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Article

Empowering Dual Teacher Classrooms in Vocational Education with Intelligent Agents: Challenges and Coping Strategies

Kaixuan Wang [1,2], Di Song [3,*], Xiaoli Zhao [4], Xiaoyang Liu [5,*] and Yong Wang [1]

[1] College of Artificial Intelligence, Xuzhou College of Industrial Technology, Xuzhou 221140, China
[2] School of Mathematics and Statistics, Jiangsu Normal University, Xuzhou 221112, China
[3] School of Mechatronic Engineering, Jiangsu Normal University, Xuzhou 221112, China
[4] School of Mechanical Engineering, Nanjing University of Science and Technology, Nanjing 210094, China
[5] School of Computer Science and Technology, Jiangsu Normal University, Xuzhou 221116, China
[*] Correspondence: disong@jsnu.edu.cn (D.S.); xyliu@jsnu.edu.cn (X.L.)

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Abstract: Discussions of intelligent agents in vocational education often hastily equate tool access with overall teaching efficiency, which is not supported by this study's interview data. The practical adoption of intelligent agents is explored in technical and vocational education and training dual-teacher classrooms from four stakeholders, including dual teachers, industry experts, students and administrators. The analysis differentiates streamlined routine tasks from new burdens arising from content validation, technical interpretation and risk assessment. Specifically, fifteen semi-structured interviews are conducted across secondary and higher vocational institutions. Firstly, all interviews are recorded and transcribed in Chinese. AI-assisted English translations of these transcripts form the primary coding corpus. The key citations are cross-referenced against the original Chinese transcripts. Besides, the constraints–mechanisms–enablers–outcomes (CMEO) framework is generated through the iterative thematic coding via NVivo 14. The results demonstrate that the respondents acknowledged limited efficiency gains only in repetitive tasks, such as material drafting and error screening. Nevertheless, intelligent agents created additional workloads, where practitioners have to verify technical accuracy and adapt artificial intelligence (AI) outputs to local training equipment and safety standards with special AI content interpretation for students. Within high-risk workshop training environments, AI outputs are only permissible when teachers and experts hold final decision-making power. Therefore, this study redefines AI teaching efficiency as bounded and multi-stakeholder professional judgment, rather than a neutral and universally applicable indicator. The constructed CMEO framework extends existing single-perspective AI education research and provides targeted institutional governance strategies for local vocational digital teaching reform.

Keywords: Artificial Intelligence; Dual-Teacher Classroom; Intelligent Agent; Teaching Efficiency; Vocational Education

1. Introduction

Artificial intelligence (AI) has gradually penetrated global daily teaching and educational practices, yet it offers limited substantive implications for educational reform [1]. In the field of technical and vocational education and training (TVET), the core dilemma is no longer whether AI can generate automated teaching content or simplify operational procedures [2]. Instead, the critical concern lies in whether AI-generated teaching solutions can adapt to vocational classrooms with unique constraints, including heterogeneous teaching equipment, standardized vocational assessment systems, and strict operation safety specifications [3]. Without effective adaptation to these vocational teaching requirements, the operational and productive efficiency of AI technologies is substantially discounted after implementation.

The inherent characteristic of vocational education is the integration of academic learning and industrial practice, serving as a bridge connecting campus teaching and workplace vocational needs. Vocational teachers have the core responsibility of transforming enterprise operational specifications, professional process guidelines, technical diagnosis procedures, and industrial quality standards into systematic, student-oriented teaching tasks, which are suitable for classroom teaching and practical training [4]. Besides, different vocational colleges differ significantly in teaching equipment configuration, practical training conditions, and industry cooperation resources. Meanwhile, core enterprise vocational data is often subject to confidentiality restrictions, and many practical training programs involve strict safety operation norms [5]. Therefore, any exploration of AI-enabled teaching empowerment in TVET must clearly clarify the practical changes brought by intelligent tools to dual-teacher classroom teaching, potential practical obstacles, and emerging operational and teaching risks arising during intelligent teaching [6].

Since the widespread application of generative AI and large language model technologies after 2022, intelligent agent tools have greatly lowered the threshold of auxiliary teaching work for vocational teachers [7]. These intelligent tools can efficiently generate teaching explanations, practical training guidance documents, classroom exercise materials, and targeted student feedback content within a short time, bringing unprecedented convenience to the daily lesson preparation and after-class management of vocational educators. Nevertheless, technical convenience alone cannot prove the practical value of intelligent agents in TVET dual-teacher classrooms [8]. In technical and practical teaching scenarios, mechanically generated AI teaching content tends to suffer professional deviation, incomplete technical logic, and disconnection from actual vocational training and industrial job requirements. In addition, the automated output of intelligent agents leads to unclear content attribution, and the plausible surface content is likely to cause teachers to over-rely on intelligent tools blindly, resulting in hidden risks in professional teaching and practical skill training [9].

Existing academic research has laid a foundational framework for AI-enabled vocational teaching, but there are still obvious research gaps targeted at dual-teacher classroom scenarios [10]. Prior studies have confirmed that AI-based formative feedback systems can optimize teacher-student interactions and shorten student skill learning cycles [11]. Besides, immersive intelligent teaching tools can effectively support vocational students' practical skill cultivation when aligned with systematic teaching theories [12]. In addition, learning analytics technology can assist teachers and administrators in teaching decision-making based on interpretable and usable teaching data [13]. However, current research fails to comprehensively unpack the application dilemmas of intelligent agents in TVET dual-teacher classrooms from three core stakeholder groups, including frontline dual teachers, industry engineering experts, and vocational students. Specifically, existing literature rarely explores dual teachers' collaborative workload conflicts and technology adaptation barriers when cooperating with intelligent agents [14]. It ignores several demands of engineering experts for industrial standard alignment and professional accuracy of intelligent teaching content, which also neglects actual learning experience, acceptance and learning confusion for vocational students in human-machine integrated dual-teacher classrooms. It remains unclear under what practical conditions intelligent agent tools can gain consistent recognition from teachers, experts and students as effective teaching assistants, and in what scenarios the repeated verification, content correction, and professional supplementation of AI output will offset the original efficiency advantages brought by these tools.

In this study, the empowerment effect of intelligent agents on dual-teacher classrooms is defined as practical work changes perceived by frontline vocational teachers and teaching administrators. Specifically, the value of intelligent agents lies in simplifying repetitive lesson preparation, reducing the workload of standardized student feedback and evaluation, and enabling dual teachers to devote more time and energy to core teaching links, such as professional knowledge interpretation, practical skill guidance, and student problem-solving tutoring. This definition focuses on micro-level teacher work efficiency and practical teaching optimization, and the interview-based qualitative data is adopted to effectively verify the shifts of dual-teacher teaching work driven by intelligent agents. It can establish the relationship between intelligent agent application and comprehensive teaching performance improvement.

To fill the above research gaps, the vocational dual-teacher classrooms is took as the research object in this study, and four core issues are explored based on the practical perceptions of vocational teachers and administrators, including practical constraints hindering the effective application of intelligent agents in dual-teacher classrooms, adaptive coping strategies adopted by frontline teachers, key enabling conditions for the effective implementation of intelligent teaching optimization, and practical teaching outcomes generated by intelligent agent empowerment. In addition, two core research questions are proposed to guide the whole research process: (RQ1) What practical challenges and contextual constraints do vocational teachers and administrators encounter when integrating intelligent agents into dual-teacher classroom teaching for efficiency improvement? (RQ2) What operating mechanisms and enabling conditions sustain steady and effective intelligent agent empowerment within TVET dual-teacher teaching practice?

Based on the above research positioning and core research questions, two clear research design principles are adopted in this study. First, this research does not regard teaching efficiency as a single fixed quantitative index measured by teaching output and working speed. Specifically, the superficial time-saving effect brought by intelligent agents is meaningless if the generated teaching content cannot meet vocational teaching standards and needs secondary comprehensive revision. Second, this study takes teachers' and administrators' practical teaching narratives and professional judgments as the core evidence of intelligent teaching process changes. This research perspective is crucial, as the existing AI education research often generalizes diverse research scenarios into a single efficiency evaluation. An intelligent agent tool may be easily accessible and widely used in vocational campuses with positive user feedback, but it may produce unstable and ineffective results in dual-teacher classrooms that demand high professional accuracy, practical safety, and industrial docking. Therefore, this study focuses on the real routine teaching practices of vocational dual teachers, systematically analyzes the practical changes, application value, and existing limitations of intelligent agent tools in teaching scenarios. It can explore the boundary conditions for realizing efficient and high-quality intelligent empowerment in vocational education dual-teacher classrooms.

2. Materials and Methods

The qualitative interpretivist research design is adopted based on one-on-one semi-structured interviews. It focuses on exploring how frontline dual teachers and vocational education administrators perceive and deploy intelligent agents in collaborative dual-teacher teaching scenarios [15]. Besides, the practical value points of intelligent agent empowerment are identified, as well as application bottlenecks, adaptive trade-offs and practical failure risks in real classroom contexts. The core of this research lies in exploring the situated professional judgments and actual workflow changes brought by intelligent agents in dual-teacher collaborative teaching. A qualitative interpretivist methodology is highly compatible with this research purpose, as it can capture rich contextual and subjective practical experiences [16].

2.1. Participants and Setting

A total of 15 participants are recruited via purposive sampling, covering diverse dimensions, including professional role, working seniority, institutional types and vocational majors. It can ensure the richness and differentiation of interview data, as shown in **Table 1**. All participants are selected from vocational colleges, including frontline dual teachers, teaching administrators, students and industry engineering experts from secondary vocational schools, higher vocational colleges and adult vocational colleges. The sampling followed the principle of information-rich case selection for qualitative research [17].

Table 1. The detailed information of the 15 participants.

ID	Role	Working/Learning Years	Institution Type	Job/Major	Core Interview Themes
T01	On-campus dual teacher	6 years	Higher vocational college	Internet of Things	Workload pressure, intelligent agent operational difficulty, collaborative teaching barriers
T02		8 years	Secondary vocational college	Computer application	
T03		11 years	Higher vocational college	Internet of Things	
T04		10 years	Secondary vocational college	Big Data	
T05		9 years	Higher vocational college	Computer Application	
E01	Industry engineering expert	15 years	Cooperative industrial enterprises	Network architect	Industrial standard mismatch, teaching content professional deviation, enterprise data access limits
E02		14 years		Programmer	
E03		18 years		Data analyst	

Table 1. *Cont.*

ID	Role	Working/Learning Years	Institution Type	Job/Major	Core Interview Themes
S01 S02 S03 S04	Vocational student	3 academic years 2 academic years 4 academic years 3 academic years	Higher vocational college Secondary vocational college Secondary vocational college Higher vocational college	Computer application Internet of things Big data Computer application	Learning experience, acceptance of human-AI collaborative classroom
A01 A02 A03	Teaching administrator	18 years 20 years 17 years	Higher vocational college Secondary vocational college Higher vocational college	Academic affairs management Teacher training Teaching reform management	Campus layout, institutional policy support, risk control of intelligent teaching

The sample size is not fixed in advance, and analytical saturation is judged gradually during the iterative thematic coding process. Four core thematic families are fully formed, covering constraints, coping mechanisms, enabling conditions and practical outcomes. The remaining three interviews only supplemented detailed practical cases, differentiated scenario feedback and contextual application conditions from students and industry experts, without generating new primary coding categories or requiring reconstruction of the overall codebook. Therefore, the sample size achieved analytical sufficiency for this research. Meanwhile, all participants have direct experience with intelligent agent tools in dual-teacher classrooms, so the interview data mainly reflects perceptions of users with practical experience rather than those of novice users.

Special attention is paid to the unique experience of vocational students for intelligent agent use, including their acceptance of AI tools, learning confusion and over-reliance risks on AI tools. It is formed as an independent analytical perspective for subsequent coding and result analysis. All student-specific interview narratives are sorted separately and categorized into exclusive student constraint codes (C6 and C7).

2.2. Data Collection

All interviews are conducted face-to-face in the campus conference room or through secure online video platforms, with each interview lasting 30 to 60 minutes. A unified semi-structured interview guide is used throughout the data collection process, covering targeted questions tailored to the four participant groups. It includes daily teaching collaboration between dual teachers and intelligent agents, the demand for industrial teaching standardization from engineering experts, real learning perceptions of students, as well as institutional support and management arrangements from administrators. The interview outline covers practical challenges, existing supportive measures, adaptive coping strategies, and expectations for tool optimization.

For purposive recruitment, clear stratified screening criteria are set covering teaching years, vocational majors and industry cooperation experience to guarantee sample diversity. To strengthen researcher reflexivity, a continuous reflexive journal is maintained throughout data collection and coding to document personal biases and timely cross-check all interpretations against raw transcripts. All Chinese interview records are anonymized prior to AI translation, and every key technical term and quotation is manually cross-verified between original transcripts and English drafts to eliminate translation discrepancies.

All interviews are conducted in Chinese to eliminate language barriers for vocational teachers and administrators, and recordings will only be collected after obtaining written informed consent from all participants. All original audio files are transcribed into full Chinese transcripts and fully anonymized by removing personal information, including name, institutional code, and student information before formal data analysis. Besides, AI-based translation is employed to generate unified English working transcripts for subsequent coding and manuscript writing, which are conducted through two rounds of manual cross-checks. The first round is conducted after preliminary translation to correct semantic deviations, and the second round is conducted when selecting representative citations for manuscript writing. For key professional terms related to dual teacher teaching and AI technology, conduct targeted retrospective checks on the Chinese original text to guarantee terminological accuracy.

The semi-structured interview outline covered concrete human-intelligent-agent interactive scenarios, including automatic generation of training teaching materials, browsing of real-time learning analytics dashboards, tripartite human-AI joint assessment, and AI-assisted operation for intelligent equipment fault diagnosis. All participants are required to elaborate on their actual operational workflows and intuitive perceptions during daily classroom interactions with intelligent agents.

2.3. Data Analysis

All English working transcripts are imported and encoded via NVivo 14 qualitative analysis software. In addition, the full coding process follows inductive logic, moving from the initial descriptive open coding to systematic correlation analysis between the four core thematic dimensions. It includes application constraints, coping mechanisms, enabling conditions and practical teaching outcomes [18].

In the initial open coding stage, the analysis focused on interview texts and extracted raw descriptive codes to identify the dual-teacher workflow shifts, frictions in intelligent agent deployment and teachers' practical workaround strategies. In the subsequent axial and selective coding stages, scattered initial codes were further categorized and integrated into the unified constraints-mechanisms-enablers-outcomes (CMEO) thematic framework matched with this research. Although English transcripts served as the main coding corpus, all ambiguous passages, l vocational technical terms and concept-sensitive text segments are traced back to original Chinese transcripts to prevent interpretive bias caused by translation gaps. **Table 2** displays detailed coding trails from original interview excerpts to overarching CMEO themes.

Table 2. Illustrative coding trail from quotation to CMEO theme.

Interview Excerpt (Participant ID & Role)	Keywords	Initial Code	CMEO Family	Interpretive Memo/Concept
"Genuine enterprise production data cannot be imported into intelligent agents due to corporate confidentiality agreements". (E02)	Enterprise data, confidentiality restrictions	C1 Lack of accessible authentic industrial data	Constraints	Confidential business data limits the alignment between intelligent agents and industrial vocational teaching standards.
"Intelligent agent teaching content is too rigid and cannot match our personalized practical learning needs". (S03)	Rigid content, personalized learning demands	C2 Poor personalized adaptation of AI teaching content	Constraints	One-size-fits-all intelligent teaching content fails to meet differentiated learning demands of vocational students majoring in Big Data and IoT.
"I spend extra time debugging intelligent agent functions, which increases my daily teaching workload instead of reducing it". (T04)	Extra debugging time, increased workload	C3 Extra workload caused by AI tool debugging	Constraints	Unstable intelligent agent functions bring additional work burden to frontline dual teachers.
"On-campus teachers focus on classroom teaching arrangement, while enterprise experts check AI content compliance with industrial standards". (T03)	Role division, collaborative work	M1 Dual-teacher and expert collaborative role allocation	Mechanisms	Clear role division realizes complementary advantages of human team and intelligent agents.
"The college has issued unified AI teaching management specifications to standardize intelligent agent application in dual-teacher classrooms". (A01)	Unified specification, institutional management	E1 Institutional policies and governance guardrails	Enablers	Top-down institutional management policies regulate orderly application of intelligent agents.

Specifically, the four-dimensional CMEO framework is not a pre-set theoretical model, which is obtained by layer from the original interview transcripts of all participants. It is supported by dual teachers, industry engineering experts, vocational students and administrators under its constraints, mechanisms, enablers and outcomes. Besides, the full logical coding trails recorded in **Table 2** verify the empirical foundation and rationality of the CMEO framework.

2.4. Trustworthiness and Ethics

To improve the trustworthiness of this qualitative research, multiple measures are adopted. A full standardized codebook is documented throughout coding procedures, with a detailed audit trail recording all iterative coding revisions and interpretive decisions. In addition, all interview text excerpts are marked with unique participant IDs and stored in encrypted secure files. During data collection and coding, continuous reflexive journaling is conducted to record subjective biases and real-time interpretive reflections. Besides, cross-case comparison across different participant roles and institutional types is implemented, and all negative cases inconsistent with dominant themes are retained rather than manually removed. Provisional codes are revised promptly when quotation content conflicted with code definitions or when certain categories became overly broad. Accordingly, the credibility strategy adopted in this research is moderate rather than maximal. It is considered as systematic documented interpretation of dual teachers' and administrators' practical working experiences, rather than fully triangulated objective findings, nor perfect semantic alignment between Chinese original transcripts and English quoted texts.

This limitation defines the research claim scope clearly, where interview data can fully reflect participants' real workflow shifts, perceived application risks and acceptable modes of intelligent agent deployment in dual-teacher classrooms.

To reduce researcher subjectivity, all coding procedures are recorded in a comprehensive standardized codebook. The author retained all contradictory negative interview cases and repeatedly cross-checked English working transcripts against original Chinese transcripts. Furthermore, all analytical conclusions are strictly bound by the original words of participants rather than subjective inferences.

In terms of research ethics, all participants signed informed consent forms prior to interviews. Participants reserved the right to terminate the interview at any time without justifying. In addition, all AI-assisted data processing procedures followed strict ethical norms. First, all confidential data and personal identifiers are fully desensitized to avoid privacy leakage. Second, all core professional terms and representative quotations are manually verified against original Chinese transcripts to prevent semantic distortion. Third, all participants are fully informed of the whole AI data processing flow before signing written informed consent.

This study is completed by an interdisciplinary research team with expertise in AI, vocational education, mechatronics, mechanical engineering, computer science, and applied mathematics. The authors independently conducted participant recruitment, semi-structured interviews, data transcription, iterative coding, and CMEO framework-based thematic analysis. Some researchers have practical teaching and research experience in vocational education, supporting an in-depth understanding of dual-teacher classroom scenarios. Notably, the team had no supervisory, instructional, or contractual relationships with participants, ensuring unbiased data collection. Potential interpretive bias originating from the researchers' disciplinary backgrounds was mitigated through multi-stakeholder triangulation and cross-author coding checks, with all research procedures fully documented to guarantee methodological transparency and result trustworthiness.

3. Results

As shown in **Table 3**, the findings are systematically structured under the unified CMEO analytical framework with four interrelated core dimensions, including constraints, mechanisms, enablers, and outcomes. It includes how multi-level practical barriers generate adaptive instructional redesign strategies, how institutional infrastructure and policy conditions shape the sustainability of these coping approaches, and why perceived teaching outcomes diverge drastically across dual-teacher classroom scenarios and participant groups for teachers, industry engineering experts, students, and administrators.

Table 3. The CMEO framework of themes, codes, definitions, and exemplar interview quotations.

Theme	Code	Definition	Exemplary Quotation
Constraints	C1 Data access & industrial confidentiality	Authentic enterprise production, processing and industrial operation data are unavailable for intelligent agent training and classroom teaching resource generation due to confidentiality agreements.	"We cannot import real industrial network operation and data processing cases into intelligent agents; all enterprise core data is under strict non-disclosure restrictions." (E02, Ex1)
Constraints	C2 Tripartite use-reason gap	Dual teachers, industry experts and students can operate intelligent agent tools or adopt AI-generated content, yet cannot independently interpret the underlying technical logic, parameter standards and industrial compliance requirements.	"Teachers only know basic agent operation, students copy AI operation steps, and experts have to spend extra time correcting all non-compliant technical logic from AI." (T03, Ex2)
Constraints	C3 Multidimensional cognitive overload	Unfiltered massive AI teaching suggestions, multi-stage practical task materials and scattered evaluation feedback raise sorting and revision burden for teachers, and information overload confuses students.	"The long practical training workflow of big data majors produces hundreds of AI auxiliary materials at once; sorting and modifying them takes more time than self-prepared courseware." (T04, Ex3)
Constraints	C4 Mismatch with on-site training conditions	Intelligent agent teaching schemes ignore heterogeneous campus training equipment, fixture resources and workshop scheduling rules, resulting in low on-site operability.	"AI designs perfect IoT training procedures, but our college lacks matching hardware, so nearly half of the content cannot be implemented in dual-teacher classes." (T01, Ex4)
Constraints	C5 AI hallucinations & training safety risks	Intelligent agents generate incorrect industrial standards and misleading operation guidance; simulated training fails to cultivate students' on-site safety judgment.	"Some AI data maintenance tutorials contain wrong parameter settings; if students follow them blindly, hidden operational risks will appear in post-internship." (S03, Ex5)

Table 3. *Cont.*

Theme	Code	Definition	Exemplary Quotation
Constraints	C6 Over-reliance on automatic AI diagnosis	Students overly depend on intelligent agent fault detection results and abandon complete systematic troubleshooting training logic.	"When equipment errors appear, I directly input fault codes to get AI answers and skip complete step-by-step checks." (S04, Ex6)
Constraints	C7 Differentiated learning pace mismatch	Unified intelligent agent learning progress cannot adapt to students' uneven foundation, leading to either repetitive simple tasks or incomprehensible advanced technical content.	"The agent pushes identical learning tasks for all students; weak learners cannot follow while advanced students feel the exercises repetitive." (S03, Ex7)
Mechanisms	M1 Explanation-first dual-teacher assessment rubrics	Dual teachers and industry experts co-design evaluation standards, requiring technical reasoning and industrial standard interpretation before scoring, to validate the rationality of intelligent agent outputs.	"We jointly revised the assessment rubric: student scores depend first on technical explanation, AI-generated operation results only serve as auxiliary reference." (T05, Ex8)
Mechanisms	M2 Teacher-expert-AI tripartite co-assessment	Intelligent agents conduct standardized data screening and preliminary scoring; dual teachers and industry engineering experts conduct joint final review and qualitative evaluation.	"AI automatically marks objective operational data, while school teachers and enterprise experts jointly evaluate students' technical thinking and safety awareness." (E01, Ex9)
Mechanisms	M3 Multilayer evidence-chain diagnostic training	Intelligent agents guide students to collect multi-dimensional evidence including sensor data, operation trends and test records, forming complete reasoning chains rather than single AI-derived conclusions.	"The intelligent agent training module forces students to upload data stream records and test results before submitting fault diagnosis conclusions." (T03, Ex10)
Mechanisms	M4 Interpretable learning analytics for targeted tutoring	Intelligent agent learning dashboards visualize students' learning bottlenecks for dual teachers, shifting repetitive knowledge explanation to targeted personalized coaching.	"I check the agent's learning analytics dashboard before class to locate students' common confusion points and focus tutoring on these links." (T04, Ex11)
Enablers	E1 Tiered dual-teacher training & secure data sandbox	Hierarchical digital literacy training for dual teachers and isolated data sandbox platforms supports safe, compliant intelligent agent trial use without real enterprise data leakage.	"We launched three-level training for dual teachers and built a data sandbox to simulate industrial data without involving confidential enterprise information." (A01, Ex12)
Enablers	E2 Campus private model deployment & edge inference	Local on-campus intelligent agent model deployment and edge computing reduce network latency and realize full controllability of student training data circulation.	"All intelligent agent tools run on the college's private server via edge inference; no student training data is uploaded to external public platforms." (A02, Ex13)
Enablers	E3 Institutional governance guardrails for human-machine collaboration	Clear school policy and technical restrictions prohibit fully AI-autonomous scoring, sensitive student data uploading and unapproved industrial content generation.	"The college formulated clear rules: all AI teaching materials must pass joint teacher-expert review, and AI cannot independently determine final course scores." (A02, Ex14)
Enablers	E4 Outcome-oriented collaborative accountability mechanism	Abnormal AI teaching cases are used as reform feedback to optimize dual-teacher curriculum design, rather than merely punishing individual teachers.	"When unqualified AI teaching content appears, the teaching team holds a joint seminar to adjust training tasks instead of blaming individual dual teachers." (A01, Ex15)
Enablers	E5 Industry-course-certification tri-aligned resource system	Desensitized enterprise resource libraries, dual-teacher course projects and vocational skill certification standards are fully aligned to standardize intelligent agent training content.	"We connect enterprise real cases, daily dual-teacher training tasks and national skill certification standards, and add data desensitization processing for all industrial resources." (A03, Ex16)
Outcomes	O1 Workload reallocation for dual teachers	Routine material generation and preliminary sorting work are undertaken by intelligent agents; dual teachers shift energy to high-value links including technical tutoring, industrial standard interpretation and student error correction.	"The agent completes courseware drafting and automatic exercise sorting; I spend more time guiding students' practical operation and communicating with enterprise experts." (T05, Ex17)
Outcomes	O2 Value-driven intelligent teaching evaluation	Administrators shift evaluation focus from the quantity of intelligent agent tools adopted to tangible improvements in students' vocational competency and industrial employability.	"We no longer count how many AI tools teachers use; we assess whether intelligent agents help students master post-matching industrial operation abilities." (A01, Ex18)

3.1. Constraints: Multi-Stakeholder Systemic, Professional and Cognitive Barriers

All four groups of participants identified a set of intertwined constraints hindering the sustainable deployment of intelligent agents in TVET dual-teacher classrooms. Specifically, strict enterprise data confidentiality clauses limit access to authentic production parameters and processing cases, reducing the authenticity and industrial alignment of AI-generated teaching resources (C1).

The tripartite reasoning gap across dual teachers, students and experts (C2) manifests in the fact that dual teacher teachers can only operate intelligent agents mechanically, which cannot adjust algorithm parameters according to vocational training needs. In addition, industry engineering experts point out that the AI outputs lack rigorous industrial logic, and vocational students can replicate the AI operational steps but cannot explain the technical principles and judgment criteria.

Frontline dual teachers have also reported severe multidimensional cognitive overload (C3). Intelligent agents generate massive scattered teaching materials, evaluation suggestions and training schemes for long-cycle IoT, big data and computing practical tasks, which increases sorting, screening and revision burden.

Feasibility mismatches between AI-generated content and physical workshop environments constitute another prominent constraint (C4). Intelligent agent-generated training schemes ignore campus equipment specifications, workshop fixture layouts and limited tool stocks, rendering auto-generated teaching materials unworkable for on-site dual-teacher instruction.

For vocational majors with high technical standard requirements, participants raised concerns over AI hallucinations and training safety risks (C5). Misleading technical reasoning generated by intelligent agents may form bad operational habits for students, and simulated training content cannot effectively develop students' real-world risk judgment capabilities. Such AI hallucination risks also bring unique ethical hazards, which may mislead students to form non-compliant vocational operation perceptions in long-term training.

Two additional participant-specific barriers are extracted from interview data. Firstly, over-reliance on automated AI fault diagnosis erodes students' systematic troubleshooting thinking (C6). In addition, uniform learning progress generated by intelligent agents fails to match students' varied academic foundations and developmental paces, triggering learning confusion and burnout (C7). The above two constraints C6 and C7 specifically reflect the student-specific challenges arising from intelligent agent adoption in daily vocational learning, which are unsuitable for the perspectives of teachers and industry experts.

Collectively, these multi-stakeholder constraints explain why intelligent agents frequently increase rather than reduce teaching and learning workloads. Dual teachers and industry experts must repeatedly filter, revise and calibrate AI outputs before they can be applied in official dual-teacher classrooms. Meanwhile, students also spend extra time to distinguish reliable AI guidance from misleading technical statements.

3.2. Mechanisms: Stakeholder Co-Designed Pedagogical and Collaborative Coping Strategies

Confronted with the above multi-dimensional constraints, dual teachers and industry engineering experts did not fully delegate teaching and evaluation work to intelligent agents. Instead, they formed a set of human-machine collaborative instructional mechanisms through joint curriculum redesign. First, explanation-oriented joint assessment rubrics (M1) jointly formulated by dual teachers and industry experts mandate students elaborate industrial technical principles and parameter bases before obtaining assessment scores, which fundamentally restrains blind dependence on raw AI outputs.

For high-stakes vocational skill evaluation, the tripartite co-assessment mechanism (M2) divides labor clearly. Specifically, intelligent agents conduct standardized data aggregation and objective preliminary scoring, while campus dual teachers and enterprise experts jointly complete subjective evaluations of operational norms, security awareness, and technical thinking. It preserves absolute human final judgment.

In equipment fault diagnosis and data analysis training and testing, the evidence-chain diagnosis training mechanism (M3) embedded in intelligent agents forces students to collect multi-source operational evidence, eliminating the disadvantage of directly replicating AI-generated diagnostic conclusions.

Leveraging a visual learning analytics dashboard, dual teachers implement interpretable data-driven coaching (M4). Intelligent agents automatically aggregate error records and learning bottlenecks, enabling teachers to eliminate repetitive generic explanations and provide personalized guidance for different students.

Each human–AI collaborative mechanism corresponds to specific classroom operational modes of intelligent agents, which record the real-time interaction behaviors of dual teachers, industry engineering experts and students during AI-assisted dual-teacher instruction.

3.3. Enablers: Institutional, Infrastructure and Industrial Supporting Conditions

Sustained human–AI collaboration relies on institutional and technical enablers identified in participant interviews. Tiered teacher training and secure local data construct low-risk environments for educators to develop intelligent teaching resources (E1). On-campus local model deployment and edge computing cut latency and confine internal training data locally to prevent industrial information leakage (E2).

Formal institutional AI governance restricts high-risk automated workflows, and prohibits unsupervised comprehensive AI assessments, which prohibits unregulated uploading of student or proprietary factory data (E3). The outcome-based shared accountability system redefines problematic AI teaching practices as opportunities for digital curriculum improvement, rather than treating them as punitive burdens on teachers (E4). In addition, the aligned school-industry certification resource library provides desensitized vocational datasets for proxy use, solving the common content mismatch constraint in dual-teacher classrooms (E5).

Overall, these five institutional safeguards offset the extra workload incurred by AI output validation and technical adjustments, forming a stable long-term supportive framework for human-AI collaborative vocational training.

3.4. Multi-Stakeholder Perceived Shifts in Workload, Learning Burden and Time Allocation

Respondents from all four stakeholder groups refuse to view intelligent agents merely as a time-saving tool. Rather than reducing overall workloads, AI redistributes labor burdens unevenly among dual teachers, industry experts, administrators, and students. Although algorithms have accelerated mechanical tasks including course drafting and student record sorting, they have also introduced new instructional and learning burdens. Frontline practitioners must validate algorithm outputs, match general AI materials with local training hardware, and assess the reliability of the generated technical content. In addition, students also need extra work to filter out misleading AI illusions and inaccurate operational guidance. Ultimately, intelligent agents will restructure cross-group labor burden rather than saving net time.

The transformation of this AI workflow constitutes a continuous iterative adaptation cycle, rather than a final digital teaching model. While daily tasks can be completed faster, previously hidden collaborative responsibilities will become ongoing daily work. Specifically, teachers explain the rules for using AI, industry experts calibrate algorithm outputs according to industry standards, and educators guide students in detecting algorithm defects. This labor transfer redistributes energy to material creation, technical auditing, classroom interpretation, and one-on-one tutoring.

The perceived efficiency of AI is closely related to the dynamics of collaborative stakeholders. Although intelligent agents reduce courseware development time for teachers, unpolished algorithm outputs can generate cascading additional work, including student clarification, industrial content revision, and repetitive classroom corrections, thereby eroding the initial time-saving benefits. Administrators hold a consistent complementary perspective, where they pay less attention to whether a single task saves time, and focus more on whether intelligent agent-assisted dual-teacher teaching can gain consistent recognition from students, enterprise partners and institutional teaching quality supervision teams. Within this sample dataset, institutional and industrial legitimacy exerts an equally strong influence on perceived efficiency as time-saving speed.

3.5. Descriptive Indicators for Analytic Transparency

For analytical transparency without statistical inference significance, some descriptive statistical indicators are employed from the qualitative interview samples and coding outputs, as shown in **Table 4**. These indicators illustrate the scale and structural distribution of the full sample, the balance of interview data from four stakeholder groups, and the comprehensive composition of the CMEO codebook formed after iterative coding.

Table 4. Descriptive indicators of the qualitative interview sample and CMEO coding outputs.

Indicator	Value	Notes
Total semi-structured interviews	15	Four stakeholder groups: dual teachers, industry engineering experts, vocational students, teaching administrators.
Participant role distribution	Dual Teachers: 5 Industry Experts: 3 Students: 4 Administrators: 3	Purposive sampling covering all core stakeholders involved in dual-teacher classrooms
Institution types involved	Higher vocational college: 8 Secondary vocational college: 7	IoT, computer application, big data majors covered in both school types
Range of working/learning tenure	Teachers & Experts: 6–18 years Students: 2–4 academic years Administrators: 17–20 years	Self-reported duration of vocational teaching, industrial practice or school learning

Table 4. *Cont.*

Indicator	Value	Notes
Total CMEO codebook size	18 independent codes	Fully listed in **Table 3** under four core thematic families
Code distribution across CMEO categories	Constraints: 7 Mechanisms: 4 Enablers: 5 Outcomes: 2	Code quantity reflects analytical coverage rather than practical influence magnitude

The indicators demonstrate that the CMEO analytical framework is built on a diversified, bounded sample covering dual teachers, industry engineering experts, vocational students and teaching administrators across three types of vocational institutions. Meanwhile, the four overarching CMEO thematic families and 18 secondary codes remained unchanged in the later coding stage, and the final three supplementary interviews only provided detailed illustrative cases without generating new primary themes or reconstructing the overall codebook. Specifically, the fixed 18 CMEO codes reflect stable stakeholder perceptions of intelligent agent application, which validates the practical value of the inductive CMEO framework rather than a hollow classification tool.

4. Discussion

The interview evidence contradicts the prevalent assumption that intelligent agents produce universal efficiency within dual-teacher vocational training. While intelligent agents have accelerated repetitive drafting and categorization, practitioners bear supplementary workloads in content validation, technical revisions, and stakeholder communication. For careers in computing and IoT-related vocational tracks, universal AI-generated outputs are impractical if it is incompatible with campus equipment, evaluation standards, and industrial safety standards [19]. Therefore, this study defines AI efficiency as a multi-stakeholder professional judgment constrained by context, rather than an objective productivity indicator. All results rely on subjective practitioner accounts across departments, and it cannot validate long-term institutional or student learning outcomes.

This finding directly challenges the prevailing linear assumption in prior AI education literature that tool availability automatically generates teaching efficiency. Most existing quantitative and small-scale qualitative studies rely solely on teacher self-reported time savings and overlook offsetting verification and interpretive workloads, a gap this study addresses through multi-stakeholder cross-verified interview data.

Besides, the critical comparison is implemented with the classic technology acceptance model, which focuses on the perceived usefulness and ease of use for individual teachers. However, it ignores the multi-party labor redistribution and workshop environment constraints, which are unique to TVET. The results supplement the background boundary conditions that limit the predictive ability of general AI in the context of vocational training.

Unlike traditional topic coding frameworks, the CMEO framework is constructed as a systematic theoretical lens for analyzing the collaborative logic between humans and AI. It reveals how core constraints reshape collaborative teaching between humans and AI, rather than treating these obstacles as secondary background variables. The tripartite mismatch between teachers, industry experts, and students has led to interpretation-focused assessments and joint tripartite assessments. The inconsistency between the output of general AI and the on-site seminar environment further requires evidence-based diagnostic training and manual content adjustment. Institutional safeguards have reduced verification costs and maintained these mitigation measures, including tiered teacher training, isolated data sandboxes, and localized algorithm deployment [20]. The previous studies have divided constraint analysis, coping strategies, and institutional support into isolated discussions. In addition, the closed-loop causal chain of CMEO fills the fragmented gap by theorizing their interactions, rather than simply grouping empirical observations.

The institutional framework reduces the adoption risk of AI through standardized functional restrictions, compliant data management, and manual supervision. If there were no such rules, repeated revisions would eliminate the efficiency improvement of AI. The unique vocational and technical education and training security and hardware limitations further exacerbate these conflicts. Existing vocational AI scholarship mostly discusses supportive mechanisms or risk barriers in isolation. Few studies systematically link structural constraints, adaptive coping behaviors and institutional safeguards into an interconnected analytical system. The closed-loop CMEO logic proposed here fills this fragmentation gap by revealing how contextual limits, practitioner responses and institutional support jointly shape final human-AI teaching outcomes [21]. It also extends teacher collaboration theories, which predominantly focus on intra-school teacher cooperation and neglect the tripartite school-enterprise-student collaborative structure embedded in TVET dual-teacher models.

The respondents only recognized marginal efficiency gains in repetitive tasks, and shifted the focus of educators to high-value coaching and risk auditing. Besides, no participants reported an overall increase in productivity. On the contrary, AI brings new cross-role burdens to content calibration and technical interpretation, redistributing labor rather than reducing overall workload [22]. Nearly all existing TVET AI literature centers on teachers as the sole research subject, ignoring workload shifts borne by industry mentors and vocational learners. By integrating student and industry expert narratives, this study expands the stakeholder scope of labor redistribution analysis and uncovers hidden cross-group burdens invisible in single-perspective research designs. This multi-stakeholder labor redistribution extends the technology integration framework, which rarely distinguishes the workload allocation of teachers, enterprise experts, and students in security-sensitive practice training.

The CMEO model identifies imbalanced AI performance in different teaching tasks. It has handled standardization work well, but has failed in relying on experience for fault diagnosis and safety judgment. Most existing research has overlooked audit risks and the specific costs of vocational and technical education and training. The background comparison does not claim widespread novelty, but rather elucidates the specific theoretical value of the framework for vocational and technical education and training safety training scenarios [23]. Unlike prior fragmented research, this proposed CMEO framework integrates constraints, pedagogical responses, institutional enablers and stakeholder outcomes into a complete closed-loop logical chain. It further supplements multi-stakeholder perspectives including students and industry experts absent in most existing vocational AI literature, which extends the current analytical paradigm of human-AI collaboration and forms the core theoretical contribution of this qualitative study [24].

Student distrust of AI-generated feedback brings extra interpretive workloads on dual teachers, making interpretability a prerequisite for practical collaboration rather than a purely moral standard. Unlike low-risk material editing tasks, high-risk seminar training restricts unverified AI results. The one-size-fits-all institutional AI rules ignore differentiated task risks and cannot support targeted classroom practices. Existing educational AI ethics literature frames algorithm transparency as a distant institutional standard, yet this study empirically demonstrates that explainability becomes an immediate daily operational burden in safety-critical vocational training, advancing context-bound ethical discussions tailored to TVET settings.

There are two key flaws in the current promotion of AI in institutions. Schools prioritize tool acquisition over supporting governance and risk mitigation, shifting all risks onto teachers. The general digital policy also fails to align with the practical demands of dual teacher classrooms [25]. Stable, effective intelligent teaching cases tie concrete supervision rules to specific training tasks, instead of relying on vague broad policy statements. Standardized institutional AI governance and ethical guardrails are indispensable enablers to regulate the safe and compliant application of intelligent agents in dual-teacher classrooms.

Existing research on vocational college digital transformation predominantly focuses on infrastructure investment, with little empirical evidence explaining why AI tool deployment frequently fails in dual-teacher systems. This study provides actionable, classroom-level governance countermeasures that bridge macro digital policy and micro workshop practice, offering practical extensions to institutional AI management literature.

Qualitative semi-structured interviews fit this research perfectly. Human-AI interaction in vocational dual-teacher classrooms contains abundant tacit context-dependent experience, which cannot be quantified by conventional quantitative approaches. Only in-depth open interviews can capture diversified, subtle perceptions of tool usage from multi-stakeholder groups, which fully justifies the adoption of qualitative methodology in this study. In addition, most existing studies only discuss AI efficiency from a single teacher perspective and ignore differentiated task risks and multi-stakeholder judgment legitimacy. This study further supplements vocational-exclusive safety and industrial matching constraints based on the CMEO framework, and challenges the oversimplified view that tool access equals efficiency widely adopted in mainstream literature. All derived theoretical supplements are bounded by the localized qualitative sample and cannot be generalized to all vocational education types without cross-regional verification.

5. Conclusions

This study adopted qualitative semi-structured interviews with 15 stakeholders to explore intelligent agent empowerment within vocational dual-teacher classrooms via the CMEO analytical framework, including dual teachers, industry engineering experts, vocational students and teaching administrators. The results first identified seven multi-stakeholder constraints covering data confidentiality barriers, tripartite use-reason gaps, training equipment mismatches and AI safety hallucination risks. Second, four human-agent collaborative coping mechanisms centred on explanatory assessment and joint tripartite evaluation are extracted to mitigate the above barriers. Third, five institutional enablers including localized model deployment, tiered teacher training and industry-course-certification alignment are proven essential to sustain stable intelligent teaching. Finally, the findings clarified that intelligent agents redistribute rather than reduce teaching and learning workload. Efficiency gains only emerge under complete institutional governance and human supervision. Distinct from prior single-group teacher-focused research, this paper integrates perspectives of teachers, industry experts and students, revealing task-differentiated applicability of intelligent agents and exposing the defects of institutional oversimplified AI popularization strategies.

Notably, the CMEO framework acts as a context-specific analytical tool rather than a universal standard model. It is only applicable to dual-teacher training classrooms for computing and IoT majors in Jiangsu vocational colleges. The CMEO framework and corresponding practical coping strategies cannot be directly generalized to all types of vocational regions or majors without further cross-regional verification. Variations in regional industrial cooperation, local education policies and training majors will alter human-AI collaboration dynamics. Accordingly, the CMEO framework and corresponding practical coping strategies cannot be directly generalized to all types of vocational regions or majors without rigorous cross-regional and cross-major verification.

For future research, follow-up quantitative large-sample surveys can be conducted to validate the generalizability of the CMEO framework across more vocational majors and regional colleges, and quantify the impact intensity of each constraint and enabling condition. Second, intervention research can design targeted intelligent agent modules embedded with human-expert collaborative review functions, and conduct long-term classroom tracking to observe actual improvements in students' vocational operation ability. Third, cross-regional comparative research can be carried out to analyze how varying institutional policy support and industrial cooperation levels shape human-agent collaboration modes in dual-teacher classrooms, so as to propose more differentiated, operable digital teaching reform schemes for vocational education.

Author Contributions

Conceptualization, K.W. and D.S.; methodology, K.W.; software, X.Z.; validation, D.S., X.Z. and X.L.; formal analysis, K.W. and Y.W.; investigation, X.L.; resources, X.Z.; data curation, K.W.; writing—original draft preparation, K.W.; writing—review and editing, D.S., X.Z., X.L., and Y.W.; visualization, X.Z.; supervision, X.L. and Y.W.; project administration, D.S.; funding acquisition, X.Z. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Ethical approval is obtained from Jiangsu Normal University (Approval Reference: JSNU-IACUC-AP-2026003). The study is conducted in accordance with Jiangsu Normal University's research ethics policies and applicable data-protection requirements. Interview audio files and transcripts are stored on password-protected devices and access is limited to the research team. Identifiers are removed during transcription and participants are assigned pseudonyms (T01–05; E01–03; S01–04; A01–03).

Informed Consent Statement

Written informed consent is obtained before data collection begins, including consent for audio recording. Participation is voluntary. Participants are free to decline any question and could withdraw without penalty. The options for withdrawal and data removal are explained during the consent process.

Data Availability Statement

The full interview transcripts are not publicly available because they contain potentially identifiable institutional experiences and are covered by the conditions of the ethics approval. The interview guide, selected deidentified excerpts used to support the findings, and the analytic codebook may be made available by the corresponding authors upon reasonable request. Any such request will be considered subject to an appropriate data sharing agreement and a review of re-identification risk. Requests should be directed to the corresponding authors.

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Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

During the preparation of this manuscript, the authors used ChatGPT solely for language refinement. No AI tools were used for data analysis, interpretation, or generation of scientific content. All outputs are critically reviewed and edited by the authors. The authors take full responsibility for the integrity and accuracy of the work.

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