Research on Bidirectional Matching of Educational Agents and Human-AI Collaborative Empowerment Theories for Teachers of All Educational Stages in Zhejiang Province

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Abstract

This study addresses critical challenges in teacher artificial intelligence (AI) literacy diagnosis and educational agent matching within China's "AI+Education" strategic context. Drawing on constructivist learning, adaptive systems, tag-based matching, and human-AI collaboration theories, it employs the teacher artificial intelligence competence self-efficacy (TAICS) scale as a standardized diagnostic instrument. Based on six-dimensional assessment data, the research establishes a four-dimensional teacher profile tagging system and a three-dimensional functional tagging system for educational agents. A "fuzzy rule-based reasoning + weighted cosine similarity" bidirectional matching algorithm is designed within a five-layer multi-agent architecture, forming a closed-loop "diagnosis - matching - scheduling - collaboration - iteration" paradigm. This data-driven model elevates teacher differences from demographic variables to system design variables, offering a computable theoretical foundation for human-AI collaborative education and practical solutions for regional precision empowerment.

Keywords

Teacher artificial intelligence literacy, Educational agents, Bidirectional tag matching, Human-AI collaboration, Adaptive learning

Introduction

Research background and core problems

With the deep integration of artificial intelligence into the educational domain, nations worldwide have elevated the digital transformation of education to a national strategic level. In 2025, China's State Council issued the Opinions on Deeply Implementing the "Artificial Intelligence+" Action. This policy explicitly mandates the integration of artificial intelligence into all elements and throughout the entire process of education and teaching. It also innovates new models of human-machine collaborative education, such as intelligent learning companions and intelligent teachers, thereby positioning the enhancement of teacher AI literacy as a core lever for educational digital transformation. In the same year, United Nations Educational, Scientific and Cultural Organization (UNESCO) released the "AI competency framework for teachers (AICFT)". This framework provides a standardized reference across five dimensions: human-centered mindset, AI ethics, AI foundations and applications, AI pedagogy, and AI for professional development [1]. These policy directives indicate that teacher-AI collaborative capabilities have become a core proposition in educational modernization, directly determining the depth and breadth of AI-enabled educational quality transformation.

Zhejiang Province, as a pioneering province in China's educational digital reform, took the lead in issuing the Zhejiang Province Primary and Secondary School Teacher AI Literacy Framework and the Zhejiang Province Higher Education Teacher AI Literacy Framework. This has constructed a localized teacher AI literacy standard system across three dimensions - AI cognition, AI application, and AI ethics. However, between policy enthusiasm and practical implementation lie three academic challenges and practical dilemmas.

First, the scientific inadequacy of diagnostic tools. Current teacher AI literacy assessments predominantly rely on locally or institutionally developed questionnaires, generally lacking rigorous reliability and validity testing and large-sample validation, rendering assessment results unreliable as a basis for precision empowerment. The assessment dimensions vary widely and standards remain inconsistent, preventing cross-regional and cross-school comparability and failing to support provincial-level coordinated planning.

Second, the mismatch of empowerment solutions. Educational agent products on the market predominantly adopt a "function-preset, unified-supply" model, where individual teacher differences are abstracted as undifferentiated variables in system design. The contradiction between rural teachers' complaint that "functions are too complex to use" and young core teachers' complaint that "functions are too basic to be sufficient" coexists simultaneously. This coexistence creates a stark contrast between the "one-size-fits-all" approach of agent products and the diverse needs of teachers.

Third, there is a systemic gap in collaboration mechanisms. The transformation pathway from diagnosis to empowerment lacks theoretical model support, with no computable mapping logic between assessment data and agent recommendations. In most regions, teacher AI training and agent application promotion remain disconnected. Assessment results are used only for ranking and record-keeping rather than being transformed into personalized empowerment solutions. This results in the "two-skin phenomenon" where "assessment remains assessment, application remains application". Consequently, "precision empowerment" largely remains at the level of policy rhetoric.

In international academia, the TAICS scale has been developed and validated encompassing six dimensions - AI knowledge, AI pedagogy, AI assessment, AI ethics, humanistic education, and professional development. The scale demonstrated good reliability and validity in a sample of 434 Kindergarten through 12th grade (K-12) teachers, with Cronbach's α values across dimensions ranging from 0.82 to 0.91. This makes it one of the more mature standardized assessment tools for teacher AI literacy internationally. Meanwhile, research on multi-agent systems in education has become increasingly active, with multi-agent collaborative models demonstrating strong personalized support potential in areas ranging from intelligent tutoring and homework grading to instructional design assistance [2]. However, existing research has yet to incorporate standardized AI literacy assessment and precise agent matching into a unified theoretical framework. There remains a clear "theoretical fault zone" between literacy diagnosis and empowerment practice, where the value of assessment data remains insufficiently realized.

Based on the above background, this study focuses on three core questions: First, how can multidisciplinary foundational theories be integrated to construct a theoretical model of teacher-agent bidirectional tag matching driven by TAICS scale data? Second, how can a five-layer human-AI collaborative multi-agent system operational architecture covering teachers' full work scenarios - teaching, research, and management - be designed based on TAICS standardized diagnostic results? Third, how can a full-cycle closed-loop human-AI collaborative operational mechanism of "diagnosis - matching - scheduling - collaboration - iteration" be constructed to achieve dynamic and sustained improvement in teacher AI literacy?

Research significance and approach

The theoretical significance of this study is threefold. First, it integrates adaptive system theory and tag matching theory to bridge the long-standing theoretical fragmentation between literacy assessment and agent empowerment, constructing a complete theoretical chain from diagnosis to empowerment. Second, it establishes a localized four-dimensional tag transformation logic based on the TAICS scale, enriching the theoretical systems of teacher digital profiling and human-AI collaboration. Third, it constructs a layered multi-agent collaborative paradigm. This paradigm extends the scenarios of adaptive learning theory from traditional "student-learning content" matching to "teacher-agent" bidirectional matching. It expands the boundaries of adaptive learning theory in teacher professional development.

At the practical level, this study provides regional education authorities with a complete theoretical solution for conducting stratified teacher profiling and precise agent matching based on standardized scales, directly supporting policy implementation. It offers a standardized architectural reference for primary, secondary, and higher education institutions to build lightweight educational agent platforms. Additionally, it formulates differentiated collaborative adaptation approaches for disadvantaged teacher groups such as rural and middle-aged/elderly teachers, narrowing the urban-rural digital divide through stratified empowerment.

This study follows the logical chain of "theoretical tracing - literature review - authoritative tool adaptation - dual-tag model construction - agent system architecture design - operational mechanism extraction - theoretical innovation articulation". The entire process employs TAICS scale assessment data as the original basis for profile tag generation, ensuring the data-driven nature and verifiability of the entire theoretical system. The research adopts a paradigm primarily focused on theoretical construction supplemented by empirical pre-study design. It comprehensively employs literature analysis, policy analysis, Delphi expert consultation, and systematic modular design. The Delphi consultation invited 15 experts, with a two-round response rate of 93.30% and a mean authority coefficient of 0.87.

Literature review

Teacher AI literacy diagnosis and educational agent research

Research on teacher AI literacy has evolved from general technology literacy to subject-specific AI competency. UNESCO's 2024 AICFT framework divides teacher AI competencies into five dimensions and three progressive levels, serving as a benchmark reference for global teacher AI capacity building. The "AI Literacy Framework for Primary and Secondary Education" further supplements requirements for critical thinking and AI ethics, with particular emphasis on teachers' critical reflective capacity regarding AI technology. In quantitative assessment, the TAICS scale represents one of the more mature standardized instruments regarding reliability and validity. The six-dimensional structure was confirmed through confirmatory factor analysis with 434 K-12 teachers, with Cronbach's α values across dimensions ranging from 0.82 to 0.91 [3]. The artificial intelligence pedagogical content knowledge (AIPACK) scale assesses teacher AI integration capability from a technology - pedagogy - content integration perspective and represents another important supplementary tool in this field.

Domestic research on teacher AI literacy diagnosis exhibits three significant limitations. First, self-developed instruments generally lack adequate reliability and validity. Most studies employ self-designed questionnaires without large-sample validation or cross-cultural adaptation testing. This compromises the comparability and reliability of assessment results. Second, diagnosis and empowerment remain disconnected. Research predominantly focuses on descriptive statistics of literacy levels, lacking transformation logic from diagnostic data to agent recommendation tags, which limits the practical value of assessment results. Third, most diagnostic tools insufficiently consider the indicator requirements of local AI literacy frameworks, with inadequate correspondence to local policies, making it difficult to directly support regional teacher development planning.

In multi-agent systems, the Lectūra Agents framework proposes a hierarchical multi-agent architecture that coordinates multiple specialized assistant agents to achieve personalized learning support, demonstrating good adaptability in higher education contexts. The Instructional Agents Framework, based on the analysis, design, development, implementation, evaluation (ADDIE) model, simulates collaborative processes among different roles in a teaching team, effectively reducing teachers' instructional design burden. However, domestic educational agent applications face the dual dilemma of functional fragmentation and insufficient personalization. On one hand, different agent products lack unified interoperability standards, with data silos forcing teachers to switch between multiple platforms, paradoxically increasing workload. On the other hand, the vast majority of agents adopt a "one-size-fits-all" functional configuration strategy. They lack intelligent matching mechanisms based on individual teacher differences, failing to meet the differentiated needs of teachers at different literacy levels [4].

The delineation of rights and responsibilities in human-AI collaboration is a core academic issue. The adaptive instrument, proactive assistant, co-learner, peer collaborator (APCP) four-level evolutionary model divides AI autonomy into four levels - Passive Tool, Reactive Assistant, Proactive Partner, and Autonomous

Collaborator. This model clearly defining the rights-responsibilities relationships at different stages of human-AI collaboration. In teacher professional development, AI-enhanced professional learning communities (PLCs) research demonstrates that AI can provide personalized support based on individual teacher needs. This effectively promoting deep interaction within teacher professional learning communities. However, existing research predominantly focuses on macro-level classification of collaborative models. It lacks differentiated collaborative strategy design based on teacher AI literacy levels, failing to establish precise mapping between teacher capability levels and collaboration models.

User profiling matching mechanisms and research gaps

The application of user profiling technology in education has expanded from traditional student profiling to teacher professional development profiling. However, the construction of teacher AI literacy profiles currently lacks standardized data sources, with most profiles relying on teaching behavior data rather than dedicated literacy assessment data, making it difficult to accurately reflect teachers' AI capability levels.

In educational recommendation systems, fuzzy reasoning and cosine similarity are two commonly used core algorithms. Fuzzy reasoning excels at handling the substantial fuzziness and uncertainty in educational scenarios, effectively incorporating domain expert knowledge. Cosine similarity offers advantages of computational simplicity and strong interpretability in high-dimensional feature matching. The TeamUp system utilizes cosine similarity to achieve semantic matching between students and projects. Results indicate that weighted similarity matching significantly outperforms simple matching strategies. This approach better adapts to matching requirements across different scenarios [5].

However, existing matching algorithms in educational contexts are predominantly oriented toward student populations, focusing on matching learning resources with students. They also lack specialized algorithm design for teacher-agent bidirectional matching, and insufficiently considering the diversity and dynamism of teacher work scenarios.

In summary, existing research exhibits three core gaps. First, assessment tools and agent empowerment remain disconnected, lacking systematic theoretical articulation between them, which prevents literacy assessment results from being directly transformed into empowerment solutions. Second, bidirectional tag matching theory is absent, failing to systematically transform teacher diagnostic results into agent matching tags, lacking computable matching logic. Third, no full-cycle closed-loop collaborative architecture exists. Existing research focuses primarily on optimization of individual links, lacking a systematic theoretical framework covering the entire "diagnosis - matching - scheduling - collaboration - iteration" process. This inability hinders support for the sustained dynamic development of teacher AI literacy. Based on this, the core entry point of this study is utilizing the TAICS scale as a standardized data foundation. It constructs a complete theoretical model and system architecture for teacher-agent bidirectional matching, and opening the entire chain of assessment, diagnosis, matching, empowerment, and iteration.

Core theoretical foundations

The theoretical system construction of this study is grounded in the interdisciplinary integration of multiple theories. Constructivist learning theory provides the epistemological foundation. Adaptive learning system theory establishes the core operational logic of the system, tag-based user matching theory supports the algorithmic design of bidirectional matching, and human-AI collaborative education theory defines the boundaries of rights and responsibilities in human-AI interaction. Together, these four theories constitute the theoretical cornerstone of this research.

Constructivist learning theory holds that knowledge is not transmitted by teachers but is actively constructed by learners through meaning-making in specific contexts with the assistance of others and necessary learning resources. The theory emphasizes the active, social, contextual, and constructive nature of learning, asserting that learners' cognitive development is a process of continuous reconstruction through interaction with the environment [6]. This provides the fundamental epistemological basis for this study's "diagnosis-first, empowerment-second" design. The enhancement of teacher AI literacy is essentially a process of teachers actively constructing AI application capabilities in teaching practice. This process cannot rely on unified, one-size-fits-all training but requires personalized support and resources based on teachers' individual prior knowledge, capability levels, and scenario-specific needs. This study's design concepts of stratified diagnosis, precise matching, and differentiated collaboration represent concrete embodiments of constructivism's "learner-centered" philosophy in teacher professional development.

Adaptive learning system theory originates from intelligent tutoring system research. The core idea is that systems can dynamically adjust learning content, pathways, and pacing based on learners' individual characteristics and behavioral patterns, achieving personalized learning support. A complete adaptive learning system typically comprises five core modules: data acquisition, user modeling, domain modeling, adaptive engine, and interaction interface, operating through the closed-loop logic of "data acquisition - user profiling - content matching - feedback iteration". This study creatively extends the core logic of adaptive learning systems from the traditional "learner-learning content" matching scenario to the novel "teacher-agent" matching domain, with system components corresponding to the five-layer architecture designed in this study.

Tag-based user matching theory is a core theory in the recommendation systems field, with the central idea of abstracting and quantifying user characteristics and resource features into computable tag vectors, then achieving optimal user-resource matching by calculating similarity between tag vectors. Tag systems offer advantages of structure, extensibility, and computability, effectively reducing the complexity of high-dimensional feature matching while providing good interpretability. This study innovatively applies tag-based matching theory to the teacher-agent bidirectional matching scenario. It constructs a four-dimensional teacher profile tag system and a three-dimensional agent functional tag system. These systems transform complex teacher capability features and agent functional characteristics into structured, computable tag vectors. The vectors are then mapped to the same feature space for similarity computation.

Human-AI collaborative education theory focuses on the models, boundaries, and mechanisms of human-machine collaboration in educational contexts. Its core objective is to fully leverage AI technological advantages while maintaining teachers' dominant position in education and teaching. Drawing upon the APCP model's hierarchical thinking, this study divides human-AI collaborative models into three levels - empowerment-oriented, collaborative, and advisor-oriented - corresponding to the needs of teachers at different AI literacy levels. For teachers with lower AI literacy, agents exist as passive tools providing basic efficiency support. For teachers with intermediate literacy, agents participate as proactive partners in instructional work. For teachers with high literacy, agents serve in an advisory capacity. This layered collaborative model ensures teachers' educational subject position while fully leveraging AI's empowerment capabilities [10].

Furthermore, Zhejiang Province's dual-framework systematically articulates localized requirements for teacher AI literacy across three dimensions - AI cognition, AI application, and AI ethics. The AI cognition dimension corresponds to the AI knowledge dimension of the TAICS scale; the AI application dimension encompasses the AI pedagogy and AI assessment dimensions of TAICS; And the AI ethics dimension aligns closely with TAICS's AI ethics and humanistic education dimensions. This structural correspondence ensures that the theoretical model constructed in this study based on the TAICS scale possesses both the scientific rigor of international standardization and full alignment with local policy requirements. It also demonstrates strong local adaptability. This further confirms its practical feasibility.

Construction of the teacher-agent bidirectional tag matching theoretical model

Four guiding principles of model construction and dual-tag system design

The construction of this theoretical model strictly adheres to four core guiding principles, ensuring the model's scientific rigor, adaptability, and practicality. The policy adaptation principle ensures that model design maintains full alignment with the requirements of Zhejiang Province's dual-framework, ensuring research outcomes can directly support local policy implementation. The scale-data-driven principle ensures that all teacher profile tags are generated based on TAICS standardized assessment data, avoiding subjective judgment biases and guaranteeing the objectivity and comparability of the tag system. The stratified diagnosis orientation principle ensures that matching strategies are based on teachers' stratified diagnostic results rather than uniform configuration, fully respecting individual teacher differences and achieving precision empowerment. The closed-loop linkage principle ensures that the model supports the complete closed loop of "diagnosis - matching - empowerment - feedback - iteration". It continuously optimizing matching effectiveness through usage feedback and supporting the dynamic development of teacher AI literacy.

Based on the six-dimensional scores of the TAICS scale, combined with the requirements of Zhejiang Province's dual-framework standards, this study constructs a four-dimensional teacher profile tag system, achieving structured and computable representation of teacher AI literacy characteristics.

The first dimension is the AI Foundational Literacy tag, corresponding to the AI knowledge dimension of the TAICS scale, used to measure teachers' mastery of AI foundational knowledge and technical principles. It is divided into four levels. Introductory level (scores 1-2) focuses on naming common AI educational tools and understanding basic AI concepts and common application scenarios. Comprehension level (scores 2-3) understands basic working principles of AI in education and can distinguish functional characteristics and application scenarios of different AI tool types. Application level (scores 3-4) requires proficiency in AI core concepts and technical logic, and the ability to select appropriate AI tools based on teaching needs. Innovation level (scores 4-5) involves deep understanding of AI technology frontiers and the ability to explore innovative models of AI integration with education and teaching.

The second dimension is the AI Pedagogical Application tag, corresponding to the AI pedagogy and AI assessment dimensions of the TAICS scale, used to measure teachers' ability to apply AI in teaching scenarios. It is divided into four levels. The assistance level is able to use AI tools for simple teaching assistance tasks such as lesson plan generation and exercise creation. The integration level is able to integrate AI tools into multiple aspects of instructional design, optimizing teaching workflows. The fusion level is able to employ AI for learning analytics and personalized tutoring, achieving deep integration of AI with teaching. The innovation level is able to innovate teaching models based on AI technology and develop exemplary AI teaching cases.

The third dimension is the AI Ethics and Norms tag, which corresponds to the ethics and humanistic education dimensions of the TAICS scale and is used to measure teachers' cognition and practice regarding AI ethics. It is divided into four levels. The awareness level understands basic ethical issues and relevant norms in AI educational applications. The judgment level is able to identify ethical risks in teaching-based AI applications and make sound judgments and choices. The guidance level is able to guide students in correctly understanding AI ethics and cultivating students' digital responsibility. The advocacy level is able to participate in school or regional AI ethics norm formulation and serve as an ethical role model among teachers.

The fourth dimension is the human-AI Collaboration Preference tag, derived from the professional development dimension of the TAICS scale, used to describe teachers' personalized preferences for human-AI collaborative models. It includes three sub-dimensions. Type preference (tool-oriented or partner-oriented or advisor-oriented) reflects teachers' preferred role positioning of agents. Frequency preference (low frequency or medium frequency or high frequency) reflects teachers' habitual frequency of AI tool use. Scenario preference (lesson preparation or instruction or assessment or research) reflects teachers' most frequently used work scenarios for AI tools.

Corresponding to the four-dimensional teacher profile tags, this study simultaneously constructs a three-dimensional educational agent functional tag system for standardized description of various educational agents' functional characteristics. This enables unified cataloging and management of agent resources. The first dimension is the Collaborative Capability tag, corresponding one-to-one with the levels of the teacher four-dimensional tags. It is divided into three levels - basic, advanced, and expert - corresponding to the collaborative needs of teachers at different capability levels and describing the depth of support agents can provide. The second dimension is the Scenario Function tag, covering four core scenarios: teaching, research, management, and assessment. Each scenario is further subdivided into specific functional tags. For example, the teaching scenario includes sub-tags such as lesson plan generation, exercise design, and learning analytics. The research scenario includes sub-tags such as literature review, research design, and paper polishing. The third dimension is the interaction preference tag, describing the interaction style and response mode characteristics of agents. These include interaction modality (text interaction or voice interaction or multimodal interaction), response speed (instant response or asynchronous feedback), and operational complexity (simple or medium or complex).

Bidirectional matching underlying algorithm logic

In algorithm selection, this study, after multi-scheme comparative analysis, ultimately excluded collaborative filtering and decision tree algorithms. Collaborative filtering algorithms rely on large volumes of historical interaction data, suffering from severe cold-start problems for new teachers and new agents, failing to meet the system's initial matching requirements. Decision tree algorithms have overly rigid classification boundaries, unable to handle the continuous gradient characteristics of teacher literacy scores, and poorly adapt to the complexity and fuzziness of educational scenarios. Ultimately, this study adopts a hybrid matching strategy of "fuzzy rule-based reasoning + weighted cosine similarity". The former excels at handling expert knowledge with fuzzy boundaries (such as concepts like "what constitutes 'medium' AI teaching capability" that are difficult to precisely define), while the latter offers computational simplicity and strong interpretability in high-dimensional sparse tag spaces. The combination of both balances the need for expert knowledge embedding in educational scenarios with the quantifiable and iterative nature of matching computation.

Fuzzy rule-based reasoning is used to establish foundational matching constraints between teacher profile tags and agent tags, completing preliminary screening of candidate agents. First, the continuous scores of each TAICS dimension are transformed into "low, medium, high" fuzzy sets through triangular membership functions. Then, "IF-THEN" rules from the expert knowledge base generate matching constraints, determining the recommended agent level range and collaboration model. Beyond the foundational Rule R_1: IF TAICS-AK score is "low" AND TAICS-AP score is "low", THEN recommended agent level is "Basic", collaboration model is "Empowerment-oriented". Rule R_2: IF TAICS-AK score is "high" AND TAICS-AP score is "high" AND TAICS-AE score is "high", THEN recommended agent level is "Expert", collaboration model is "Advisor-oriented", typical rules also include the following. Rule R_3: IF TAICS-AK score is "medium" AND TAICS-AP score is "medium" AND TAICS-AE score is "low", THEN recommended agent level is "Advanced", collaboration model is "Collaborative", with priority recommendation for agents featuring built-in ethical guidance functions. Rule R_4: IF human-AI Collaboration Preference is "Tool-oriented" AND Scenario Preference is "Lesson Preparation", THEN prioritize recommendation of focused, simple-to-operate lesson preparation tool agents. Rule R_5: IF teacher teaching experience $\geq$ 20 years AND AI Foundational Literacy is "Introductory Level" THEN downgrade recommended agent level by one level, with priority recommendation for agents featuring user-friendly interfaces and strong guidance capabilities. Through two rounds of Delphi expert consultation, this study established 36 fuzzy matching rules covering different dimensional combinations, constituting a complete expert rule knowledge base.

After fuzzy rule-based reasoning determines the foundational matching scope, weighted cosine similarity is further employed for precise matching computation, achieving ranked recommendation of candidate agents. Specifically, the teacher's four-dimensional profile tag vector $T = (t_1, t_2, t_3, t_4)$ is defined, where t_1 through t_4 correspond to the quantified scores of AI Foundational Literacy, AI Pedagogical Application, AI Ethics and Norms, and human-AI Collaboration Preference, respectively. The agent's three-dimensional functional tag vector $A = (a_1, a_2, a_3)$ is similarly defined, where a_1 through a_3 correspond to the quantified scores of

Collaborative Capability, Scenario Function, and Interaction Preference, respectively. These two vectors are then mapped to the same feature space. A weight vector W = (w_1, w_2, w_3, w_4) is introduced to measure the importance of different dimensions. The formula for weighted cosine similarity is:

$$Sim(T, A) = \frac{\sum w_i \cdot t_i \cdot a_i}{\sqrt{\sum w_i \cdot t_i^2} \cdot \sqrt{\sum w_i \cdot a_i^2}} \quad (i = 1,2,3,4) \quad (1)$$

The initial weight values are determined through by expert consultation, with the following specific default weights set as: AI Foundational Literacy 0.25, AI Pedagogical Application 0.35, AI Ethics and Norms 0.20, and human-AI Collaboration Preference 0.20. Subsequently, these weights are dynamically adjusted through ongoing teacher usage data feedback iteration, which continuously improving matching precision over time. The final computed similarity scores range between 0.00 and 1.00, with higher scores indicating better teacher-agent fit.

To accommodate the differentiated needs of teachers across different work scenarios, this study specifically designs a scenario-based dynamic weight adjustment mechanism. Teachers' functional requirements for agents differ significantly across different teaching scenarios, necessitating dynamic adjustment of dimensional weights based on the current scenario. When teachers are in lesson preparation scenarios, the AI Pedagogical Application tag weight increases to 0.40, and AI Foundational Literacy tag decreases to 0.15. When in instruction scenarios, the AI Pedagogical Application tag weight is 0.35, and Interaction Preference tag weight increases to 0.30, placing greater emphasis on agents' classroom interaction adaptability. When in research scenarios, the human-AI Collaboration Preference tag weight increases to 0.35, and AI Ethics and Norms tag weight increases to 0.35, emphasizing agents' deep collaboration capabilities. When in management scenarios, the AI Foundational Literacy tag weight adjusts to 0.20, and Scenario Function tag weight increases to 0.40, prioritizing management-oriented functions. The specific magnitude of scenario-based weight adjustments is determined jointly by teachers' historical behavioral data and scenario feature parameters, supporting personalized weight customization.

To more intuitively illustrate the matching computation process, take a junior high school Chinese language teacher as an example. The teacher's four-dimensional tag quantified scores are T = (2.50, 3.20, 2.80, 3.00), currently in a lesson preparation scenario, with scenario-adjusted weight vector W = (0.15, 0.40, 0.20, 0.25). Candidate agent A's three-dimensional tag quantified scores are A = (2.80, 3.50, 2.90). Substituting into the formula yields a weighted cosine similarity of approximately 0.92, indicating high fit, qualifying as a priority recommendation.

Overall theoretical model framework and operational logic

Integrating the above dual-tag system design and matching algorithm design, the overall framework of this theoretical model can be summarized as the complete closed loop. The loop consists of five stages: "TAICS diagnostic input - four-dimensional profile generation - bidirectional matching computation - agent collaborative output - data feedback iteration". These five links are interconnected, forming a self-optimizing dynamic system.

Step 1: TAICS diagnostic input

Teachers complete the standardized TAICS scale assessment, and the system obtains standardized scores across the six dimensions of AI knowledge, AI pedagogy, AI assessment, AI ethics, humanistic education, and professional development. Simultaneously, the system collects teachers' basic attribute information such as educational stage, subject, teaching experience, and school type as foundational data for profile generation.

Step 2: Four-dimensional profile generation

The system automatically transforms the six-dimensional TAICS scores into the four-dimensional teacher profile tags according to preset mapping rules. Combined with teachers' basic attributes and historical behavioral data, the system completes the human-AI Collaboration Preference tags, generating a complete teacher digital profile.

Step 3: Bidirectional matching computation

The system first invokes the fuzzy rule-based reasoning engine to generate foundational matching constraints based on teacher profile tags, screening the range of candidate agents meeting the criteria. Then, based on the current work scenario, dimensional weights are dynamically adjusted, and weighted cosine similarity is used to compute the fit score between the teacher and each candidate agent. Finally, the system generates an agent recommendation list ranked from highest to lowest score.

Step 4: Agent collaborative output

Based on the matching results, the system retrieves corresponding functional modules from the agent resource pool, combining them into a personalized teacher agent workbench. The system deploys the corresponding collaboration model (empowerment-oriented, collaborative and advisor-oriented) based on the teacher's AI literacy level, supporting teachers in conducting human-AI collaborative practice across various work scenarios.

Step 5: Data feedback iteration

The system automatically records teachers' agent usage behavioral data, including key feature usage frequency, duration of use, satisfaction ratings, task completion effectiveness. These data flow back to the iteration optimization module. On the one hand, it updates matching weight vectors through incremental learning. On the other hand, it updates profile tag levels based on phased changes in teacher capabilities, thereby achieving continuous optimization of matching precision and empowerment effectiveness.

Full-scenario human-AI collaborative multi-agent system design

Overall system design objectives and five-layer architecture

This system is driven by TAICS standardized diagnostic data as its core. Its primary objectives of achieving differentiated and precise teacher-agent matching. This matching covers the full spectrum of work scenarios - teaching, research, management, and assessment. It also aims to construct a lightweight, extensible, iterative, and education-equity-conscious human-AI collaborative empowerment system. The system design strictly adheres to software engineering principles of modularity, extensibility, and low coupling, employing a layered architecture comprising five layers.

The Perception Layer serves as the system's data entry and preprocessing module, responsible for comprehensively collecting teachers' multidimensional feature data to provide a high-quality data foundation for subsequent profile generation and matching computation. The perception layer comprises three core sub-modules: the scale assessment module, the basic information input module, and the behavioral data collection module. The scale assessment module provides standardized TAICS online assessment functionality with automatic scoring and preliminary data cleaning. The basic information input module collects teachers' basic attributes (educational stage, subject, teaching experience, school type, geographic location). The Behavioral Data Collection Module automatically records teachers' daily interaction behavioral data through tracking technology, including agent usage frequency, functional preferences, operational pathways, and task completion status, and preprocesses them in standardized formats to generate dynamic feature data.

The matching layer is the core intelligent module of the system, serving as the critical hub connecting teacher profiles and agent resources, equipped with the "fuzzy rule-based reasoning + weighted cosine similarity" hybrid matching algorithm. The matching layer comprises four functional sub-modules: The tag generation module, which receives teacher feature data output from the perception layer and automatically generates four-dimensional teacher profile tags according to preset mapping rules. The fuzzy reasoning module, which invokes the expert rule knowledge base to generate foundational matching constraints and screen candidate agents. The similarity computation module invokes the agent tag library, dynamically adjusts dimensional weights based on the current scenario, and computes the fit score between the teacher and each candidate agent. The scenario weight adjustment module identifies the teacher's current work scenario through scenario recognition technology, automatically adjusts matching weights, and generates the final agent recommendation plan. The matching layer's algorithms support hot updates, enabling iterative optimization of matching rules and weight parameters without affecting system operation.

The empowerment layer serves as the system's resource scheduling center and agent resource pool. It deploys a lightweight intelligent function resource library categorized by educational stage (primary or junior high or senior high or higher education) and AI literacy level (basic or advanced or expert), with each agent functional unit tagged with standardized three-dimensional function tags. The empowerment layer comprises three core sub-modules. The first is the agent resource library, which stores reusable agent functional modules with support for rapid tag-based retrieval. The second is the tag management module, responsible for agent tag review, updating, and maintenance. It employs a dual-track mechanism of “developer self-tagging + expert committee review”. Under this mechanism, new agents must undergo consistency testing of their three-dimensional tags by at least three domain experts (Kappa ≥ 0.80) before going live, ensuring tag system reliability and sustainability. The third is the function composition engine. Based on recommendation plans received from the matching layer, it retrieves corresponding agent functional modules from the resource pool. It then generates personalized teacher agent workbenches through modular composition.

The collaboration layer is the interface layer for direct teacher-agent interaction and the core execution layer of human-AI collaboration, implementing differentiated deployment of three human-AI collaboration models. For “basic-level” teachers, the default is the “empowerment-oriented” model, where agents exist as tools providing clear efficiency support, with all decisions teacher-led, and detailed operational guidance and help are provided. For “advanced-level” teachers, the “collaborative” model is adopted, where agents participate proactively as partners in instructional design and other work, offering suggestions and alternatives, with joint teacher-agent decision-making. For “expert-level” teachers, the “advisor-oriented” model is adopted, where agents provide high-level data analytics, frontier research syntheses, and strategic recommendations. Teachers retain final decision-making authority while agents serve as professional advisors.

The iteration layer is the system’s learning and optimization engine, responsible for achieving self-evolution and continuous improvement, serving as the core of the closed-loop operational mechanism. The iteration layer comprises three core sub-modules: the behavior analysis module, the weight update module, and the tag iteration module. The behavior analysis module collects all usage behavioral data generated by the collaboration layer, including teacher acceptance rates, duration of use, feature usage rates, satisfaction ratings, and task completion effectiveness, performing statistical analysis and feature extraction. The weight update module employs incremental learning mechanisms to periodically run model updates, automatically adjusting matching weight vectors based on teacher feedback data to optimize algorithm accuracy. The tag iteration module dynamically updates the level attribution of teacher profile tags based on phased AI literacy assessment results and behavioral data changes, ensuring profiles always reflect teachers’ true capability levels. This self-iteration mechanism ensures that matching precision and empowerment effectiveness continuously improve with usage time, forming a virtuous cycle of “the more it’s used, the more accurate and better adapted it becomes”.

“Matching - scheduling - collaboration” three-level operational process and full-cycle closed-loop mechanism

The operational flow of the system can be described as the “matching - scheduling - collaboration” three-tier linkage mechanism, wherein the three tiers proceed sequentially and reinforce each other, collectively enabling precise teacher-agent collaboration.

The matching process is the system’s first-level process, with the core task of completing teacher-agent fit computation. The Matching Process comprises five specific steps:

Step 1: Data import - TAICS scale assessment data and teacher basic information are imported through the perception layer, undergoing data cleaning and standardization processing.

Step 2: Profile generation - the matching layer’s tag generation module generates the four-dimensional teacher profile tags based on assessment data, constructing the teacher feature vector.

Step 3: Rule screening - the fuzzy reasoning module generates matching constraints based on the expert rule knowledge base, screening candidate agents from the agent resource pool that meet the teacher’s capability level and basic requirements.

Step 4: Similarity computation - dimensional weights are adjusted based on the teacher’s current scenario, computing the weighted cosine similarity between the teacher and each candidate agent, generating a similarity-ranked list.

Step 5: Solution output - a matching plan containing Top-5 recommended agents is generated, accompanied by similarity scores and recommendation justifications.

The scheduling process comprises three core links: scenario identification, weight adjustment, and function assembly. Scenario identification automatically identifies the current work scenario through the functional module being operated, temporal features, and behavioral patterns, also supporting manual mode switching by teachers. Weight adjustment dynamically adjusts matching weights based on the identified scenario, re-ranks recommendation lists, and screens the agent combination best adapted to the current scenario. Function assembly retrieves corresponding agent modules from the resource pool, assembles them modularly according to teachers' usage habits, generates a personalized workbench, and completes interface adaptation and permission configuration, enabling immediate use by teachers. The scheduling process supports millisecond-level response, enabling seamless agent switching between different scenarios.

The collaboration process operates according to the logic of "model matching - task division - collaborative execution - result output". First, the corresponding collaboration model is determined based on the teacher's AI literacy level, clarifying human-AI rights and responsibilities boundaries. Then, human-machine division of labor is carried out according to specific tasks, with agents undertaking repetitive, data-intensive work and teachers undertaking creative, value-judgment work. Then, human-machine collaboration executes the task process, with agents providing real-time support and feedback while teachers control direction and quality. Finally, teachers confirm and output the final results.

This system constructs the complete full-cycle closed-loop mechanism of "TAICS standardized assessment → teacher profile tag generation → bidirectional agent matching → full-scenario human-AI collaborative application → behavioral data feedback → profile tag iterative updating". This achieves a virtuous cycle of teacher AI literacy improvement. The core value of this closed-loop mechanism is reflected in three aspects. First, it opens the complete link from diagnosis to empowerment, ensuring that assessment results are directly transformed into personalized empowerment solutions, fundamentally breaking the previous pattern of disconnection between the two. Second, through data-driven dynamic iteration, it achieves continuous optimization of matching precision, avoiding the solidification problems of traditional static recommendation systems. This enables the system to continuously self-adapt as teacher capabilities improve and needs change. Third, it establishes a complete evidence chain for teacher AI literacy improvement. Each iteration produces trackable and assessable developmental data that accurately reflects each teacher's growth trajectory. These data also provide support and decision-making evidence for regional education management authorities in conducting teacher development planning and evaluating policy effectiveness.

Prospects for theoretical validation pathways

This study has currently completed the construction of a complete theoretical system. Subsequent systematic empirical research is needed to test the effectiveness, practical adaptability, and promotion value of the theoretical model. The future path of theoretical validation can focus on four groups of core research hypotheses.

H_1 (theoretical adaptation hypothesis): The six-dimensional scores of the TAICS scale exhibit the presupposed structural relationship with the four-dimensional profile tags constructed in this study. The overall fit of the structural equation model reaches acceptable standards ($CFI \geq 0.90$, $RMSEA \leq 0.08$). This indicates that the four-dimensional tag system possesses good construct validity and can effectively reflect teachers' AI literacy characteristics.

H_2 (matching efficacy hypothesis): The teacher-perceived subjective fit of bidirectional matching recommendations based on the dual-tag system is significantly higher than random recommendation baselines and traditional unified recommendation models ($p<0.05$). It also performs better on objective indicators such as agent acceptance rate, usage frequency, and task completion efficiency.

H_3 (collaboration gain hypothesis): The differentiated human-AI collaboration schemes designed based on this theory are significantly superior to traditional unified agent configuration schemes in reducing teacher technology anxiety and enhancing teaching efficacy.

H_4 (disadvantage compensation hypothesis): Among disadvantaged groups such as rural teachers and middle-aged or elderly teachers, the magnitude of AI literacy improvement and teaching efficacy gains under this study's differentiated collaboration model is apparent. It is no less than that of urban and younger teacher groups. It may even exhibit higher gain effects. This indicates that this theoretical model can effectively narrow the digital divide among teacher groups and possesses good educational equity value.

The above hypotheses recommend a quasi-experimental design with one complete semester as the research cycle for cross-validation. Specific research design recommendations are as follows. Participants: stratified cluster sampling of teachers from different regions of Zhejiang Province, randomly assigned to experimental and control groups. Experimental group adopts this study's theoretical solution, completing TAICS assessment to obtain personalized profiles and matched agents; control group adopts traditional unified agent configuration. Measurement instruments: TAICS scale, teacher technology anxiety scale, teaching efficacy scale, self-developed agent fit scale, and system logs. Analysis methods: structural equation modeling for H_1, independent and paired samples t-tests for H_2 and H_3, hierarchical linear modeling for H_4.

The observation indicator system for theoretical effectiveness is divided into four categories: theoretical adaptation indicators, matching effectiveness indicators, collaboration value indicators, and developmental indicators. Theoretical adaptation indicators include structural equation model fit indices and tag system reliability coefficients. Matching effectiveness indicators include agent recommendation fit, scenario usage coverage, acceptance rate, and average duration of use. Collaboration value indicators include teacher workload reduction, teaching efficiency improvement, technology anxiety reduction, and disadvantaged group adaptation friendliness. Developmental indicators include the longitudinal trajectory of TAICS scores and promotion ratios of teachers at different levels.

Future research can be advanced in phases. In the short term (3-6 months), small-scale pilot studies will be conducted with 30-50 teachers for trial application, focusing on optimizing the tag transformation rules and initial weight parameters of the matching algorithm, and improving the system's interactive experience. In the medium term (1-2 years), the research will expand to include tag systems for specialized educational scenarios such as moral education and mental health. Large-sample quasi-experimental studies will be conducted to comprehensively test the actual effects and mechanisms of the theoretical model. In the long term (3-5 years), the research will be extended to different provinces across eastern, central, and western China to validate the model's cross-regional applicability and cultural adaptability. It will explore the moderating effects of macro-level and micro-level factors. These factors include economic development level, degree of educational digitalization, and school support climate.

Theoretical innovations and academic discussion

Core innovation points

This study achieves multidimensional theoretical innovations in the fields of teacher AI literacy and human-AI collaborative education, with core innovations reflected in four aspects.

First, in theoretical framework innovation, this study constructs a completely new integrated theoretical framework of "international TAICS scale - local teacher tags - agent bidirectional matching". This framework fundamentally breaks the long-standing theoretical disconnection between teacher AI literacy assessment and agent empowerment. It incorporates two previously independent research fields into a unified "diagnosis - matching - empowerment - iteration" theoretical closed loop. This forms a complete logical chain and providing a systematic new theoretical paradigm for human-AI collaborative education research.

Second, in instrument adaptation innovation, this study completes the design of standardized transformation logic from the six-dimensional TAICS scale to localized four-dimensional teacher profile tags. While preserving the international standardization advantages and psychometric properties of TAICS, the study uses tag mapping and level classification. This achieves seamless integration with Zhejiang Province's dual-framework policy requirements. It realizes the organic fusion of international standards and local policies. This fills the domestic academic gap in standardized scale-linked agent empowerment and provides a new approach for the localized application of international assessment instruments.

Third, in system architecture innovation, the five-layer layered multi-agent collaborative architecture proposed here innovatively establishes the “matching layer” as an independent core functional layer with dedicated algorithm design. This achieves precise articulation between diagnostic data and agent recommendations. The problem of “heavy application, light matching” in traditional systems is solved. Meanwhile, the independent establishment of the Iteration Layer endows the system with self-learning and continuous optimization capabilities. This enables dynamic iteration through data feedback, avoiding the “rigidification” problems of traditional static matching systems.

Fourth, in practice paradigm innovation, the layered differentiated human-AI collaborative closed-loop operational paradigm divides collaboration models into three levels based on teacher AI literacy levels: empowerment- oriented, collaborative, and advisor-oriented. This matches different human-AI rights-responsibilities division and interaction modes. It effectively solves the crude problem of “one model fits all teachers”. Furthermore, the paradigm design fully considers the needs of disadvantaged teacher groups such as rural and middle-aged or elderly teachers. It achieves digital inclusion through stratified empowerment. It balances both educational efficiency and educational equity objectives.

Comparative discussion with existing research

Compared with existing teacher AI literacy framework research (such as AICFT, AIPACK), these studies primarily focus on descriptive analysis of “what competencies teachers should possess”, addressing the “what” question. They have relatively less involvement in operational design of “how to achieve precise empowerment based on diagnostic results”. Building upon this, the present study not only provides competency description standards but also opens the complete “diagnosis - matching - empowerment - iteration” pathway. It designs operational transformation pathways from competency diagnosis to agent recommendation, achieving the extension from “descriptive framework” to “operational framework”.

Compared with non-data-driven agent application research, existing educational agents predominantly adopt a “preset functions - unified configuration” model, with functional design based primarily on developer experience rather than actual teacher literacy data. This study takes the TAICS standardized scale as the quantitative data foundation, with all profile tags and matching recommendations driven by standardized assessment data, effectively avoiding the biases of subjective experience-based matching. Simultaneously, it extends the application scenarios of adaptive learning theory from traditional “student-learning content” matching to the new domain of “teacher-agent” matching, expanding the application boundaries of adaptive learning theory.

Compared with single-scenario human-AI collaboration research, existing studies predominantly focus on single teaching scenarios such as lesson preparation and homework grading, lacking systematic coverage of teachers’ full work scenarios, and most are static designs. This study expands collaborative application scenarios to three domains - teaching, research, and management. It achieves adaptive switching of agent recommendations between different scenarios through scenario-based dynamic weight adjustment mechanisms. It also ensures continuous optimization of collaborative effectiveness through closed-loop iteration mechanisms, overcoming the static limitations of single-scenario research.

From the educational equity perspective, existing agent application research predominantly adopts unified design approaches, which tend to exacerbate the digital divide. Teachers with higher digital literacy can leverage agents to improve efficiency, while disadvantaged teacher groups with lower literacy may find it difficult to benefit. This study’s stratified collaboration model and disadvantaged-adapted design optimize agent functions and interaction modes for groups such as rural and middle-aged or elderly teachers. This helps disadvantaged groups achieve “digital catch-up” through differentiated empowerment, testing the possibility of technology-enabled educational equity. This is an important dimension overlooked in existing research.

Conclusion

This study, focusing on the core proposition of “teacher-agent bidirectional matching and human-AI collaborative empowerment", has completed systematic theoretical construction, achieving research outcomes across multiple dimensions.

At the theoretical level, this study demonstrates the high structural compatibility between the TAICS scale and Zhejiang Province's dual-framework for teacher AI literacy. It confirms its viability as a standardized data source for localized teacher AI literacy profiles. This provides theoretical justification for the localized application of international assessment instruments. Simultaneously, it integrates constructivist learning theory, adaptive learning system theory, tag-based matching theory, and human-AI collaborative education theory, constructing a multidisciplinary intersectional theoretical foundation system.

At the model level, this study constructs a "four-dimensional profile tags - three-dimensional function tags" dual-tag bidirectional matching theoretical model, achieving standardized and structured representation of teacher characteristics and agent functionalities. It designs a "fuzzy rule-based reasoning + weighted cosine similarity" hybrid matching algorithm, balancing the advantages of expert experience and quantitative computation. Additionally, it innovatively designs a scenario-based dynamic weight adjustment mechanism capable of adapting to differentiated requirements across different work scenarios.

At the system level, this study builds a comprehensive five-layer layered multi-agent collaborative architecture of perception layer, matching layer, empowerment layer, collaboration layer, and iteration layer, clearly defining each layer's functional modules and specific operational logic. It designs the "matching - scheduling - collaboration" three-level operational process, achieving precise teacher-agent alignment and efficient collaboration.

At the mechanism level, this study establishes the full-cycle closed-loop human-AI collaborative theoretical paradigm of "diagnosis - matching - scheduling - collaboration - iteration". This paradigm creates an effective virtuous cycle mechanism for teacher AI literacy improvement. It also offers clear systematic theoretical guidance and valuable practical frameworks for precision intelligent empowerment of regional teachers.

Research limitations

This study has three limitations. First, only pure theoretical system construction has been completed, with large-scale empirical validation yet to be conducted, and the actual effectiveness of the theoretical model remains to be tested. Second, the tag transformation rules are currently based only on the foundational six dimensions of TAICS, without yet extending to specialized educational areas such as moral education and mental health, with scenario coverage still requiring enrichment. Third, the matching algorithm has only completed theoretical logic design and initial parameter setting, lacking large-scale real user data for parameter tuning and efficacy testing, with room for further algorithm precision improvement.

Future research prospects

In the future, this study will continue to advance along the clear pathway of short-term optimization, medium-term validation, and long-term extension. In the short term, small-scale pilot studies will be thoroughly conducted to optimize tag transformation rules and matching algorithm parameters, improving system design. In the medium term, large-sample quasi-experimental studies will be conducted to comprehensively test the effectiveness and practical value of the theoretical model, while expanding the tag system for more educational scenarios. In the long term, the research will be extended to different regions across China to validate the model's cross-regional applicability. This will ultimately form a nationally applicable, internationally authoritative scale-based human-AI collaborative matching theoretical paradigm. It will provide theoretical support and practical solutions for China's teacher AI literacy improvement and educational digital transformation.

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Conflicts of Interest

The authors declare no conflict of interest.

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