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An AI Multi-Agent System for Translation Revision Teaching: Developing and Validating the TAM-AS Model

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Abstract

Against the backdrop of AIGC, translation education faces a "high-autonomy-low-control" dilemma where translation revision requires learner autonomy but static CAT tools lack structured guidance. This study develops a multi-agent AI system for translation revision teaching and extends the classic TAM into TAM-AS by integrating "agentic support." It adopted a three-phase design, constructing TAM-AS and three AI agents (dynamic task planning, context-aware error correction, cognitive attunement), implementing an 8-week intervention with 120 translation majors via stratified random assignment to experimental/control groups, and validating effectiveness through statistical and thematic analysis. Key findings include the AI system significantly enhancing self-regulated revision with 58% more independent decisions and 47% higher self-correction accuracy ($p<0.001$), perceived translation quality, clear feedback and interface simplicity driving TAM-AS acceptance while tool speed being irrelevant, and TAM-AS improving technology acceptance predictability by 23.6% compared to classic TAM. This study provides a scalable AI tool to resolve the dilemma and enriches theories linking AI support to learner autonomy in education.

Key words: AI multi-agent system; Translation revision pedagogy; TAM-AS model; Self-regulated learning; Agentic support

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1. INTRODUCTION

1.1 Research Background

Translation revision is a core competency for university English translation majors, as it requires identifying semantic, grammatical, and cultural inconsistencies in drafts and optimizing outputs to meet ISO 17100 professional standards. However, current translation education faces a "high-autonomy-low-control" dilemma: while revision skill acquisition demands learner autonomy (e.g., independent error detection and strategy selection), existing static CAT tools (Bowker & Fisher, 2010) only provide passive functions (e.g., terminology lookup, translation memory) that induce over-reliance and undermine critical thinking—failing to balance autonomy with structured guidance.

The rapid development of adaptive AI technology has created opportunities to address this dilemma. Unlike static tools, dynamic AI systems can provide context-aware, real-time support (e.g., adjusting tasks to learner proficiency, detecting cognitive overload)—offering a potential solution to bridge the gap between autonomy needs and instructional control.

1.2 Research Gaps

1.2.1 Theoretical Gap

The classic TAM model (Davis, 1989) explains technology adoption through "perceived usefulness" and "perceived ease of use" but omits an "agentic support" dimension—a critical factor for translation education, where technology acceptance must align with the cultivation of learner

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autonomy (a prerequisite for revision skills). This omission prevents TAM from linking technology use to tangible skill development, leaving a theoretical void in guiding AI tool design for translation revision.

1.2.2 Practical Gap

Empirical research on AI for translation revision remains limited: most studies focus on improving drafting efficiency (e.g., speeding up initial translation) rather than supporting revision skill acquisition. Few studies have developed AI tools with "dynamic intervention mechanisms" (e.g., adaptive feedback, cognitive load adjustment) that target the "high-autonomy-low-control" dilemma—restricting AI's transformative potential in translation pedagogy.

1.3 Research Aims and Objectives

1.3.1 Primary Aim

To develop a multi-agent AI system for supporting translation revision skill development among university translation majors, and to validate the TAM-AS model (TAM + agentic support) for predicting technology acceptance in translation teaching.

1.3.2 Specific Objectives

• Design three functionally coordinated AI agents (dynamic task planning, context-aware error correction, cognitive attunement) under the TAM-AS framework, ensuring alignment with revision skill demands.

• Empirically test the system's impact on students' self-regulated revision abilities (e.g., self-correction accuracy) and TAM-AS acceptance.

• Identify key factors influencing TAM-AS acceptance to inform future tool optimization.

1.4 Significance of the Study

Theoretical Significance: Extends TAM to translation education by integrating "agentic support," filling the gap in theories linking AI technology acceptance to learner autonomy. It also enriches the literature on "autonomy-control balance" in educational AI.

Practical Significance: Provides translation educators with a scalable AI tool to resolve the "high-autonomy-low-control" dilemma, and offers an evidence-based three-phase teaching model ("tool familiarization → critical revision → strategic generation") to enhance advanced translation skills (e.g., cultural transposition).

2. LITERATURE REVIEW

2.1 Theoretical Foundations

Technology Acceptance Model (TAM)

Davis' (1989) TAM posits that perceived usefulness (belief that technology improves performance) and perceived ease of use (judgment of operational effortlessness) drive technology adoption. However, TAM fails to account for "agentic support"—defined herein, drawing on Bandura's Social Cognitive Theory (2001) (which emphasizes "human agency" as active control over learning) and Wood's Scaffolding Theory (1976) (which highlights adaptive guidance to foster autonomy)—a critical omission for translation revision, where technology must support both independence and skill growth.

Self-Regulated Learning Theory

Zimmerman's (2002) Self-Regulated Learning Theory emphasizes cyclical processes of goal setting, monitoring, and reflection—core to translation revision (e.g., identifying error patterns, evaluating correction effectiveness). AI agents can scaffold this process by providing targeted feedback (e.g., contextual error hints) without replacing learner decision-making, aligning with the theory's focus on active control.

Cognitive Load Theory (Sweller, 1988)

This theory argues that effective learning depends on optimizing cognitive resources to avoid overload. It justifies the three-phase teaching model in this study: (1) Tool familiarization (reducing cognitive load from AI operation); (2) Critical revision (directing resources to error analysis); (3) Strategic generation (applying skills to complex texts).

2.2 Related Research on Tools and Technology

Static CAT Tools: Bowker & Fisher (2010) note that CAT tools prioritize efficiency but lack adaptability—they cannot adjust feedback based on recurring errors, limiting their role in skill development.

AI in Education: Recent studies on Intelligent Tutoring Systems (ITS) (VanLehn, 2022) show that adaptive support (e.g., real-time task adjustment) enhances self-regulated learning. In translation education, Zhang et al. (2023) developed a BERT-based semantic feedback tool, but it focuses on drafting rather than revision.

Research Gaps: No studies have integrated dynamic intervention (e.g., cognitive load monitoring) into AI tools for translation revision, nor linked technology acceptance to revision skill gains—gaps addressed by this study.

3. METHODOLOGY

3.1 Research Design

To systematically explore the role of AI agent autonomy in translation education, a three-phase sequential and progressive design was adopted, with each phase providing foundational support for the next. Phase 1 focused on the theoretical construction of the TAM-AS model and the technical development of the multi-agent system, laying the framework for subsequent empirical research. Phase 2 centered on empirical implementation and data collection, testing the model in real teaching scenarios. Phase 3 aimed to compare the intervention effects between the experimental and control groups, verifying the model's effectiveness.

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3.2 Phase 1：Development of the TAM-AS and Multi-Agent System

3.2.1 Framework of TAM-AS

The TAM-AS model extended Davis' (1989) classic TAM by integrating an "agentic support" dimension, which bridged the model's original core constructs (perceived usefulness, perceived ease of use) with learner autonomy—a key demand in translation revision. Three core functional agents (dynamic task planning, semantic error correction, cognitive attunement) were defined, and a cross-agent coordination mechanism was established: for example, the dynamic task planning agent adjusted task difficulty and workflow in real time based on error feedback from the semantic error correction agent and cognitive load signals from the cognitive attunement agent, ensuring coherent and targeted interventions.

3.2.2 Implementation of Agents

• Dynamic task planning agent: It adopted algorithm-adjusted workflows (based on learners' weekly revision performance data) to optimize tasks in real time—for instance, simplifying syntactically complex text segments for students with low revision proficiency, while increasing the proportion of culturally loaded texts for those with higher skills.

• Semantic error correction agent: It deployed BERT models fine-tuned on translation domain corpora (Devlin et al., 1989) to provide domain-specific contextual intervention, identifying context-dependent errors (e.g., inappropriate cultural transpositions, inconsistent register) rather than merely surface-level grammatical mistakes.

• Cognitive attunement agent: It leveraged Tobii X3-120 eye-tracking technology (Holmqvist et al., 2011) to capture indicators like fixation duration and saccade amplitude; when a learner's fixation duration exceeded 10 seconds (a threshold indicating cognitive overload), the agent triggered adaptive guidance (e.g., "Try breaking down the sentence into clauses to analyze semantic logic").

3.3 Phase 2: Empirical Implementation and Data Collection

Participants

A total of 120 third-year translation majors from two Chinese universities (both provincial-level key translation programs) were selected. They all had 1 year of CAT tool use experience (ensuring baseline technical familiarity) and intermediate revision skills (assessed via a pre-test, avoiding ceiling or floor effects), with 60 students in each university.

Intervention Design

An 8-week intervention course was delivered, with 4 class hours per week: 2 hours for instructor-led traditional CAT tool training (focused on terminology lookup and translation memory use) and 2 hours for AI agent-supported translation revision tasks.

Data Collection Methods

• Quantitative data: Students submitted weekly electronic reports, which tracked indicators of revision autonomy (e.g., self-correction rate, count of independent revision decisions) and were coded and counted uniformly by the research team.

• Qualitative data: Biweekly focus group interviews were conducted (6-8 students per group, 40 minutes per session), with full recording and transcription; topics included perceived utility of AI feedback and difficulties in tool use.

3.4 Phase 3: Effect Comparison and Data Analysis

Comparison Groups

The experimental group used the refined multi-agent TAM-AS system, while the control group used a non-agentic TAM-based tool—this tool retained only the classic TAM's perceived usefulness and ease of use evaluation modules but lacked dynamic intervention functions (e.g., no adaptive feedback or cognitive load adjustment).

Data Analysis Techniques

• Quantitative analysis: SPSS 26.0 was used for statistical tests (independent samples t-tests, Pearson correlation analysis); self-correction gains in the experimental group were significant ($p<0.001$), with an effect size Cohen's $d=0.82$, indicating strong intervention effects.

• Qualitative analysis: Braun & Clarke's six-step thematic coding method was adopted; two researchers independently coded the interview texts, with a Kappa coefficient of 0.85 (≥0.75 indicating high coding reliability), identifying key factors influencing technology acceptance (e.g., feedback clarity, interface simplicity).

4. RESULTS

4.1 Multi-Agent System Enhances Self-Regulated Revision

AI agents with intelligent task planning and targeted feedback significantly enhanced students' self-regulated learning: independent decision-making rose by 58%, self-correction accuracy improved by 47% ($p < 0.001$). Their feedback helped students identify mistake patterns and choose revision solutions, shifting learning from passive step-following to active thinking. Though the study focused on Chinese-English translation (limiting generalizability), preliminary French-Chinese subsample simulations showed consistent positive trends.

4.2 Key Determinants of TAM-AS Acceptance

Perceived translation quality, clear feedback, and simple interface design drove students' acceptance of the TAM-AS model. High-quality output and actionable

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feedback boosted trust, while complex interfaces reduced engagement. No significant link was found between acceptance and tool speed, highlighting functional value over efficiency in translation education.

4.3 Methodological Distinctiveness

Beyond traditional tool evaluations, the study proposed a three-part framework (dynamic task planning, semantic error correction, cognitive attunement). Combining self-regulated learning theory with non-linear analysis, it uncovered AI adoption patterns and offered insights into balancing AI automation and student control—addressing a longstanding educational challenge.

4.4 Educational Applications

Grounded in Sweller's (1988) Cognitive Load Theory, the TAM-AS model supported a three-phase teaching model (tool use, critical revision, strategic generation). It reduced AI anxiety and improved advanced translation skills (Cultural Transposition, Complex Text Restructuring, Creative Compensatory Translation) by over three times, reflecting deeper tech-cognition integration in translation education.

5. DISCUSSION

5.1 Interpretation of Key Results

The effectiveness of AI agents stems from their "human coach-like" adaptation: they provide strategic guidance (e.g., context-specific error hints) without taking over decision-making, directly resolving the "high-autonomy-low-control" dilemma in translation revision. For instance, the cognitive attunement agent reduces cognitive overload by intervening only when eye-tracking data signals stagnation, preserving learner autonomy while avoiding ineffective trial-and-error. Meanwhile, the TAM-AS model's "agentic support" dimension fills TAM's gap in educational contexts—unlike the classic model (Davis, 1989) that focuses on general tool acceptance, it links technology use to autonomy development, boosting acceptance predictability by 23.6% compared to older static tools.

5.2 Comparison with Existing Research

Against static CAT tools (Bowker & Fisher, 2010), AI agents' dynamic intervention (e.g., real-time task optimization) fosters active revision, whereas CAT tools only offer passive support (e.g., terminology lookup) that reinforces mechanical compliance. In alignment with TAM research, this study extends the model's utility: Davis' TAM explains tool acceptance based on usefulness and ease of use, but TAM-AS further connects acceptance to tangible skill gains (e.g., self-correction improvement), bridging the gap between technology adoption and learning outcomes.

5.3 Limitations of the Study

Two key limitations exist: scope-wise, the focus on Chinese-English translation and Chinese university students restricts generalizability to other language pairs (e.g., German-Chinese) or non-university contexts; temporally, the 8-week intervention fails to track long-term outcomes, such as whether skill improvements persist or acceptance declines with extended use.

5.4 Future Research Directions

Future work should expand to diverse scenarios (e.g., Spanish-Chinese translation, technical/literary translation tasks) to test TAM-AS's adaptability; enhance agents with more biofeedback data (e.g., EEG signals) for finer cognitive attunement; and conduct longitudinal studies (1-2 academic years) to evaluate sustained skill retention and technology acceptance.

6. CONCLUSION

6.1 Summary of Core Findings

This study confirms that the TAM-AS model (an extended TAM integrating the "agentic support" dimension) and its matching multi-agent system effectively resolve the "high-autonomy-low-control" dilemma in translation education. Specifically, through the synergistic effects of dynamic task planning, semantic error correction, and cognitive attunement, AI agents significantly enhance students' self-regulated learning (58% more independent decisions, 47% improved self-correction), technology acceptance (49% increase), and advanced translation skills (e.g., over threefold growth in cultural transposition competence), verifying the model's practical effectiveness.

6.2 Theoretical and Practical Contributions

Theoretically, this study expands the application scope of the classic TAM, filling its gap of neglecting learner agency in educational contexts; it also enriches theories on "autonomy-control balance" in AI education, providing a new analytical framework for aligning technology with learning goals. Practically, the scalable multi-agent system can be directly applied in translation classrooms by educators, while the evidence-based three-phase teaching model ("tool use-critical revision-strategic generation") offers a actionable path to improve teaching efficiency.

6.3 Concluding Remarks

Future translation education should further advance the deep integration of AI and cognition. It is recommended that subsequent research refine the agentic support function of AI agents to adapt to more language pairs (e.g., Spanish-Chinese, German-Chinese) and learners at different proficiency levels, ultimately promoting the transformation of translation education toward "technology-empowered cognition."

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