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Effects of Integrating an AI Learning Companion into a Self-Regulated Learning 4L Framework on Elementary Mathematics Learning

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Abstract: This study investigates whether integrating TALPer, an AI learning companion, into a self-regulated learning four lesson framework (SRL 4L framework) enhances fifth-grade students' mathematics learning. Using a quasi-experimental design, instruction supported by TALPer was compared with SRL 4L framework–based instruction without AI support. Epistemic Network Analysis (ENA) and self-regulated learning coding systems analyzed cognitive structures and learning strategies. Results showed that students supported by TALPer achieved significantly higher learning outcomes. Process analyses further revealed that high-ability students demonstrated deep and multidirectional self-regulation with robust cognitive networks, whereas low-ability students exhibited more surface-level and fragmented patterns. Overall, the findings suggest that the effectiveness of TALPer is closely related to learners' regulatory awareness, highlighting the importance of strategy guidance and reflective scaffolding, particularly for low-ability students.

Keywords: Generative AI, Taiwan Adaptive Learning Platform (TALP), TALPer, Self-Regulated Learning, Epistemic Network Analysis

1. Introduction

With the rapid advancement of artificial intelligence (AI), intelligent tutoring systems (ITS) have contributed significantly to educational sustainability by enabling differentiated instruction through big data analytics (Chen, Xie, & Hwang, 2020; Labadze et al., 2023; Lin et al., 2023; Silva et al., 2022). In particular, generative AI (GenAI) serves as a digital scaffold for cultivating self-regulated learning (SRL) competencies, providing real-time feedback and step-by-step guidance (Chiu, 2024; Wu et al., 2023). However, a paradox exists in the use of GenAI: while structured guidance facilitates SRL, inappropriate usage may undermine learner agency (Jin et al., 2023; Lee & Low, 2024). This tension is especially relevant given that AI-supported learning may inadvertently undermine learner agency if students passively rely on AI guidance rather than actively engaging in self-regulation (Jin et al., 2023). Whether such risks differ across ability levels, however, remains underexplored. Accordingly, clarifying the interaction patterns between students and GenAI across various SRL stages is critical for mitigating educational risks (Trinovita et al., 2025).

Zimmerman (2002) theorized SRL as a cyclical process comprising forethought, performance, and self-reflection. Building on this model and flipped classroom principles (Bergmann & Sams, 2012), Ho (2014) operationalized the SRL 4L Framework across four phases that map onto Zimmerman's cycle: self-learning (forethought: goal setting and prior knowledge activation), co-learning and mutual learning (performance: monitoring, strategy exchange, and peer adjustment), and teacher-guided learning (self-reflection: misconception addressing and consolidation). This framework has been adopted in Taiwan's national digital learning program as a core strategy for technology-assisted autonomous learning (Kuo et al., 2023). The theoretical alignment directly informs the present study's coding scheme (Table 1), which captures metacognitive and cognitive regulatory behaviors across these phases, while

Epistemic Network Analysis (ENA) models their structural co-occurrence—moving beyond frequency counts to capture patterns of association within learners' cognitive networks (Shaffer, Collier, & Ruis, 2016).

This study investigates the effectiveness of integrating TALPer—an AI learning companion for elementary mathematics problem solving (Kuo et al., 2026)—into the SRL 4L Framework (Ho, 2014). Given the documented paradox that GenAI may scaffold SRL for some learners while fostering procedural dependence in others (Jin et al., 2023; Lee & Low, 2024), this study moves beyond aggregate learning outcomes (RQ1) to examine whether high- and low-ability students differ in their SRL strategy use (RQ2) and in the structural organization of their cognitive networks as captured by ENA (RQ3). This design enables a process-level account of how TALPer scaffolds—or fails to scaffold—conceptual understanding across ability levels.

RQ1. Does integrating TALPer into a SRL 4L framework result in superior learning outcomes compared to a SRL 4L Framework without TALPer support?

RQ2. Within a SRL 4L framework learning environment supported by TALPer, are there significant differences in the SRL strategies exhibited by high- and low-ability students?

RQ3. Within a SRL 4L framework learning environment supported by TALPer, are there significant differences in the cognitive network structures between high- and low-ability students?

2. Method

2.1 Research Design and Participants

This quasi-experimental study recruited 44 fifth-grade students (experimental: n = 21; control: n = 23) from a public elementary school in Taiwan. Both groups received five lessons on "Ratios and Percentages" over two weeks, with no significant baseline differences confirmed by pre-test (p = .376). The experimental group received SRL 4L framework instruction supported by TALPer, whereas the control group followed an identical structure without TALPer access.

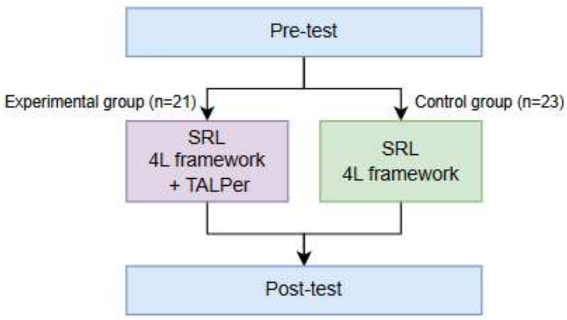

Figure 1. The experimental framework for the two groups

2.2 Instructional Design

Both groups followed a three-phase structure—pre-class, in-class, and post-class—grounded in the SRL 4L Framework (see Figure 2). In the experimental group, the pre-class phase involved self-directed learning via TALP instructional videos, with TALPer recording students' questions and learning traces to inform subsequent instruction. During the in-class phase, teachers drew on these records to introduce key concepts, after which students engaged in TALPer-supported co-learning (scaffolded feedback and logical verification), cross-group mutual learning (peer strategy sharing), and teacher-directed consolidation (misconception addressing). The post-class phase consisted of paper-based workbook exercises. The control group followed an identical structure without TALPer access.

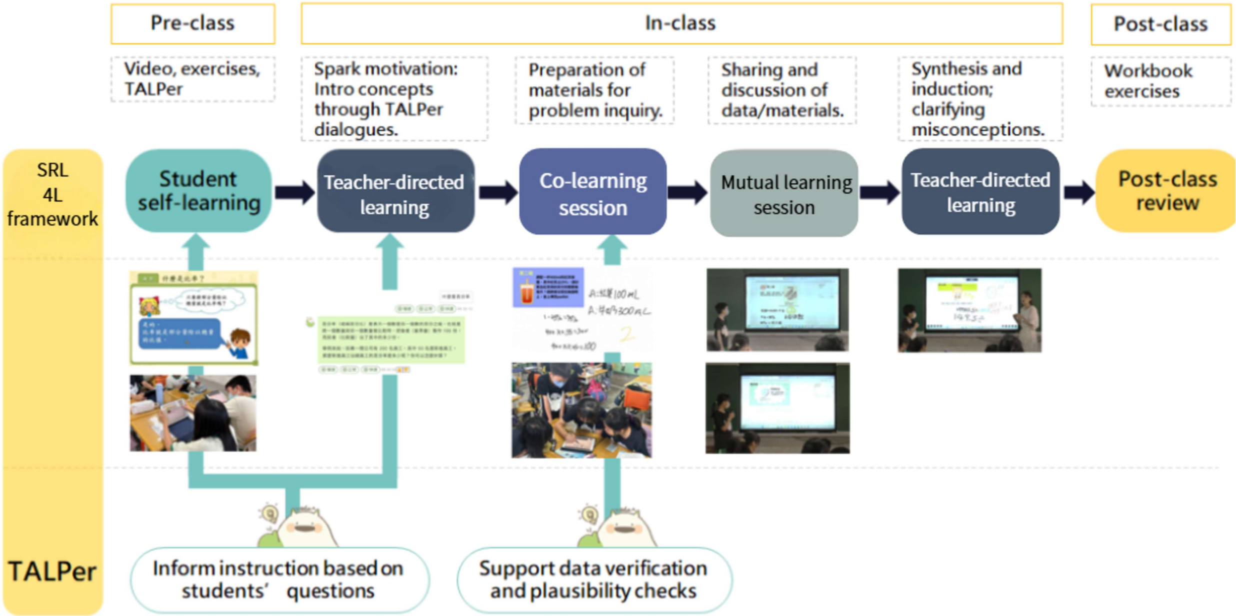

Figure 2. Pedagogical framework: Integrating TALPer into the SRL 4L framework

2.3 Assessment and Coding Framework

Learning effectiveness was measured using pre- and post-tests on the Ratios and Percentages unit, administered via TALP. SRL strategies were analyzed using a coding framework encompassing metacognition and cognition (see Table 1). ENA transformed coded dialogue events into two-dimensional cognitive network representations, where the X-axis reflects relative differences in overall cognitive tendencies and the Y-axis captures variations in structural complexity and diversity.

Table 1. *SRL Strategy Coding Framework and ENA Dimension Descriptions*

Main category	Sub-category	code	explanation
Metacognition	Setting Goals	M.SG	Proactively sets or adjusts learning objectives or sequences.
	Selecting Strategies	M.SS	Students choose or modify learning strategies, modalities, or task formats.
	Monitoring & Evaluation	M.ME	Real-time awareness and evaluation of understanding during problem-solving.
	Reflection	M.R	Reviews prior problem-solving to identify errors or revise strategies.
Cognition	Conceptual Understanding-Ask	C.CUA	Students pose questions regarding mathematical concepts, definitions, underlying meanings, or real-world applications.
	Conceptual Understanding-Explain	C.CUE	Students proactively articulate or construct their understanding of mathematical concepts.
	Procedural Knowledge-Ask	C.PKA	Inquires about computational methods or problem-solving steps.
	Procedural Knowledge-Execute	C.PKE	Students perform actual computations, formulate equations, or input final answers.

2.4 Statistical and Analytical Justification

A multi-method approach was adopted, combining paired-samples t-tests and ANCOVA (with pre-test scores as covariate) to assess learning outcomes, and Epistemic Network Analysis (ENA) to map the structural co-occurrence patterns of SRL behaviors within dialogue sequences.

3. Results

3.1 Learning Effectiveness

Both groups demonstrated statistically significant pre-to-post improvement (control group: M_{gain} = 14.45; experimental group: M_{gain} = 26.45, both $p < .001$). One-way ANCOVA revealed that, after controlling for pre-test scores, the experimental group achieved significantly higher adjusted post-test scores (M = 85.49) compared to the control group (M = 76.56), $F(1,41) = 4.71$, $p = .036$. The effect size was medium according to Cohen's (1988) guidelines ($\eta^2 = .114$). These results indicate that integrating TALPer into instruction aligned with a SRL 4L framework led to greater learning gains than instruction without TALPer support.

3.2 Epistemic Network Analysis and Strategy Differences

ENA revealed substantial structural divergence between high-achieving (n = 10) and low-achieving (n = 11) students in the experimental group (all model fit indices > .94). On the X-axis, high-achieving students scored significantly higher (M = 0.07, SD = 0.10) than low-achieving students (M = −0.07, SD = 0.04), $t(12.07) = 4.05$, $p < .001$, Cohen's $d = 1.83$, indicating pronounced differences in cognitive engagement patterns.

Network visualizations showed that high-achieving students formed multidirectional, densely connected cognitive structures, with discourse frequently co-occurring around goal setting (M.SG), conceptual understanding-ask (C.CUA), and procedural knowledge-execute (C.PKE), alongside recurrent links to reflection (M.R)—indicating iterative transitions among planning, inquiry, execution, and monitoring. In contrast, low-achieving students exhibited fragmented, sparsely connected networks centered on strategy selection (M.SS) and procedural knowledge-ask (C.PKA), reflecting predominantly linear transitions among questioning, receiving answers, and executing procedures, with limited reflective or conceptual engagement (see Figure 3).

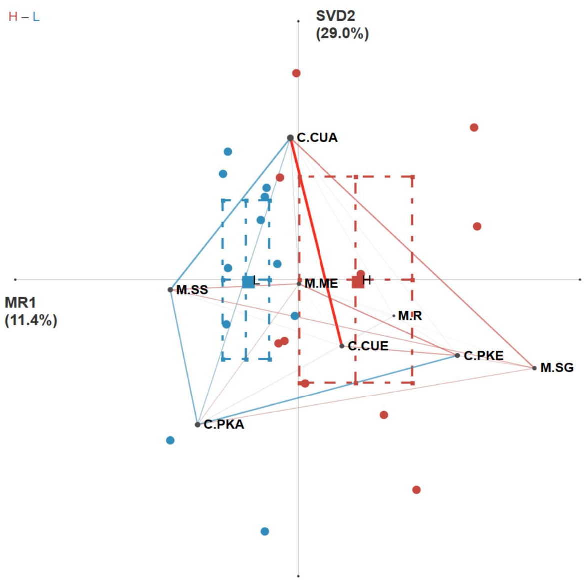

Figure 3. Comparison of ENA network structures between high-achieving (H) and low-achieving (L) groups

4. Discussion and Conclusion

4.1 Key Research Findings

This study identifies three key findings: TALPer functions as an effective cognitive scaffold within the SRL 4L framework, where immediate and personalized AI feedback promoted higher-order exploration and improved learning performance; high- and low-achieving students exhibited distinct SRL profiles, with high-achievers demonstrating complete regulatory cycles involving conceptual analysis and reflection while low-achievers remained procedurally focused—reflecting differences in regulatory awareness rather than tool access; and ENA revealed contrasting cognitive networks, with high-achievers forming integrated, multidirectional structures supporting knowledge synthesis and low-achievers showing fragmented, linear patterns centered on procedural execution.

4.2 Pedagogical Implications

The findings highlight that the pedagogical effectiveness of TALPer cannot be assumed to arise from tool availability alone but is closely tied to learners' cognitive and self-regulatory strategies. Accordingly, teachers' roles may extend beyond providing TALPer toward guiding students' strategic engagement with TALPer. In particular, targeted scaffolding for low-ability students, such as guided questioning, structured reflection, and modeling productive TALPer-mediated dialogue, may help transform procedural interactions into opportunities for deeper cognitive engagement.

4.3 Conclusion

This study highlights differential ways in which TALPer supports learning within a SRL 4L framework. High-ability students leverage dynamic TALPer feedback for conceptual deepening, while low-ability students tend toward surface-level procedural dependence. These findings emphasize the importance of learners' self-regulatory capacities in AI-supported instruction. Future research should examine interventions that foster regulatory awareness among low-ability students and explore the long-term sustainability of TALPer integration across mathematical domains.

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