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Construction and Application of a "Teacher-Machine-Student" Interactive Symbiotic Teaching Model in Vocational Education

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Abstract: *Vocational education is under pressure from two directions at once: industrial upgrading keeps raising the bar for skilled talent, while the conventional classroom, built around one teacher and a fixed textbook, struggles to give each student timely guidance. Drawing on symbiosis theory, constructivist learning theory and recent work on human-AI collaboration, this paper constructs a "Teacher-Machine-Student" (TMS) interactive symbiotic teaching model. In the model the teacher acts as instructional designer and value guide, the artificial intelligence agent works as adaptive tutor, analyst and resource generator, and the student remains the constructor of knowledge; the three parties exchange tasks, data and feedback across pre-class, in-class and post-class stages, forming a closed loop of co-construction, co-adaptation and co-evolution. A 16-week quasi-experiment was carried out in the course "Industrial Robot Programming and Operation" with two intact classes (experimental group n=48, control group n=46). Results show that the experimental group outperformed the control group on the post-test (82.5 vs 74.2 points, t=6.09, p<0.001, Cohen's d=1.26), obtained 1.5 to 1.8 times the score gains of the control group on every competency dimensions, and maintained a steadily rising trajectory of human-machine interaction. Interaction frequency, feedback adoption and learning engagement correlated moderately with achievement (r=0.49-0.64), and 85.4% of the experimental students reported being satisfied or strongly satisfied with the model. The findings suggest that a structured symbiosis among teacher, machine and student can improve both the efficiency and the quality of vocational classroom teaching, and the paper closes with boundary conditions and governance suggestions for wider application.*

Keywords: *vocational education; artificial intelligence; teacher-machine-student symbiosis; teaching model; quasi-experiment*

1. Introduction

Vocational education supplies the technicians and skilled workers on which modern manufacturing and service industries depend. In China alone, more than eleven thousand secondary and higher vocational institutions enrol over twenty million students, and the scale keeps growing. Yet the classroom inside many of these institutions has changed far more slowly than the workshops and production lines outside it. A teacher typically faces forty or more students with one textbook and one pair of hands; demonstrations are crowded, feedback arrives days after practice, and students who fall behind rarely receive individual repair. The contradiction between personalised skill formation and standardised mass instruction has become one of the most stubborn problems in the field [5].

Artificial intelligence offers a possible way out, but also a new puzzle. Over the past decade, intelligent tutoring systems, learning analytics and, more recently, large language models have been introduced into classrooms at every level of education [1][2][3]. International organizations have responded by urging education systems to adopt these technologies deliberately, with attention to both their potential and their risks [4]. Reviews of this literature agree on one point: the technology works best not when it replaces the teacher, but when a clear division of labour is negotiated among the teacher, the machine and the learner [2][8]. In vocational education the question is particularly acute, because competence there is embodied and situational; it grows through repeated practice on real or simulated tasks, not through listening alone [5][6]. An AI agent that answers questions quickly may accidentally weaken the very struggle through which skill is formed, while an AI agent that is well integrated into the teaching structure can free the teacher to do what machines cannot: demonstrate

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craft, judge quality in context, and encourage the hesitant student [15].

Existing studies describe human-AI collaboration in education mostly at the level of tools or paradigms [8][9][16]. Far fewer studies translate the idea into an operable classroom model for vocational settings, specify what each party should do at each stage of a lesson, and then test the model against a comparison group. That translation is the purpose of the present paper. We construct a "Teacher-Machine-Student" (TMS) interactive symbiotic teaching model, borrowing the concept of symbiosis from ecology to describe a relationship in which three unlike parties exchange resources and grow together rather than merely coexist. We then apply the model for one semester in the course "Industrial Robot Programming and Operation" at a vocational college, and evaluate it with a quasi-experimental design combining achievement tests, platform logs, questionnaires and interviews.

Three questions guide the study: (1) Does the TMS model improve students' academic achievement and competency gains compared with conventional blended teaching? (2) How do students' interaction behaviours evolve over a semester under the model, and how do these behaviours relate to learning outcomes? (3) How do students and teachers perceive the model, and what boundary conditions does its application require?

2. Theoretical Foundations and Related Work

2.1 Artificial intelligence in education: from tools to paradigms

Research on artificial intelligence in education (AIED) has moved through recognisable stages. Early intelligent tutoring systems modelled the learner's knowledge state and delivered step-level hints, achieving effects close to human tutoring in well-defined domains [10][11]. Bloom's famous observation that one-to-one tutoring outperforms group instruction by two standard deviations supplied the field with its long-standing motivation [12]. The past five years brought a second wave built on large language models, which can converse, generate examples and critique drafts in natural language, widening the range of tasks that machines can support [18]. Bibliometric evidence shows that AIED publications have grown rapidly since 2014, with personalised learning, automated assessment and learning analytics as the dominant themes [7].

In parallel, the way researchers frame the teacher-machine relationship has also evolved. Ouyang and Jiao distinguish three paradigms: AI-directed learning, where the machine leads; AI-supported learning, where the machine assists; and AI-empowered learning, where human and machine form an integrated system [9]. Hwang and colleagues similarly argue that the productive question is no longer whether AI belongs in education but which roles it should take and which must remain human [8]. Hybrid human-AI arrangements, in which regulation of learning is shared between the learner, the teacher and the machine, are now an active research direction [16][17].

2.2 Symbiosis as an organising idea for the vocational classroom

Symbiosis, a term from ecology, describes a durable relationship between different organisms that exchange resources and increase each other's fitness. Transplanted into education, the idea fits the vocational classroom better than the more common metaphor of the machine as a "tool" or "assistant", for three reasons. First, vocational competence is co-produced: the teacher contributes craft knowledge and judgement, the machine contributes data processing and tireless responsiveness, and the student contributes purposeful activity; remove any one of the three and the value of the other two drops. Second, the relationship is reciprocal over time: student behaviour trains the machine's recommendation, machine analytics reshape the teacher's design, and the teacher's scaffolding changes what students ask of the machine. Such guided support extends what learners can accomplish on their own, much as Vygotsky described for the zone of proximal development [13]. Third, symbiosis implies boundaries: ecological partners remain distinct organisms, which reminds us that teacher, machine and student should keep their own responsibilities rather than dissolve into one another [19].

This framing also answers a common worry. Selwyn cautions that handing teaching to machines risks hollowing out the relational core of education [15]; Kasneci and colleagues note that large language models can fabricate content and invite over-reliance [18]. A symbiotic design addresses these risks structurally: the machine handles high-frequency, low-stakes interaction, while consequential judgement, value formation and safety certification remain with the teacher. Similar arguments appear in recent reviews that call for clearly assigned roles and ethical guardrails when AI enters classrooms

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[14][19][20][21].

2.3 Gaps addressed in this study

Three gaps remain. Conceptually, few models specify the reciprocal duties of teacher, machine and student across the full teaching cycle rather than at a single moment. Methodologically, much of the human-AI collaboration literature reports design cases or small pilots; controlled comparisons in vocational courses are scarce [7][19]. Practically, vocational teachers need operational guidance, not abstractions. The TMS model and the semester-long experiment reported below attempt to address all three gaps at once.

3. Construction of the TMS Interactive Symbiotic Teaching Model

3.1 Component structure

The model contains three interactive subjects and two boundary layers, as shown in Fig. 1. The teacher is repositioned as instructional designer and value guide: she authors projects and prompts, interprets the analytics the machine produces, resolves higher-order confusion, and takes charge of safety norms and professional ethics, which matter greatly in industrial courses. The machine, an AI agent assembled from a large language model, a course knowledge base and a learning-analytics module, serves as adaptive tutor, analyst and resource generator: it answers routine questions at any hour, assembles personalised practice, profiles groups, and flags students who stall. The student is the constructor of knowledge and a skilled practitioner in formation: he sets goals, works through tasks, interrogates the machine, and carries the results back into hands-on operation.

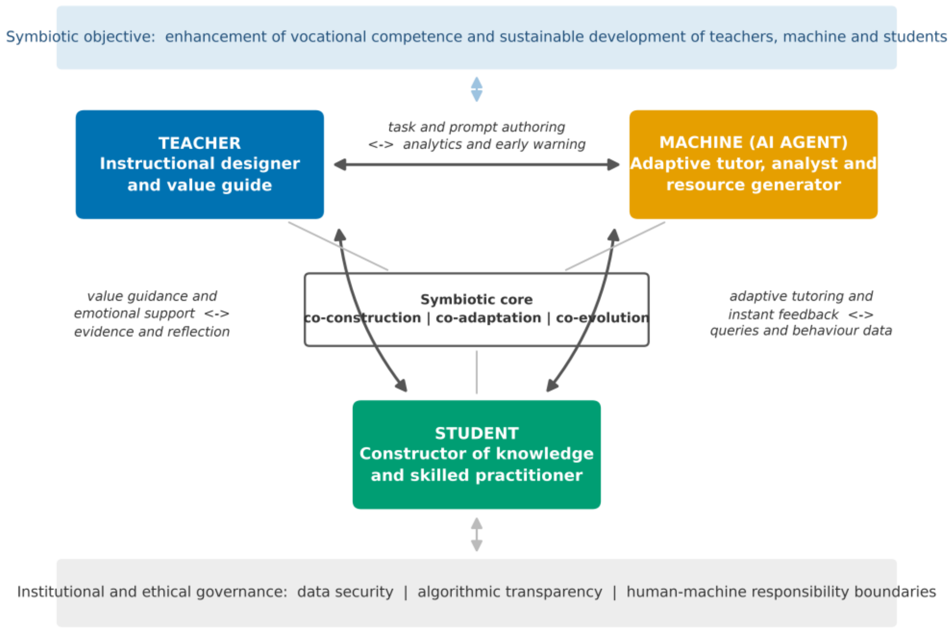

Fig. 1 Architecture of the Teacher-Machine-Student interactive symbiotic teaching model

Around the three subjects sit two boundary layers. Above them, a symbiotic objective layer states what the partnership is for: enhancement of vocational competence together with the sustainable development of all three parties, including the teacher's professional growth and the machine's improvement through accumulated course data. Below them, a governance layer fixes the rules of the game: data security, algorithmic transparency and explicit responsibility boundaries between human and machine. Without this layer, symbiosis easily slides into either technological abuse or technological refusal.

3.2 Interaction mechanism and the symbiosis index

Interaction in the model runs along three bidirectional channels. Between teacher and machine, the

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teacher supplies instructional design, tasks and prompts, and receives analytics and early warnings in return. Between machine and student, the machine supplies adaptive tutoring and instant feedback, and receives queries and behavioural data that refine its models. Between teacher and student, the teacher supplies value guidance, emotional support and expert demonstration, and receives learning evidence and reflective accounts. The three channels close into a loop, which we describe as co-construction of content, co-adaptation of behaviour, and co-evolution of capability.

To make the strength of symbiosis discussable rather than rhetorical, we define a simple symbiosis index. Let I_tm, I_ms and I_ts denote the normalised weekly interaction densities of the teacher-machine, machine-student and teacher-student channels respectively, each scaled to [0,1] by dividing the observed count of effective interactions by a course-specific benchmark. The symbiosis index of week k is then

$$SI_k = w_1 I_{tm}(k) + w_2 I_{ms}(k) + w_3 I_{ts}(k) \quad (1)$$

where the weights satisfy w1 + w2 + w3 = 1 and are set, in this study, to 0.25, 0.50 and 0.25 after a small Delphi consultation with six vocational teaching experts, reflecting the central place of machine-student exchange in the model. SI(k) close to 1 indicates that all three channels are active near benchmark level; a low value signals that at least one channel is silent and the symbiosis is nominal rather than real.

3.3 Operational process: a three-stage closed loop

Operationally the model unfolds across pre-class, in-class and post-class stages, as shown in Fig. 2. Before class, the teacher designs projects and prompts and reviews the machine's diagnostic analytics; the machine pushes personalised resources and analyses pre-learning data; the student studies with the AI tutor and submits questions and first attempts. In class, the teacher organises inquiry and concentrates on higher-order problems the machine cannot judge; the machine provides real-time tutoring, group profiling and formative feedback; students complete collaborative tasks through man-machine exploration. After class, the teacher redesigns the next lesson from evidence and mentors weak learners individually; the machine generates learning reports and recommends remediation paths; students consolidate reflectively and transfer what they learned to workplace-like tasks. The post-class evidence feeds the next pre-class design, closing the loop.

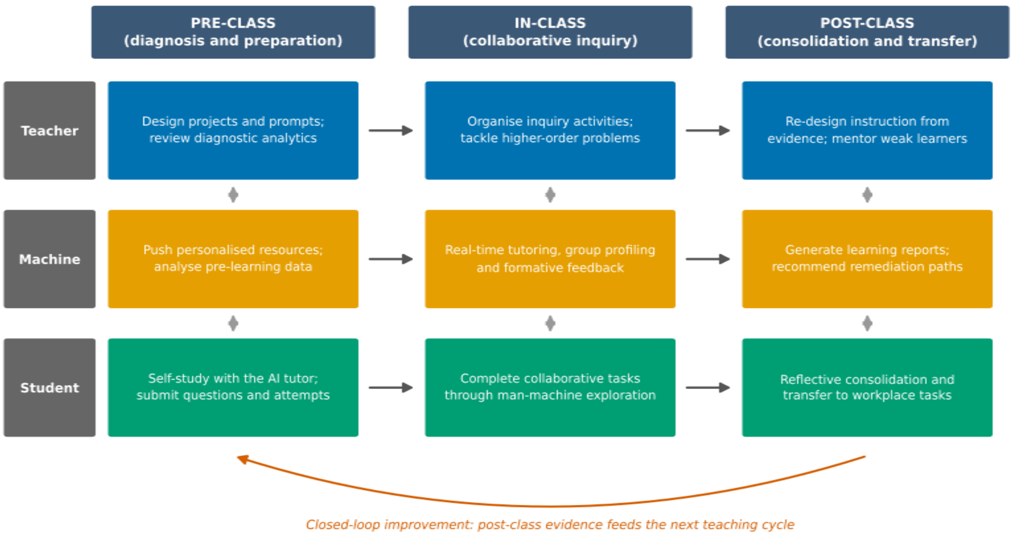

Fig. 2 Three-stage operational workflow of the TMS model

Two design rules keep the loop healthy. The first is graded delegation: a task is handed to the machine only when it is high-frequency, rule-based and low-risk; anything involving safety certification, workplace judgement or value choice stays with the teacher. The second is visible handover: at every stage students can see which party is responding to them, so that trust is calibrated rather than blind. Together these rules turn the model from a slogan into a set of checkable classroom routines.

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4. Application: A Quasi-Experimental Study

4.1 Research design and hypotheses

A non-equivalent control group quasi-experiment was adopted, a design widely used in education when random assignment of intact classes is impractical [24]. Two parallel classes of the course "Industrial Robot Programming and Operation" were followed for 16 weeks. The experimental class was taught with the TMS model; the control class used the college's conventional blended approach, in which the teacher lectures and demonstrates in class and students review recorded materials on a platform afterwards, without an AI agent embedded in the teaching structure. We hypothesised that the experimental class would show (H1) higher post-test achievement after controlling for prior attainment, (H2) larger gains on five competency dimensions, and (H3) a rising rather than flat trajectory of learning interaction.

4.2 Participants

Participants were 94 second-year students of the intelligent-manufacturing major cluster at a vocational college in eastern China. Table 1 summarises the two groups. They were comparable in gender composition, age and, importantly, prior attainment: an independent-samples t-test on the pre-test showed no significant difference ($t(92)=0.36$, $p=0.720$). The same teacher taught both classes, which removes teacher-effect confounds at the cost of requiring careful treatment fidelity checks; weekly logs and classroom observations confirmed that the AI agent was used only in the experimental class.

Table 1 Profile of the participants

Group	n	Male / Female	Mean age (SD)	Pre-test score M (SD)
Control group	46	28 / 18	19.8 (0.9)	61.8 (7.9)
Experimental group	48	30 / 18	19.6 (1.0)	62.4 (8.2)
t / p value	-	$\chi^2=0.03$, $p=0.865$	$t=1.02$, $p=0.31$	$t=0.36$, $p=0.720$

4.3 Instruments

Four instruments were combined, as listed in Table 2. The achievement measure was a pair of parallel 100-point tests covering programming logic, robot operation, fault diagnosis, safety norms and collaborative problem solving, reviewed by two curriculum experts and piloted with a previous cohort. Interaction behaviour was captured from platform logs. Student perceptions were collected with a 20-item five-point Likert questionnaire, and twelve students plus four teachers were interviewed at the end of the semester. Feedback quality, a recognised driver of learning gains, was a recurring theme in both questionnaire and interview design [22][23].

Table 2 Instruments and their reliability

Instrument	Content	Reliability / validity evidence
Pre-test and post-test	Parallel forms, 100 points, five competency dimensions	Cronbach's alpha = 0.85 / 0.87; expert review
Platform behaviour logs	Interaction counts, feedback adoption, task completion	Automatic capture; weekly audit
Perception questionnaire	20 items, five-point Likert scale	Cronbach's alpha = 0.87
Semi-structured interviews	12 students, 4 teachers, 30-40 min each	Double coding; inter-rater agreement 0.82

4.4 Implementation procedure

The experimental class ran the full TMS loop of Fig. 2 for 16 weeks. In week 1 students received accounts, a short course on prompt writing, and a pre-test. From week 2 to week 15, each weekly unit followed the same rhythm: machine-supported self-study before class, a 90-minute in-class session organised around two collaborative tasks, and post-class remediation driven by the machine's report. The teacher checked the early-warning list every Friday and personally contacted any student flagged twice in a row. The control class covered identical content with the same teacher, the same textbook and the same total contact hours; its platform offered videos and exercises but no conversational agent, no adaptive recommendation and no learning analytics for the teacher. In week 16 both classes took the post-test, and the questionnaire and interviews followed.

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4.5 Data analysis

Achievement was analysed with descriptive statistics, independent-samples t-tests and analysis of covariance (ANCOVA) with the pre-test as covariate. Effect size is reported as Cohen's d [25],

$$d = \frac{M_E - M_C}{s_p} \tag{2}$$

where M_E and M_C are the two group means and s_p is the pooled standard deviation. Because intact classes differ in starting point even when the difference is not significant, we also computed the normalised learning gain

$$g = \frac{S_{post} - S_{pre}}{S_{max} - S_{pre}} \tag{3}$$

where, following the convention widely used in educational intervention studies, improvement is expressed as the fraction of the improvement that was still possible. improvement is expressed as the fraction of the improvement that was still possible. Platform logs were aggregated weekly per student; questionnaire items were summarised as proportions; interview transcripts were coded thematically. Analyses were run with alpha = 0.05.

5. Results and Analysis

5.1 Academic achievement

Fig. 3 and Table 3 give the core comparison. The two groups started at the same place (61.8 vs 62.4 points) but ended far apart: the experimental group averaged 82.5 on the post-test against 74.2 for the control group, a gap of 8.3 points (t(92)=6.09, p<0.001, d=1.26, a large effect). The normalised gain tells the same story in a fairer metric: the experimental group realised 0.54 of the improvement still available to it, the control group 0.32. ANCOVA with the pre-test as covariate confirmed the result (F(1,91)=37.86, p<0.001, partial eta squared = 0.294), so the advantage cannot be explained by initial differences. H1 is supported.

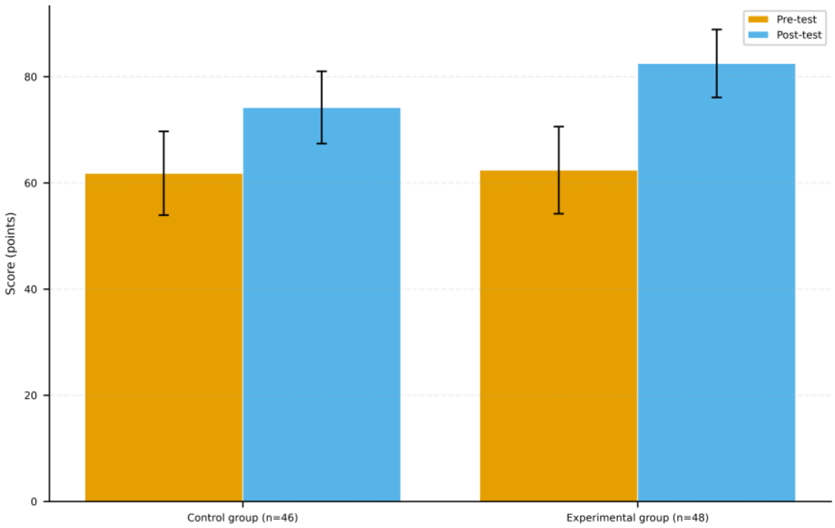

Fig. 3 Pre-test and post-test scores of the two groups (error bars show SD)

Table 3 Achievement comparison between the two groups

Measure	Control (n=46)	Experimental (n=48)	t / F	p	Effect size
Pre-test M (SD)	61.8 (7.9)	62.4 (8.2)	t = 0.36	0.720	d = 0.07
Post-test M (SD)	74.2 (6.8)	82.5 (6.4)	t = 6.09	<0.001	d = 1.26
Normalised gain g	0.32	0.54	-	-	-
ANCOVA (group effect)	Adjusted M = 74.4	Adjusted M = 82.3	F(1,91) = 37.86	<0.001	partial eta2 = 0.294

The box plots in Fig. 4 add distributional detail. The experimental distribution shifts upward as a whole rather than being pulled by a few top students: its lower quartile (79.6) sits above the control median (75.0), and its spread narrows slightly, suggesting that the model helped the middle and lower

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bands most. This pattern matches the model's intention, since the machine's remediation paths and the teacher's Friday follow-ups target precisely the students who would otherwise drift.

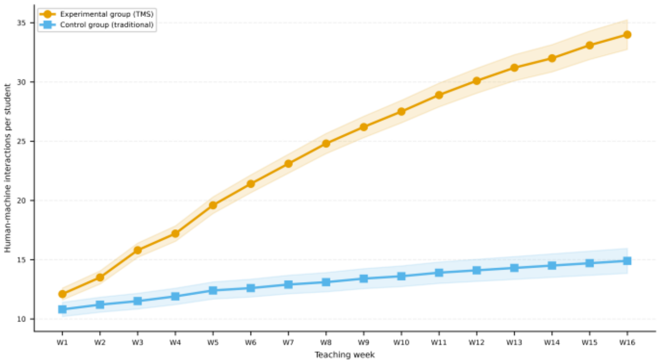

Fig. 4 Distribution of post-test scores in the two groups

5.2 Gains on the five competency dimensions

Breaking the tests into their five dimensions shows where the model earns its keep (Fig. 5). The experimental group's gains exceed the control group's on every dimension, but not uniformly. The largest relative advantages appear in fault diagnosis (1.75 times the control gain) and programming logic (1.70 times); the smallest appears in safety and norms (1.45 times). This ordering is instructive. Dimensions that benefit from iteration, dialogue and trial-and-error, such as diagnosing a fault through successive hypotheses, are exactly those an always-available conversational agent supports best. Safety norms, by contrast, are learned through supervised practice and institutional habit, where the machine contributes less and the teacher's demonstration remains decisive. H2 is supported, with a caveat that the model itself predicts: the machine amplifies some kinds of learning more than others.

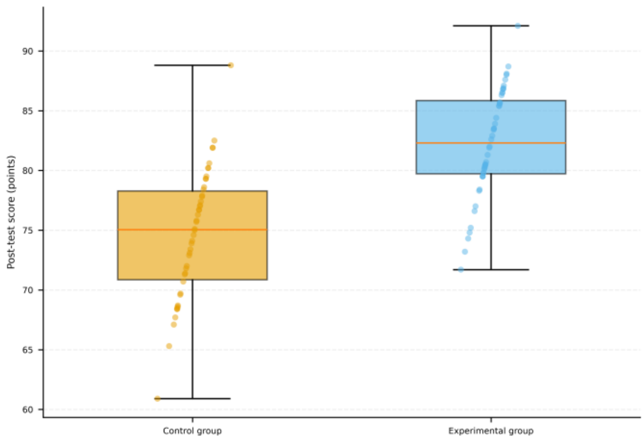

Fig. 5 Score gains by competency dimension (ratio labels: experimental relative to control)

5.3 Trajectory of learning interaction

Weekly platform logs show how behaviour evolved (Fig. 6). The control group's interaction count rose slowly from 10.8 to 14.9 per student per week, the gentle slope of ordinary platform use. The experimental group started only slightly higher (12.1) but climbed steadily to 34.0, with no plateau in sight by week 16. Three features of the curve deserve comment. The inflection around weeks 3-4 coincides with students mastering prompt writing, which the interviews confirmed: several students said the machine "started to understand me" once they learned to ask properly. The absence of a mid-semester dip, common in technology-supported courses when novelty fades, suggests the weekly task cycle kept the agent useful rather than decorative. And the continuing rise implies the teacher's evolving prompts kept opening new uses, consistent with the co-evolution claim of the model. The symbiosis index SI(k), computed with the weights of Section 3.2, rose from 0.41 in week 2 to 0.83 in week 16 for the experimental class, while remaining between 0.30 and 0.36 for the control class. H3 is supported.

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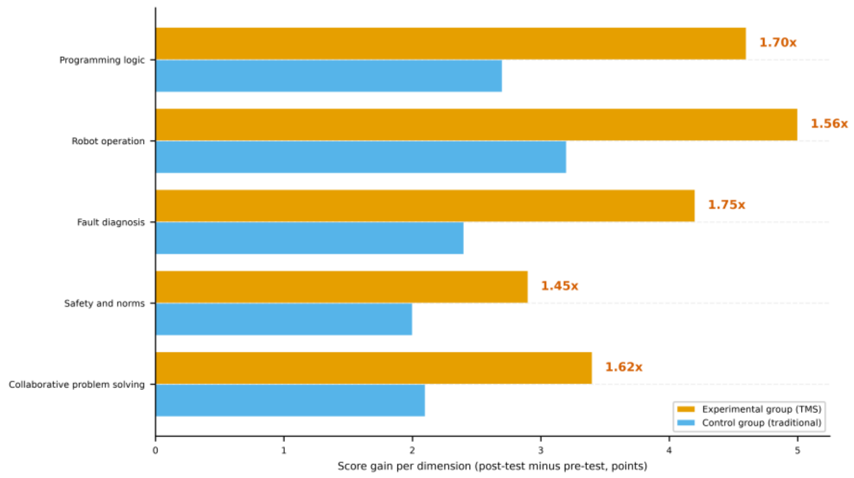

Fig. 6 Weekly human-machine interaction counts per student across the semester

5.4 How interaction relates to outcomes

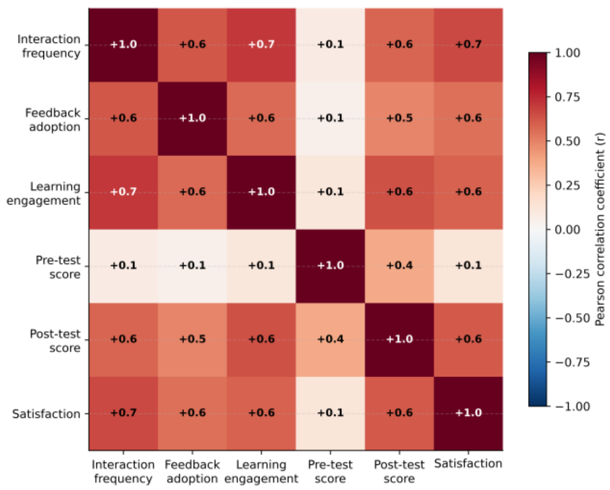

Fig. 7 Correlation matrix of interaction variables and learning outcomes (experimental group)

If the model works through interaction rather than through mere exposure to technology, interaction variables should correlate with outcomes. Fig. 7 reports the correlation matrix for the experimental group. Interaction frequency correlates with the post-test at r=0.58, feedback adoption at r=0.49, and learning engagement at r=0.64; all are moderate and statistically significant ($p<0.01$). Two negative results are equally informative. The pre-test correlates with the post-test only weakly to moderately (r=0.38), meaning prior attainment did not destiny the outcome in this class. And interaction frequency correlates with feedback adoption at r=0.62, which supports the mechanism the model assumes: students who interact more receive more feedback and, more importantly, act on it more often. Feedback of this kind, immediate and specific, is what the feedback literature identifies as most effective [22][23]; the machine makes its frequency affordable, and the teacher keeps its direction sound.

5.5 Perceptions of students and teachers

Questionnaire results (Fig. 8) show broad acceptance. Combining "agree" and "strongly agree", 85.4% of experimental students were satisfied with the model overall; approval was highest for teacher guidance under the new division of labour and for timely feedback (both 85.4% positive, and for teacher guidance 52.1% chose "strongly agree"). Skill transfer to real tasks, the dimension most often doubted in discussions of AI-assisted learning, still reached 81.3% positive. Interviewees filled in the texture behind these numbers. Students repeatedly described the machine as "the patient classmate" they could ask without embarrassment, while reserving final judgement for the teacher: "the AI tells you how, the teacher tells you whether it is good enough for the workshop." Teachers reported that the weekly analytics changed their preparation from intuition to evidence, and estimated that time spent on repetitive answering and grading fell from about 11.2 to 6.7 hours per week, time they redirected to task design and individual mentoring.

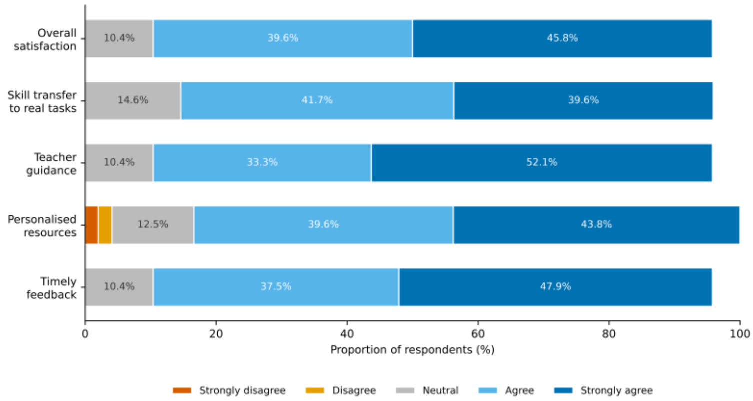

Fig. 8 Student satisfaction with the TMS model (experimental group, n=48)

6. Discussion

The results support all three hypotheses, and they do so in a way that sheds light on why the model works. The large achievement effect (d=1.26) is comparable to effects reported for intelligent tutoring in structured domains [10][11], but it was obtained in a messy, practice-heavy vocational course rather than a controlled tutor study. The mechanism evidence points away from novelty: outcomes tracked interaction behaviour, interaction behaviour tracked feedback adoption, and the dimension-level pattern matched the division of labour the model prescribes. In short, the gains appear to come from the structure of cooperation, not from the mere presence of an AI tool, which echoes the paradigmatic argument of Ouyang and Jiao [9] and the hybrid-regulation position of Molenaar and of Jarvela and colleagues [16][17].

Three boundary conditions emerged. First, teacher readiness is the binding constraint: the model asks teachers to write prompts, read analytics and redesign weekly, a professional-knowledge demand close to what Celik calls Intelligent-TPACK [21]. Second, governance is not optional. Data security, transparency about what the machine can and cannot decide, and explicit responsibility for safety certification must be settled before deployment, not after an incident [14][18][20]. Third, the machine's answers need editorial control: twice during the semester the agent produced a plausible but wrong wiring suggestion, which the teacher caught and converted into a teaching moment about verification. Symbiosis, in other words, includes the duty to distrust one's partner at the right moments [15].

The study has limitations. It involved one course, one teacher and two classes at one college, so generalisation is limited; the design is quasi-experimental rather than randomised; interaction was measured by counts, which say nothing about depth; and the 16-week window cannot show whether the effect persists or decays. Multi-site replications, finer-grained dialogue analysis, and longer follow-ups are the obvious next steps. Whether the same structure transfers to less technical vocational programmes, such as hospitality or nursing, also deserves testing.

7. Conclusion

This paper constructed a Teacher-Machine-Student interactive symbiotic teaching model for vocational education, specified its components, interaction channels, symbiosis index and three-stage workflow, and tested it in a semester-long quasi-experiment. The model produced a large and statistically robust achievement advantage, doubled gains on most competency dimensions, sustained a rising interaction trajectory, and won strong acceptance from students and teachers. The broader lesson is that the value of AI in vocational classrooms lies less in the model's algorithms than in the quality of the partnership built around them: teacher, machine and student each doing what they do best, exchanging evidence continuously, and keeping clear boundaries. For practitioners, the model offers concrete routines; for researchers, it offers a testable structure that can be refined, contested and

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extended.

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