Research on the Construction and Management Mechanism of a "Dual-track Parallel" Model for Human-machine Collaborative Teaching in Vocational Colleges

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Abstract

To address the challenges of teacher marginalization and diminished instructional control arising from the integration of generative artificial intelligence (AI) into higher vocational classrooms, this study constructs a teacher-led "dual-track parallel" human-machine collaborative teaching model. This model delineates the teacher's leadership authority across the four phases of "context-principle-intervention-reconstruction" while harnessing AI's enabling capabilities characterized by "personalization" and "immediacy". It pioneers a five-dimensional management mechanism encompassing "input-process-output-ethics-evaluation", achieving a balance of unified pedagogical depth and scalable differentiated instruction. Statistical results demonstrate promising outcomes: interactions involving higher-order thinking accounted for 65% of student engagements; the experimental group exhibited an average 44% improvement in core skill mastery, significantly outperforming the control group; and over 90% of students reported enhanced learning directionality and autonomy. This model effectively enables teachers to concentrate on diagnostic assessment and the stimulation of higher-order cognition, while simultaneously significantly enhancing student classroom participation, autonomous learning capabilities, and problem-solving skills. It offers a replicable solution for vocational education classroom reform in the era of artificial intelligence.

Keywords

Human-machine collaboration, Teaching model, Teacher-led approach, Five-dimensional management, Artificial intelligence

Introduction

Generative artificial intelligence technologies, exemplified by platforms such as DeepSeek and Doubao, are reshaping industries globally, thereby imposing new demands on the specifications for cultivating highly skilled professionals. As the educational sector is intricately intertwined with industrial economics, vocational education must proactively adapt to this transformation, leveraging AI technology as a pivotal force to empower pedagogy and elevate the quality of talent development [1]. However, a significant gap persists between technological sophistication and the practical effectiveness of its educational application.

Contemporary challenges and literature review

Current exploratory practices of integrating large language models into higher vocational classrooms reveal two notable tendencies. The first is role confusion leading to a lack of instructional depth. Certain approaches treat AI as an "omniscient tutor", allowing students unrestricted dialogue for knowledge acquisition [2]. This overlooks the irreplaceable role of teachers in structuring subject knowledge systematically, designing learning processes precisely, grasping classroom dynamics in real-time, and guiding students' effective and valued development - tasks beyond AI's current capacity. Such practices risk fostering fragmented and superficial knowledge acquisition among students, undermining the systematicity and depth of instruction.

The second is management lapses leading to deviation from learning objectives. Allowing students to be unrestricted AI use is problematic, particularly for vocational students who may have weaker theoretical foundations and lower tolerance for learning setbacks yet possess active minds and a propensity for practical engagement. Without effective guidance, students may exploit AI to obtain answers directly, fostering intellectual passivity and bypassing critical thinking and practice, ultimately precipitating academic integrity crises and failure to achieve teaching goals.

Existing research predominantly focuses on exploring the educational applications of AI technology or issuing generalized warnings about its potential risks. However, there remains a paucity of systematic, practice-tested solutions for establishing concrete operational models within authentic vocational education settings-models that feature clear responsibility delineation, robust operational stability, and the capacity to fully leverage the agency of both teachers and students.

Research objectives

This study aims to establish a human-machine collaborative classroom teaching model centered on teacher professional leadership, empowered by AI, and equipped with a comprehensive, meticulously controlled management mechanism. Its effectiveness is validated through implementation in the Database Management and Design course, thereby addressing the fundamental question of how teachers should teach, and students should learn in the AI era [3].

Model construction: The teacher-led “dual-track parallel” model

The core philosophy of this model is: technology as an enabler, not a substitute; teacher-led, not teacher-replaced. It views classroom teaching as a complex system driven jointly by the teacher’s expertise and AI computational power, achieving optimal effectiveness through clear role division and process design (Figure 1).

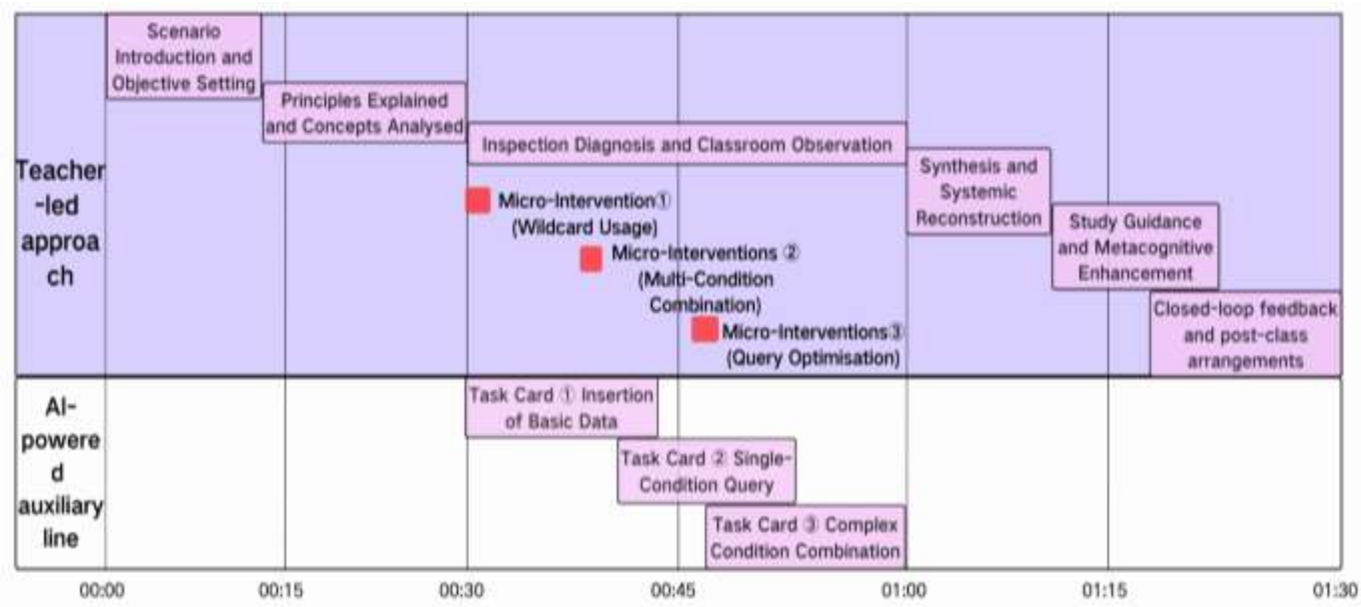

Figure 1. Sequential diagram of the teacher-led “dual-track parallel” classroom teaching model.

Theoretical core: The four irreplaceable core anchors of teachers

Anchors point one: designing and initiating learning contexts. Teachers serve as the “chief architects” of instructional activities. By integrating subject knowledge, logic, occupational requirements, and student cognitive patterns, they transform abstract concepts into structured “authentic tasks”. This approach fosters intrinsic motivation, addressing the fundamental question of “why we learn”.

Anchors point two: deepening and systematising core knowledge. Teachers serve as the “chief architects” of students’ knowledge frameworks. Whilst AI can furnish vast information and case studies, educators must employ concise explanations, blackboard demonstrations, probing questions, and critical thinking guidance to help students penetrate phenomena to grasp core principles and methodologies [4]. This weaves disparate knowledge points into cohesive networks, ensuring pedagogical depth and quality.

Anchors point three: diagnostic and interventional teaching process. Teachers serve as the "diagnosticians" of classroom dynamics. Through patrols, observation, and data analysis, they keenly identify individual learning difficulties and common challenges across the class, implementing pinpoint micro-interventions. This real-time decision-making and intervention based on learning conditions remains beyond AI's capabilities [5].

Anchors point four: the sublimation of learning outcomes and metacognitive enhancement.

Teachers serve as the "refining masters" and "guiding mentors" of student thinking. Following practice sessions, they organize demonstrations, discussions, and reflections, guiding pupils to systematically elevate AI-provided fragmented techniques and individual experiences into transferable strategies and methodologies. Simultaneously, through critiques of AI usage processes, they cultivate students" metacognitive abilities and competencies in efficient human-machine collaboration.

Operational framework: the dual-track classroom practice model and time allocation. This model is by no means a simplistic "teacher lectures half the time; students practice the other half" approach. Rather, it constitutes an organic whole within the 90-minute lesson period, where the "teacher-led thread" and the "AI-empowered thread" dynamically interweave and precisely coordinate (Figure 2).

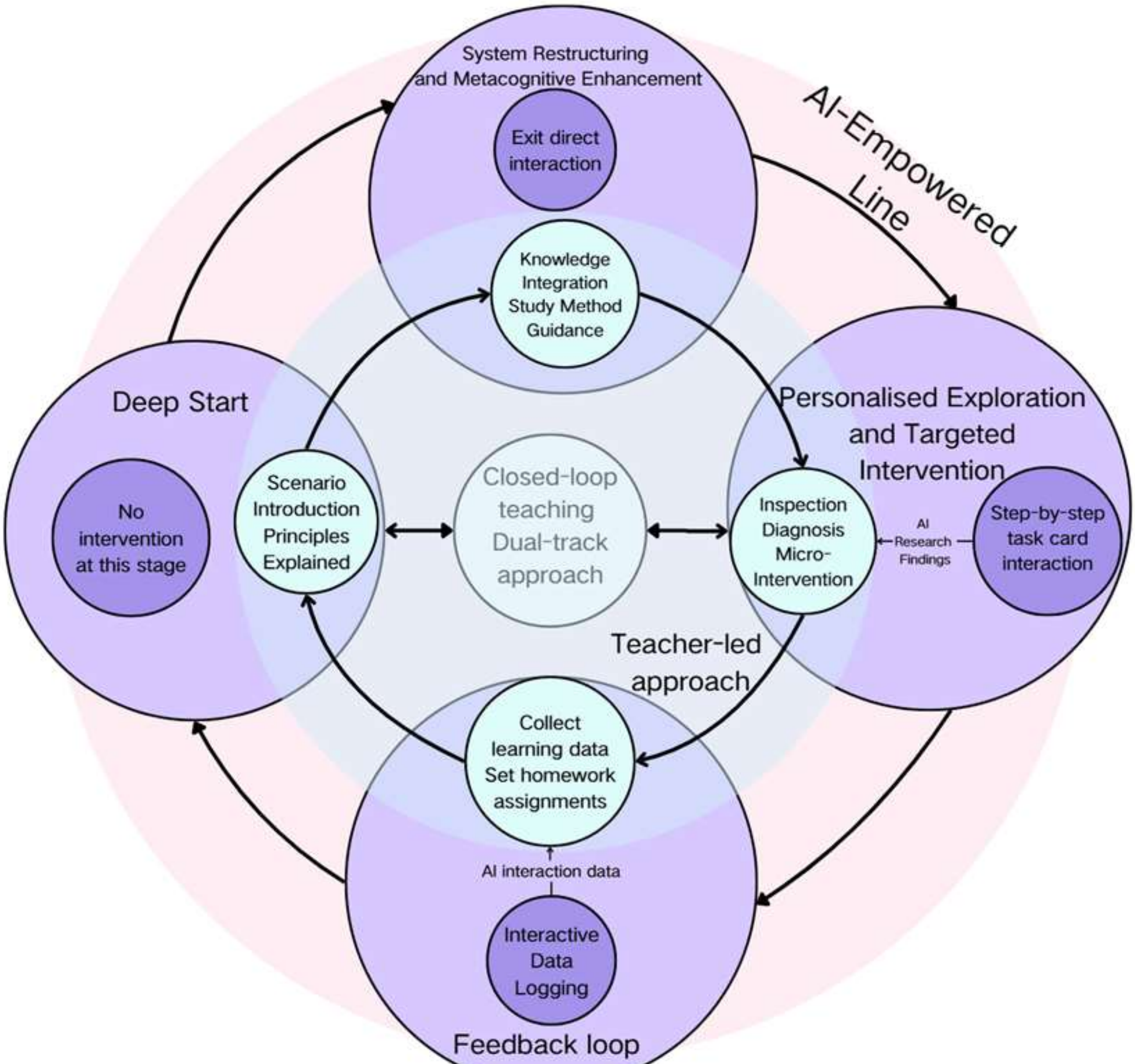

Figure 2. Dual-track classroom practice cycle model (source: self-developed).

Its core lies in achieving a unity of pedagogical depth and personalized breadth through clear role allocation and temporal structuring. The specific implementation process and time allocation are illustrated in Table 1 .

Table 1. Implementation process and timetable for dual-track classroom delivery.

Teaching phase	Time allocation	Teacher-led activities	AI empowerment series	Design intent
Deep start	0-25 minutes	Scenario introduction (5 minutes): Establish authentic professional contexts to clarify learning objectives and value propositions. Principles lecture (20 minutes): Systematically explain core knowledge concepts to construct cognitive frameworks.	None	To ensure that teachers possess the authority to interpret knowledge at its source, thereby establishing a systematic cognitive foundation.
Personalized exploration and targeted intervention	25-60 minutes	Observing lessons to identify common difficulties, implementing 5-10 minute “micro-intervention” explanations.	Students interact with AI using standardized question templates to complete step-by-step task cards.	Achieving personalized teaching at scale, with teachers transitioning from “question-answerers” to “diagnosticians”.
Systemic restructuring and metacognitive enhancement	60-85 minutes	Organizing sharing sessions and discussions, conduct systematic summarization of knowledge, and provide guidance on learning methodologies.	None	To elevate fragmented knowledge to a methodology, cultivating metacognitive and human-machine collaboration literacy.
Feedback loop	85-90 minutes	Setting homework assignments and collect learning journals.	None	Establishing a closed-loop teaching system to provide data support for lesson planning.

However, the table above merely outlines the model’s static structure. The vitality of this framework lies in the intrinsic logic of dynamic interconnection and coordination across its various stages, as elaborated below. Phase one (deep dive) anchor point function: This 25-minute phase serves as the critical component ensuring instructional depth. Teachers establish the lesson objective - mastering core SQL commands such as INSERT, WHERE, and LIKE to address practical business query requirements - within the context of “e-commerce customer data management”. Systematic analysis covers the customer’s table structure, INSERT syntax, and LIKE wildcard logic. AI intervention is deliberately excluded here to ensure all students develop a structured, unambiguous foundational understanding of core concepts under unified teacher guidance [6]. Omitting this stage risks students becoming mired in the fragmented, indiscriminate information provided by AI.

The art of precision in phase two (exploration and intervention): This represents the most challenging aspect of human-machine collaboration. As students embark on personalized exploration, the teacher's role undergoes a fundamental shift from "lecturer" to "diagnostician and strategist". Their work ceases to be universal knowledge dissemination, instead becoming a process of "detection-assessment-decision-making" based on continuous classroom monitoring and real-time data from shared log dashboards.

Students engage with AI through step-by-step task cards at this stage, such as: (1) Inserting 10 simulated customer records using INSERT statements (AI provides syntax prompts). (2) Querying all customers surnamed "Wang" (some students erroneously used LIKE "%Wang"). (3) Performing multi-condition queries to filter customers from "Haidian District" whose mobile numbers contain "888" (some students omitted the AND logical operator). During this process, the teacher's intervention procedure is as follows:

(1) Reconnaissance: Observing the student's operational status and facial expressions while swiftly reviewing their dialogue logs with the AI. (2) Individual problems are addressed through ongoing AI tutoring. Common issues, on the other hand, trigger immediate intervention decisions when the log dashboard indicates over 20% of students have marked "requires assistance" on the same task card. (3) Decision and execution: Teachers then implement "micro-interventions". These interventions are characterized by being "brief (2-8 minutes), concise (using precise language), and swift (addressing core issues directly)". Their essence is to "guide" rather than "interrupt". For instance, upon detecting widespread confusion regarding the LIKE wildcard, the teacher may swiftly project a demonstration comparing query results for LIKE "Wang%" (correct usage) versus LIKE "%Wang" (incorrect usage), while reinforcing the application of the AND logical operator. This efficiently resolves obstacles, showcasing the teacher's professional judgement and irreplaceable pedagogical insight.

The "sublimation" value of phase three (systematic reconstruction): Should teaching conclude at exploration and intervention, students would retain only fragmented experiential points. To counter this, the model mandates the final 25 minutes for teacher-led systematic reconstruction of learning outcomes, achieving cognitive elevation. Teachers guide students to share diverse solutions (For instance, queries such as WHERE phone LIKE "139%" AND address LIKE "% Haidian District%") into transferable strategic knowledge. Simultaneously, feedback is provided based on the student-AI interaction process, emphasizing the precise issuance of AI commands according to business logic. This elevates teaching beyond mere tool usage to cultivate metacognitive and collaborative literacy, teaching students how to learn and how to collaborate effectively with AI for learning.

The significance of closed-loop design: The endpoint of this model is not the conclusion of the lesson, but rather the commencement of a continuous improvement cycle. By collecting and analysing learning log data from the current session, teachers can accurately diagnose teaching effectiveness and identify areas for improvement, thereby optimising subsequent lesson designs. For instance, the next lesson may incorporate dedicated exercises on LIKE wildcards and supplement AI task cards with usage prompts for UNION ALL. Thus, teaching practice forms a data-driven closed loop of "design-implementation-diagnosis-optimization", fully embodying modern educational decision-making principles [7].

In summary, the "dual-track parallel" model constitutes a sophisticated system where AI is deeply embedded within the teaching process under the teacher's absolute stewardship. Through precise dynamic interventions and systematic refinement, it ultimately achieves dual enhancements in both teaching quality and efficiency.

Implementation safeguards: The "five-dimensional control" mechanism and lightweight technical solutions

However perfect a teaching model may be, without robust implementation safeguards, it remains a mere theory. To this end, we have established a five-dimensional control mechanism that spans the entire teaching process (as shown in Figure 3).

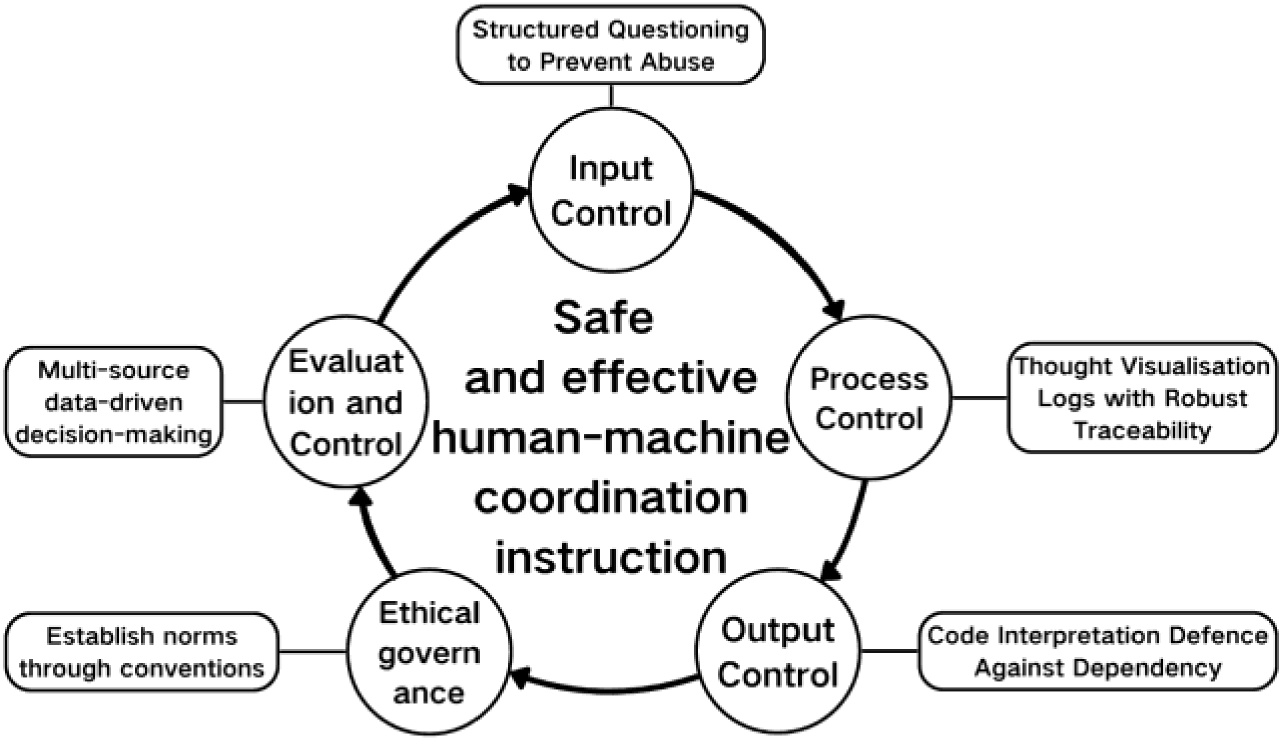

Figure 3. Closed-loop system diagram for full process control in human-machine collaborative teaching.

Detailed explanation of the "five-dimensional control" mechanis

(1) Input control: Structured questioning to prevent abuse. The mandatory question template serves as the primary gatekeeper. It functions not merely as a standard but as a metacognitive scaffold, compelling students to undertake self-diagnosis and reflection before posing queries. This process clarifies the nature of their confusion, thereby transforming aimless assistance-seeking into purposeful learning [8].

For core integrated challenge tasks (e.g., "Retrieve complete customer information for Haidian District's 139 prefix segment"), alongside submitting SQL code, an additional "code explanation defence" component is introduced: students must explain the code logic line by line to the instructor (e.g., "Why use phone LIKE "139%" rather than "%139%?"; "The necessity of the AND conjunction condition"), verifying genuine comprehension rather than plagiarising AI-generated answers.

(2) Process control: visualised thinking logs for robust traceability. We designed a minimalist fill-in-the-blank learning log and collected entries via Tencent Docs' online spreadsheet. Upon completing each task card, students must fill in the corresponding row of the spreadsheet with the task card ID, the most crucial AI prompt, the final SQL code, completion status, and a self-assessment star rating. This online spreadsheet instantly becomes the teacher's "monitoring dashboard". Teachers can oversee the entire class's progress from their computer, swiftly identify students who are lagging, and pinpoint common errors with precision [9].

(3) Output control: code interpretation defence to prevent dependencies. For core integrated challenge assignments, we have instituted a "code explanation and defence" component. Students must clearly articulate to their tutors or group peers why each section of their code was written as such and the underlying rationale behind it. This measure immediately discerns whether students have genuinely grasped the concepts or merely copied AI-generated answers, serving as the ultimate safeguard for ensuring knowledge internalisation.

(4) Ethical governance: establishing standards through conventions. At the outset of the course, the teacher shall jointly discuss and sign an AI Classroom Usage Agreement with the students. This agreement clearly defines the AI's role as an "intelligent practice companion", strictly prohibits the direct solicitation of answers, emphasizes the importance of academic integrity, and fosters a culture of responsible and productive technology use.

(5) Evaluation and control: multi-source data-driven decision-making. Shifting away from the sole reliance on end-of-term examinations, a comprehensive assessment

framework based on multi-source data has been established. This integrates process-based data (completeness and quality of learning journals), behavioral data (task completion efficiency), outcome-based data (code quality and presentation performance), and affective data (post-lesson satisfaction surveys). Teachers utilise this framework to conduct holistic evaluations of teaching effectiveness, thereby providing a scientific basis for personalised interventions and overall optimisation in subsequent teaching [10].

Technical implementation pathway

This solution deliberately avoids complex system development, adopting a "lightweight" technical approach to ensure its universality and ease of deployment: Core platform: A pre-established online shared spreadsheet (Tencent Docs) for task distribution, log collection, and learning progress monitoring. AI tools: Directly utilise any mainstream web-based large language model (e.g., DeepSeek, Doubao), with students advised to enable "anonymous dialogue" mode to focus on the task itself and protect privacy. Execution environment: database management systems (e.g., MySQL) in school computer labs or personal computers. Teaching practice case study: a complete teaching cycle based on the "customer information management system".

(1) Research topic selection and design approach

The unit "Data Operations and Complex Queries" from Database Management and Design has been selected, centring on a hypothetical "Customer Information Management System". This case study aligns closely with real-world enterprise applications, seamlessly integrating DDL (Data Definition Language), DML (Data Manipulation Language) and DQL (Data Query Language) knowledge, whilst allowing for flexible, tiered task difficulty design.

(2) Design of fourth-tier task cards

This table outlines four core SQL tasks, progressing from a basic data insertion (DML) to three increasingly complex query challenges (DQL). The DQL tasks involve filtering customer records by specific name, address, and telephone number patterns, culminating in a comprehensive identification challenge (as shown in Table 2).

Table 2. Summary table of core SQL tasks (DML/DQL).

Task number	Task name	Core requirements	SQL operation types
1	Data foundation	Insert 10 simulated customer records into the customers table, containing diverse names, telephone numbers, and addresses.	DML (Insert)
2	Basic query	Please retrieve all customers with the surname "Wang" for the Marketing Department to contact.	DQL (Query)
3	Complex filtering	Identify customers with an address in "Haidian District, Beijing" and a telephone number containing "888", then return their name and telephone number.	DQL (Query)
4	Comprehensive challenge - problem identification	Identify customers originating from Haidian District with telephone numbers within the 139 prefix and return their full details for customer service follow-up.	DQL (Query)

(3) A dynamic transcript of a 90-minute lesson

Deep dive (0-25 minutes): The teacher introduces the topic through a narrative about "Precision-Targeting Post-Sales Issues for Singles' Day". This is followed by a 20-minute detailed blackboard explanation of INSERT VALUES usage, combined with WHERE and LIKE clauses, demonstrating key examples such as LIKE "Wang%" and LIKE "%Haidian%".

Exploration and intervention (25-60 minutes): Students commence practical work. After approximately 15 minutes, while monitoring, the teacher observes a surge in "Teacher Assistance Required" flags on Task Cards 2 and 3 within the shared board, alongside numerous log entries indicating "Incorrect wildcard usage". He immediately halted the session for a 7-minute "micro-intervention": projecting comparative query results for LIKE "Haidian", LIKE "Haidian%", LIKE "%Haidian", and LIKE "%Haidian%" onto the screen, providing an intuitive explanation of their distinctions. This swiftly resolved the class's shared confusion.

Sublimation and Guidance (60-85 minutes): The teacher invited two students who had completed the challenge task using different approaches (subqueries and multiple AND conditions) to share their code. This prompted a class discussion on efficiency and readability. Finally, the teacher summarised the "Three-Step Method for Constructing Complex Queries": identify the target field, locate the source table, and build a chain of filtering conditions. The teacher also commended and provided learning guidance based on a case where a student successfully modified their code independently using the "error analysis" option.

Effect analysis, reflection, and challenges

Practical outcomes

Content analysis and statistical evaluation of students" submitted "AI Learning Logs" reveal: Interaction quality has markedly improved: guided by the model, interactions between students and AI saw higher-order thinking interactions - specifically "conceptual inspiration" and "error analysis" - accounting for 65.2% of total interactions. Direct requests for final answers constituted merely 12.3% (as shown in Figure 4).

Figure 4. Student-AI interaction intent classification statistics chart.

This data robustly demonstrates the success of input control and teacher guidance in effectively mitigating potential cognitive inertia associated with AI use. Precision in learning diagnosis: By compiling the "points of difficulty" recorded in logs, we generated a "word cloud of common skill challenges" (as shown in Figure 5). This visualisation clearly indicates that student assistance requests are most concentrated around core skill areas such as writing ON conditions for multi-table join queries. This provides teachers with highly precise data-driveninsights for implementing "micro-interventions", facilitating a shift in classroom decision-making from "experience-driven" to "data-driven" approaches).

Figure 5. SQL skill difficulty keyword cloud.

Skill Proficiency Comparison: Before and after instruction, we conducted specialised assessments on five core skill points. The average proficiency levels across the entire class were plotted on a radar chart (as shown in Figure 5). The post-test radar chart exhibited a significantly larger area compared to the pre-test, with the average skill proficiency increasing by 44%. This indicates that the students" overall skill structure has been optimised and strengthened.

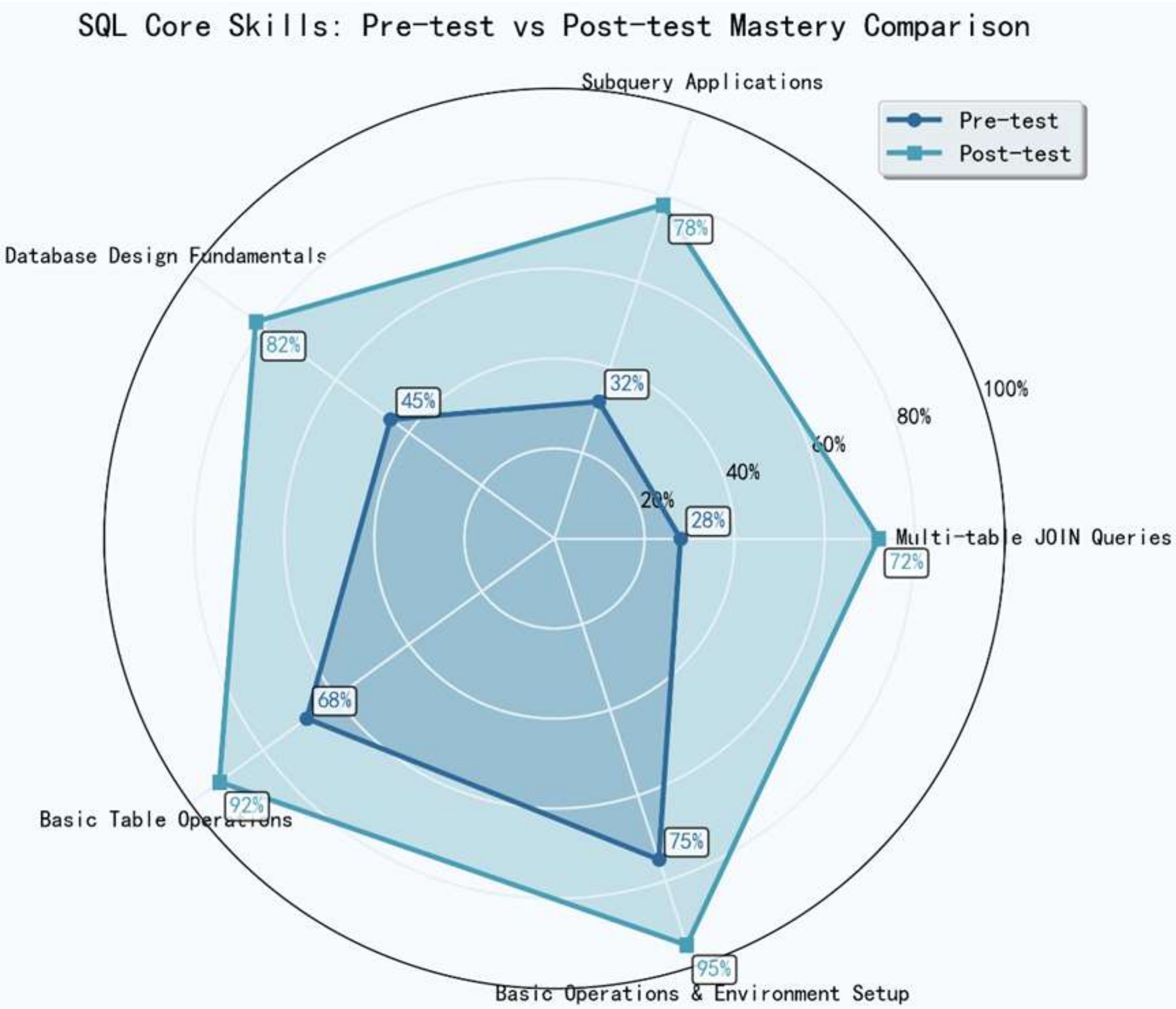

Figure 5. Radar chart comparing mastery levels before and after SQL core skills instruction.

This model also has multiple benefits:

(1) Teaching efficiency level

Teachers are freed from the predicament of repeatedly addressing similar foundational queries, enabling them to dedicate approximately 60% of their classroom time to diagnosing learning needs, implementing targeted interventions, and guiding higher-order thinking. This significantly enhances the precision and relevance of instruction.

(2) Student learning level

Enhanced engagement: The gamified "task card "progression model and instant feedback mechanism significantly increased students" classroom focus and hands-on participation rates.

Competency development: Mandatory structured questioning and log-keeping effectively trained students' metacognitive abilities and problem-decomposition skills. Mid-term project assessments revealed that experimental group students outperformed the control group in tackling non-standard complex data query tasks.

Confidence enhancement: Leveraging AI tools provided instant responses to any query, reducing learning frustration. This emboldened students to experiment more readily, fostering the development of learning confidence.

Reflections and challenges faced

The ultimate test of teaching competence: this model not only maintains but elevates the standards demanded of educators. It requires teachers to embody the capabilities of subject specialists, instructional designers, classroom diagnosticians, and human-machine collaboration coordinators. Systematic cultivation and enhancement of “teachers’ new foundational skills” is a prerequisite for the model’s implementation.

Precision in timing: The moment and duration of teacher intervention demand rigorous control. Premature or excessive intervention deprives students of opportunities for independent exploration; delayed intervention risks stalling learning progress. This requires teachers to hone their skills through continuous practice.

Stability of technical tools: Reliance on public AI services carries risks of network fluctuations, service interruptions, or inconsistent response quality. Teachers must therefore maintain alternative teaching plans.

Conclusion

This study successfully constructs and validate a human-machine collaborative teaching model for higher vocational education classrooms, centered on the “soul” of teachers’ professional wisdom, the “instrument” of AI technology, and the “vitality” of refined management. It compellingly demonstrates that in the intelligent era, the role of teachers will not diminish but will become increasingly vital due to their unique value in emotional care, intellectual stimulation, and systematic design. Future research will advance along two trajectories: firstly, exploring the adaptive modification and application of this model across diverse vocational disciplines such as electromechanical engineering and nursing; secondly, developing a comprehensive training curriculum and certification framework to cultivate human-machine collaborative teaching competencies among vocational educators. This systematic approach will deepen the integration of artificial intelligence within vocational education, laying a robust pedagogical foundation for cultivating future-ready, highly skilled professionals.

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Conflicts of Interest

The authors declare no conflict of interest.

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