub-task two is "Drawing three views of complex combinations". Guiding questions are inserted between the sub-tasks.
- Form a closed-loop mechanism of "evaluation - feedback - revision". It is suggested to establish a regular revision mechanism: After each teaching unit is completed, teachers should summarize the AI evaluation data (accuracy rate of knowledge points, task time consumption, common errors) and make targeted revisions in accordance with the corresponding content of the loose-leaf textbook. The revised textbooks are put back into teaching, and the revision effect is evaluated and verified by AI, forming a closed loop of continuous optimization.
- A textbook revision mechanism driven by multi-source feedback. In addition to AI evaluation data and the review opinions of enterprise mentors, the common difficulties reflected in students' self-evaluations are also important inputs for the revision of loose-leaf textbooks. This forms a closed loop of textbook optimization driven by three sources: "AI data (objective performance) + enterprise feedback (job standards) + student self-assessment (learning pain points)", enabling loose-leaf textbooks to not only meet the demands of enterprises but also precisely address students' learning obstacles.

6. Conclusion

This study utilises the Mechanical Drawing course as a case study to investigate the efficacy of AI classroom analysis tools in the real-time evaluation of industry-education integration classrooms. Empirical evidence indicates that lightweight AI tools, such as Chaoxing Learning Pass, enable immediate evaluations within 30 minutes post-class, thereby significantly improving both the efficiency and comprehensiveness of assessments. Furthermore, the data generated by AI evaluations—such as identified knowledge deficiencies and time-consuming tasks—can provide an objective foundation for the dynamic optimisation of loose-leaf textbooks, thereby establishing a closed-loop mechanism of "evaluation - feedback - revision". In addressing the two-skin dilemma encountered in the classroom evaluation of industry-education integration, characterised by the lack of time for enterprise mentors to conduct evaluations and the inability of on-campus teachers to assess accurately, this study proposes a hybrid evaluation model. This model comprises "AI real-time evaluation, key point evaluation by enterprise mentors, and self-evaluation by students". Enterprise mentors can asynchronously review the key skill points within AI-generated reports, thereby compensating for the limitations of AI in assessing deeper competencies, such as professional ethics and operational standardisation, without imposing a significant additional time burden. However, this study acknowledges certain limitations. Specifically, AI tools fall short in evaluating deeper capabilities, such as the standardisation of skill operations, and their effectiveness is heavily dependent on students' terminal devices. Future research should further investigate the evaluation of multimodal data fusion and assess the scalability of this model across a broader range of professional courses.

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