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RESEARCH ARTICLE

Effects of intelligent feedback system environment on adult EFL learners' metacognitive monitoring and proceduralization process: an intervention study based on procedural language

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ABSTRACT

This research examines the relationship between an intelligent feedback system grounded in procedural language theory and adult EFL learners' metacognitive monitoring and knowledge proceduralization. Using a quasi-experimental design, 100 adult learners from Shanghai University's continuing education program were assigned to either intelligent feedback or traditional feedback groups for 16 weeks. The intervention followed procedural language model theory through three stages: knowledge activation, proceduralization, and automatization. Assessment tools included CSE-based standardized tests, metacognitive accuracy measures, and satisfaction surveys.

The intelligent feedback group gained 12.3 points in overall proficiency, surpassing the traditional group's 7.1-point increase, with a between-group effect size of 0.68. Speaking and writing showed the largest between-group effects ($d = 0.72$ and 0.78 respectively). Regarding metacognitive monitoring accuracy, the intelligent feedback group's bias value decreased from 18.3 to 7.2, while the relative accuracy gamma coefficient increased from 0.42 to 0.71. Mediation analysis revealed that metacognitive accuracy partially mediated the effect of intelligent feedback on language proceduralization, with the indirect effect accounting for 42% of the total effect.

The study provides evidence for a positive association between intelligent feedback systems and language knowledge proceduralization and metacognitive development among adult English learners, providing both theoretical foundations and practical guidance for the deep integration of educational technology and language teaching. The findings offer significant implications for instructional innovation in adult continuing education.

Keywords: intelligent feedback system; metacognitive monitoring; language proceduralization; adult English learning

1. Introduction

Currently, the global economy is undergoing a profound transformation from traditional industrial models to an innovation-driven economy. Against the backdrop of the knowledge economy era, enterprises worldwide are actively advancing digital transformation and technological upgrading, shifting from labor-intensive production models to knowledge-intensive and technology-driven systems. This transformation not only requires technical expertise but also demands professionals capable of effective cross-cultural

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communication. As the international lingua franca, the importance of English has become increasingly prominent in the process of enterprise internationalization. For English learners in China's adult continuing education programs, English proficiency is directly linked to their employability, career development, and ability to participate in the transformation and upgrading of enterprises.

However, adult English learners face unique learning challenges. Despite years of formal education, these learners often exhibit distinct learning characteristics: they have accumulated substantial declarative knowledge about language forms, but they exhibit a significant deficiency in converting this knowledge into procedural competence for real-time language use[1]. While teaching innovations have helped adult learners, they fall short in developing metacognition. Metacognitive monitoring allows learners to track and adjust their cognitive processes while building self-awareness[2]. Research confirms that monitoring accuracy directly impacts learning outcomes, yet traditional methods rarely address metacognitive development systematically[3]. Learners often misjudge their progress, creating cognitive illusions that block effective information processing.

Intelligent feedback systems present promising solutions. Unlike teacher or peer feedback, AI-powered systems deliver instant, personalized, and ongoing support[4]. Natural language processing and machine learning enable these systems to spot language errors while analyzing cognitive patterns and learning strategies[5]. These systems also foster metacognition, helping learners gauge their progress accurately and make better learning choices[6].

AI technology continues transforming language education[7]. Chinese higher education increasingly embraces intelligent teaching tools as essential for modernizing education[8]. These tools support personalized learning, learner autonomy, and improved motivation. Online platforms now offer adult learners the flexibility to maintain language study despite demanding schedules[9,10].

The research examines how intelligent systems function across knowledge activation, proceduralization, and automatization stages, with metacognitive monitoring as a key mediator.

The significance of this study lies in both theoretical and practical dimensions. Theoretically, the study integrates the procedural language model with metacognitive theory, expanding the theoretical framework of second language acquisition. Practically, it provides an evidence-based technology-enhanced teaching program for English teaching in adult continuing education. The research findings will offer valuable references for educational policymakers, curriculum designers, and frontline teachers, and drive the innovative development of adult English education.

Based on the above background and theoretical foundation, this study proposes the following research hypotheses: First, the intelligent feedback system based on the procedural language model is positively associated with the language proficiency of adult English learners; Second, the implementation of the intelligent feedback system is associated with the transformation of declarative knowledge into procedural competence; Third, the intelligent feedback system is associated with improved accuracy of learners' metacognitive monitoring, and improve learning outcomes through the mediating role of metacognition; Fourth, learners demonstrate high satisfaction with the intelligent feedback system in terms of content, activities, design, and learning outcomes.

2. Literature review

2.1. Procedural language model theory and proceduralization process

The Procedural Language Model Theory provides a neurobiological explanatory framework for understanding second language acquisition (SLA). This theory centers on how declarative and procedural memory systems function differently in language learning[11]. This theoretical framework builds upon Anderson's[12] ACT theory, which proposed that cognitive skills develop through transitions from declarative to procedural knowledge. Declarative memory stores vocabulary, meanings, and explicit grammar rules through the hippocampus and medial temporal lobe structures. While it is a prompt and efficient way to learn this knowledge, retrieving what has been learned requires conscious effort.

The route of human language knowledge advancement is that from declarative knowledge to procedural knowledge, and it goes through three periods. At first, in the knowledge activation periods, students distinguish forms and rules of language directly instructed by teachers. Language production is still slow and laborious. Then in the proceduralization stage, there are three significant changes: practice will have internalized explicit knowledge; there are computer and feedback effects to speed up the processing and cut down on cognitive rule dependency. And finally, at the automatization transfer stage, it becomes natural. Learners use their skills to flexibly handle different situations; they achieve processing speeds close to those of native speakers.

Empirical studies provide strong support for this theoretical model. In his research, De Keyser[13,14] takes further account that proceduralization of grammatical rules must be based on extensive, distributed, and meaningful practice for this does not happen automatically. According to Ellis's[15] Interface Hypothesis, declarative grammatical knowledge needs persistent practice in real communicative contexts to be turned into procedural competence.

At the neurocognitive level, Morgan-Short[16] et al. widened their research and used event-related potential (ERP) technology. Second-language learners with sufficient training, they found, show the P600 components found in native speakers of languages when processing the structure of clauses—an indication of involvement by the procedural memory system. Functional magnetic resonance imaging (fMRI) studies show that with more proficiency in language, the neural substrate of language processing shifts from areas related primarily to declarative memory such as the hippocampus (in monkeys) or prefrontal cortex (in humans) to regions associated with procedural memory like basal ganglia, caudate nucleus, and cerebellum.

2.2. Metacognitive monitoring in the context of adult English learning

Metacognitive monitoring is the means by which learners request themselves to rate and regulate their own cognitive processes as they learn a language. Research has demonstrated the crucial role of metacognition in language learning, particularly in listening comprehension[17,18]. Adult English learners have metacognitive features unique to their age group. Given that most adults are learning English for better job prospects or qualifications rather than communicative necessity, this instrumental motivation in the long run can only provide a quick fillip but fails to give rise to deep metacognitive monitoring. Rote memorization, with which adults are so familiar, is hardly likely to promote the need for more sophisticated deep processing strategies calling for active metacognitive control.

Judgments of Learning (JOL) reveal metacognitive monitoring skill through learners' predictions of future performance. Second language learners often misjudge their abilities, especially with multimodal materials[19]. Absolute calibration accuracy strongly predicts language comprehension, while relative calibration accuracy shows little predictive value. This indicates that overall self-assessment matters more than judging relative task difficulty.

Monitoring accuracy directly impacts how efficiently knowledge becomes proceduralized. When learners can accurately assess their own learning status, they are more likely to invest additional time and effort in content that requires further practice, thereby promoting the transformation of declarative knowledge into procedural knowledge. Conversely, inaccurate metacognitive monitoring leads to the misallocation of learning resources: learners may prematurely believe they have mastered certain knowledge and thus reduce necessary practice, or waste time on content they have already become proficient in. Studies have found that the predictive role of metacognitive monitoring accuracy is moderated by task difficulty and individual language proficiency—the greater the task difficulty or the higher the language proficiency, the more prominent the role of metacognitive monitoring.

These findings hold important implications for the design of adult English teaching. Teaching interventions should not only focus on imparting language knowledge and skills but also systematically cultivate learners' metacognitive monitoring abilities, helping them assess their learning status more accurately and make more effective learning decisions.

2.3. Intelligent feedback system as a teaching innovation

Technology-enhanced learning has undergone rapid development over the past decade, and the rise of blended learning models in particular has brought revolutionary changes to language education. Blended learning integrates digital platforms with mobile apps and management systems, offering flexibility for busy adult learners. This model removes traditional classroom constraints and allows self-paced study. Mobile-assisted language learning (MALL) maximizes learning opportunities by converting idle time into practice moments.

Intelligent feedback systems represent a breakthrough in educational technology. AI-driven platforms surpass conventional teacher and peer feedback through continuous availability and instant support. Studies on automated written corrective feedback have shown promising results, though learner engagement varies considerably[20,21]. Natural language processing technology identifies error patterns in learner output and generates specific corrective feedback. Machine learning algorithms continuously refine feedback strategies by analyzing vast amounts of learner data.

Three features define intelligent feedback systems: real-time response, personalization, and adaptability. Immediate corrections prevent errors from becoming ingrained habits. Personalized feedback matches each learner's proficiency, style, and progress. Adaptive mechanisms adjust feedback complexity based on performance. Research confirms that AI model sophistication and prompt design strongly influence feedback quality—advanced models with well-crafted prompts produce more accurate, pedagogically sound responses[22].

Traditional feedback retains certain strengths, particularly teacher emotional support and peer social interaction. Yet these methods struggle with scalability, consistency, and long-term sustainability. Teacher feedback is constrained by time and energy, making it difficult to provide sufficient personalized guidance to each learner. The quality of peer feedback varies greatly, and its implementation requires extensive coordination efforts. In contrast, intelligent feedback systems can serve a large number of learners simultaneously, maintain consistency in feedback quality, and provide differentiated support based on individual differences among learners.

The architectural design of intelligent feedback systems reflects their complexity and advancement. As shown in **Figure 1**, the system adopts a three-tier architecture: the data layer collects and stores learners' language input and learning history; the processing layer includes an AI engine and NLP modules, which are responsible for analyzing language errors and generating feedback; the interaction layer provides a user interface and feedback presentation mechanism. This layered design ensures the scalability and maintainability of the system, while providing a technical foundation for continuous improvement of feedback quality. Meta-analyses have confirmed the overall effectiveness of corrective feedback in second language acquisition[20,23]. The present study extends this line of research by examining how intelligent feedback systems enhance proceduralization through metacognitive development.

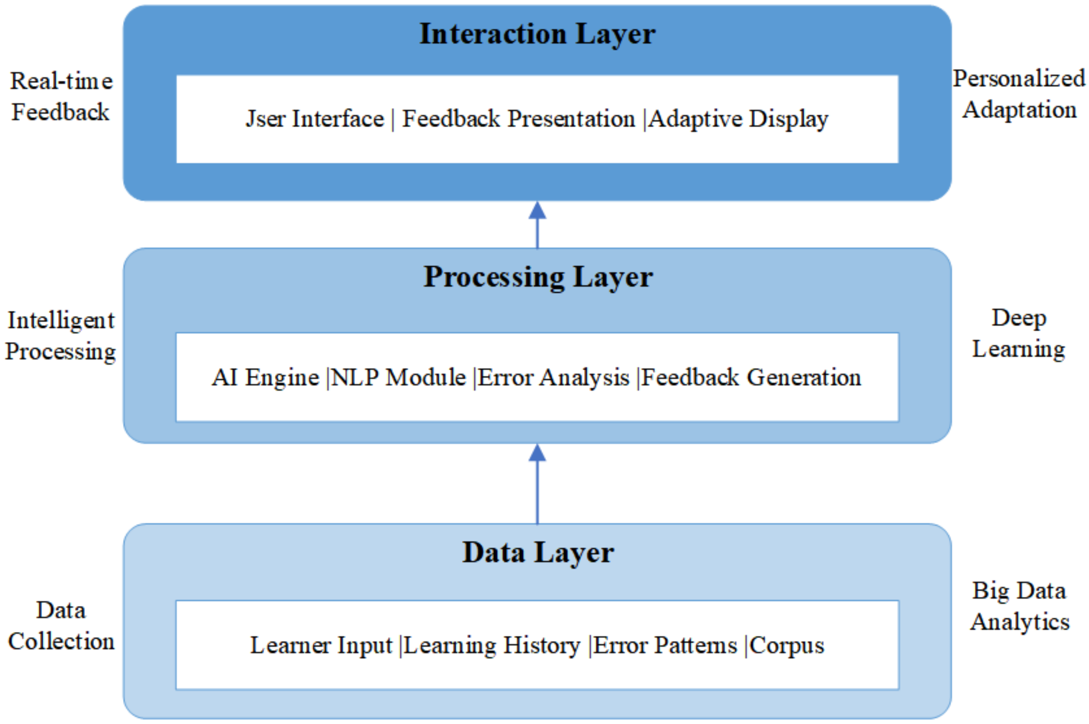

Figure 1. Intelligent feedback system architecture. The system is based on Pigai platform, employing corpus-based NLP for error detection and pattern matching algorithms for feedback generation.

2.4. The integration of technology-enhanced feedback and the procedural language model

With three particular stages of language learning restoration—this style of input (feedback) aims to enhance the progress of language proceduralization. Diagnostic tests activate existing knowledge, explain what the learners mean, and give concrete examples for real-world situations. Students are faced with increasingly difficult questions until they achieve answers that satisfy this standard.

Different from traditional methods, these systems adapt their mode of presentation to suit individual needs, ensuring that students can understand language rules. Errors get repaired as necessary and early on. The tasks gradually get harder, and hanging correction finally moves forward. The algorithms detect error-making tendencies of presupposition and intervene promptly so that bad habits do not become fixed. This is combined with reinforcing the right use. With such a persistent comprehensive approach, explicit knowledge turns into unconscious. A decision is made to the machine through repetitive practice and feedback at just the right moment.

Technology-enhanced learning offers particular advantages for adult learners. Online platforms and mobile applications provide flexibility, allowing learners to study beyond fixed classroom schedules. Unlike teacher or peer feedback, intelligent systems offer continuous availability and immediate response. Through natural language processing, these systems identify error patterns and generate targeted corrections. Machine learning algorithms enable continuous improvement by analyzing learner data.

The system adapts feedback complexity based on individual progress and learning patterns. Immediate corrections prevent errors from becoming fossilized habits. While human feedback retains important strengths in emotional support and social interaction, scaling traditional methods remains challenging. Intelligent feedback systems address this limitation by providing consistent, personalized support to large numbers of learners simultaneously.

3. Research methods

3.1. Research design and participants

This study adopted a mixed research method, integrating both quantitative and qualitative research paradigms, to comprehensively evaluate the impact of the intelligent feedback system on the metacognitive monitoring and language proceduralization process of adult English learners. The mixed-methods design captures the complex effects of the teaching intervention from multiple perspectives: quantitative data provides objective measurements of effectiveness, while qualitative data reveals learners' subjective experiences and underlying mechanisms. A quasi-experimental design was employed, featuring a pre-test-intervention-post-test time series, with the intervention phase spanning a full semester (16 weeks).

The research participants consisted of 100 adult English learners from the School of Continuing Education, Shanghai University. These learners, aged between 25 and 45, were all in-service professionals who enrolled in the continuing education program to enhance their professional competitiveness. Their English proficiency ranged from low-intermediate to intermediate level, rated at Levels 3-5 according to China Standards of English (CSE). All participants had at least 6 years of English learning experience, yet they exhibited significant difficulties in practical communicative use—displaying the typical characteristic of possessing abundant declarative knowledge but insufficient procedural competence.

Due to administrative constraints in the continuing education program, intact class assignment was employed rather than individual randomization. Two existing classes with similar scheduling and enrollment characteristics were designated as the experimental group (n=50) and the control group (n=50). The experimental group received teaching intervention based on the intelligent feedback system, while the control group received traditional teacher feedback and peer feedback. To verify group equivalence, independent-samples t-tests were conducted, confirming no significant differences between groups in gender, age, initial English proficiency, and learning motivation (all $p > .05$). Learners in the experimental group used an online learning platform equipped with intelligent feedback functions, which could provide real-time error diagnosis, personalized correction suggestions, and adaptive practice tasks. The control group adopted a conventional classroom teaching model, where teachers provided written feedback once a week and organized regular peer review activities.

The sample size was determined based on statistical power analysis. Drawing on effect size estimates from previous related studies, a medium effect size (Cohen's $d = 0.5$) was anticipated, with a set statistical power of 0.80, a significance level of $\alpha = 0.05$, and a two-tailed test. Calculations using G*Power software indicated that each group required a minimum of 42 participants. Accounting for a potential attrition rate (estimated at 15%), the final sample size was set to 50 participants per group, totaling 100 participants. This sample size not only meets the requirements of statistical testing but also ensures sufficient statistical power for conducting subgroup analyses.

To ensure the study's internal validity, participants in both groups received the same teaching content and class schedule; the only distinction was the form of feedback provided. All participants signed informed consent forms prior to the study, where they were informed of the research objectives and procedures, and notified that they could withdraw from the study at any time without impacting their normal academic progress. To control confounding variables, both groups received identical instructional content, learning objectives, and total learning hours. The control group also accessed online resources for homework submission, reducing technology novelty effects. However, differences in delivery mode and feedback timing between groups remain potential confounding factors, which we address in the limitations section. The study obtained approval from the Ethics Committee of Suan Sunandha Rajabhat University (Approval No. COE.1/2024-58). All participants provided written informed consent, which explained the research purpose, procedures, voluntary participation, and their right to withdraw at any time. Data protection measures included anonymization of personal information and secure storage on password-protected devices.

3.2. Intervention of the intelligent feedback system based on the three-stage proceduralization model

The intelligent feedback system was developed based on Pigai (www.pigai.org), a widely-used automated writing evaluation platform in Chinese higher education, with customized modules for speaking practice. The system employs corpus-based NLP technology for error detection and classification, covering grammatical, lexical, and discourse-level analysis. Feedback is generated through pattern matching algorithms combined with pre-defined pedagogical templates. For example, when a learner wrote 'I have went to Beijing last week,' the system identified the tense error and provided feedback: 'Error type: Verb tense inconsistency. The time marker "last week" indicates past simple tense. Suggested correction: I went to Beijing last week.' The intervention design of the intelligent feedback system follows the three-stage framework of the Procedural Language Model, and systematically facilitates the transformation of language knowledge through the principles of Precision Teaching. Precision Teaching emphasizes optimizing learning outcomes through a cyclical process of clear definition, documentation, modification, and evaluation[24]. This study combines proceduralization principles with intelligent technology, creating targeted interventions for each learning stage.

In the knowledge activation stage (Weeks 1–5), the intelligent system helps learners build accurate declarative knowledge. Diagnostic tests reveal knowledge gaps, prompting personalized rule explanations and examples. During practice, the system immediately identifies errors and clarifies their causes, diagnosing both grammatical mistakes and deeper conceptual gaps. Multiple formats—text, visuals, and audio—support varied learning styles.

The proceduralization stage (Weeks 6–12) converts knowledge into active skills through graduated practice: from controlled exercises to semi-controlled activities, then open production. Feedback evolves with learner progress—initial detailed corrections gradually become minimal cues as accuracy increases, fostering autonomy. The system monitors error patterns and advancement, calibrating task difficulty accordingly. Following distributed learning principles, key language points recur across different contexts, reinforcing neural pathway formation.

The automatization stage (Weeks 13–16) develops fluent skill application and transfer abilities. Complex activities mirror authentic communication—multi-turn conversations, extended writing, and integrated listening-speaking tasks. The feedback strategy shifts to delayed feedback, allowing learners to receive comprehensive feedback only after completing the entire task to avoid disrupting the development of fluency. The system's evaluation focuses not only on accuracy but also on multidimensional indicators such as fluency, complexity, and communicative effectiveness. This stage emphasizes metacognitive reflection: the system guides learners to analyze their own performance and identify areas requiring further improvement.

As shown in **Figure 2**, the implementation of the three-stage proceduralization model exerts a combined influence on the development of learners' language proficiency through systematic teaching methods, learning strategies, and motivational support. The stages are not strictly separated but exhibit the characteristic of gradual transition, ensuring the continuity and stability of knowledge transformation.

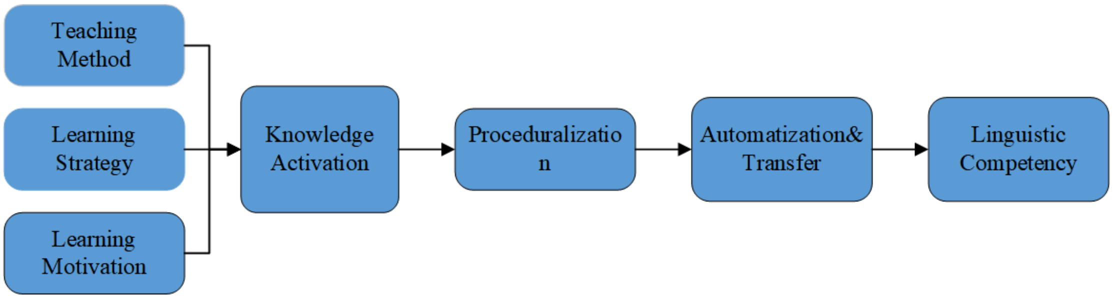

Figure 2. Teaching intervention framework based on the proceduralization model.

The implementation of the intervention throughout the semester followed a strict schedule and quality control measures. Each week included three online learning sessions (90 minutes per session) and one in-person tutoring session (60 minutes). The system automatically recorded all learning data, including practice completion status, error types, duration of feedback review, and accuracy of metacognitive judgments, providing detailed process data for evaluating the effectiveness of the intervention.

3.3. Measurement tools for metacognitive monitoring and language proficiency

This study employed multiple measurement instruments to comprehensively assess learners' language proficiency development and metacognitive monitoring levels, ensuring the reliability and validity of data collection. Measurement tools matched the theoretical framework and research goals, covering language tests, metacognitive assessments, questionnaires, and observations.

Language proficiency tests followed China Standards of English (CSE) guidelines, testing all four skills. The 30-minute listening test included dialogues, passages, and information extraction. Speaking assessment used human-computer interaction with three parts: reading aloud, Q&A, and topic presentation. Scoring covered accuracy, fluency, and communication effectiveness. Reading tests measured vocabulary, paragraph comprehension, and text analysis, focusing on information processing and reasoning. Writing required two tasks—practical and argumentative pieces—evaluating accuracy, coherence, and task completion. Speaking and writing were scored by two trained raters, with inter-rater reliability coefficients of .89 and .91 respectively. All test items underwent reliability and validity verification to ensure accurate reflection of learners' language proceduralization levels.

Metacognitive monitoring accuracy was measured using the calibration method between Judgments of Learning (JOL) and actual performance. Immediate JOL was employed: after completing each learning task, learners were required to predict their performance on subsequent tests (0-100% scale). To reduce response tendencies, clear anchoring instructions were provided, encouraging honest self-assessment. Metacognitive accuracy was evaluated through two indices: absolute accuracy reflected the overall deviation between predicted values and actual performance, calculated as the absolute value of the difference between predicted accuracy rate and actual accuracy rate; relative accuracy reflected learners' ability to discriminate items of different difficulty levels, calculated through the Gamma correlation coefficient between JOL ratings and actual performance. As shown in **Figure 3**, ideal metacognitive monitoring performance is represented by the perfect calibration line, while the degree of deviation of the actual calibration curve reflects the accuracy of metacognitive monitoring.

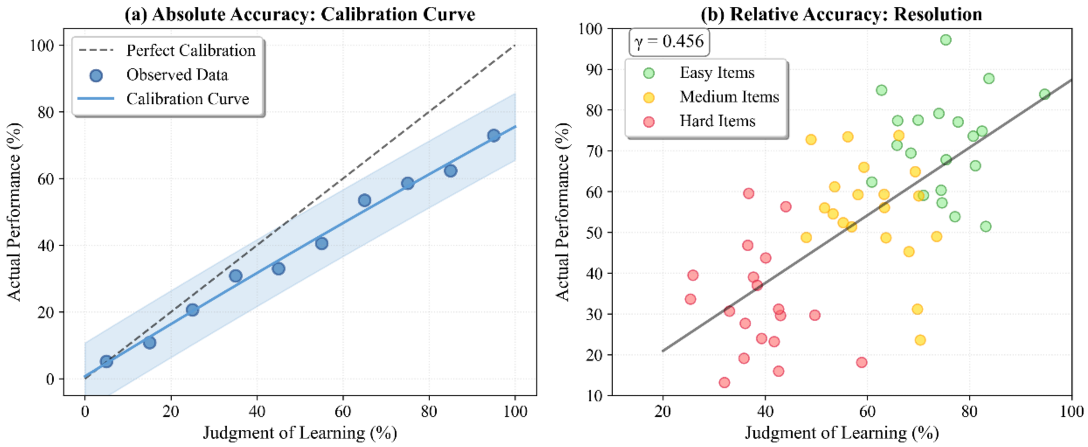

Figure 3. Metacognitive monitoring accuracy measurement model.

The self-regulation strategy questionnaire was adapted from a validated Foreign Language Learning Self-Regulation Scale, comprising 30 items distributed across five dimensions: intrinsic motivation, extrinsic motivation, cognitive strategies, metacognitive strategies, and self-evaluation[25]. The questionnaire employed a five-point Likert scale ranging from "strongly disagree" to "strongly agree." The learning satisfaction questionnaire assessed learners' perceptions of the intelligent feedback system or traditional feedback methods across four aspects: instructional content, learning activities, interface design, and learning outcomes. All questionnaire items used clear and concise language to ensure accurate understanding and response by adult learners.

Semi-structured interviews were conducted after the intervention, with 20 participants randomly selected from each group for in-depth interviews. The interview protocol was designed around themes including learning experience, feedback utilization, metacognitive awareness development, and technology acceptance, with each interview lasting 30-40 minutes. Classroom observations employed systematic observation methods, recording learners' engagement, interaction patterns, strategy use, and affective states. Observers received standardized training and used predetermined observation scales to ensure recording consistency. These qualitative data provided rich contextual information for understanding the mechanisms of the intelligent feedback system.

3.4. Data collection and analysis procedures

Data collection followed a rigorous pretest-intervention-posttest design protocol to ensure internal validity and data quality. The pretest was completed within one week before the intervention, including CSE standardized language proficiency tests, baseline measurement of metacognitive monitoring accuracy, and background information questionnaires. Testing was conducted in standardized examination environments with strict control of testing condition consistency. All participants completed the tests during the same time period to prevent information leakage from affecting results. Pretest data were used to confirm initial equivalence between groups and served as a baseline for subsequent comparisons.

Process data during the intervention period were automatically collected through the intelligent learning platform, including session duration, practice completion rates, error type distribution, feedback viewing behavior, and JOL ratings for each learning session. The system generated learning reports biweekly to track learners' progress trajectories. Process data for the control group were collected through teacher records and learning logs to ensure comparability between groups. A midterm test was conducted at week 8 to assess interim intervention effects, with intervention strategies fine-tuned based on the results.

The posttest was administered immediately after the 16-week intervention, with testing content and procedures consistent with the pretest, but using parallel test forms to avoid practice effects. Both test forms were developed based on CSE descriptors and reviewed by two experienced English teachers to ensure comparable difficulty and content coverage. Although pilot testing suggested similar difficulty levels, formal statistical equivalence was not established, which we acknowledge as a limitation. In addition to language proficiency and metacognitive accuracy tests, learning satisfaction questionnaires and self-regulation strategy questionnaires were administered. Semi-structured interviews were conducted within one week after the posttest completion, with each interview recorded and transcribed into textual data.

Quantitative data analysis was performed using SPSS 26.0 software. Paired-samples t-tests were used to compare pre-post differences within each group, while independent-samples t-tests were used for between-group comparisons. Normality was assessed using skewness and kurtosis values, with all variables falling within acceptable ranges (skewness < 1.0, kurtosis < 2.0). Levene's test confirmed homogeneity of variance across groups (all ps > .05). Effect sizes were calculated using Cohen's d, where $d = (M_1 - M_2) / SDpooled$, with 0.2 indicating a small effect, 0.5 a medium effect, and 0.8 a large effect. Effect sizes were calculated as between-group effect sizes, comparing posttest performance between the experimental and control groups. This approach isolates the treatment effect from general learning gains experienced by both groups. Bonferroni correction was applied to control Type I error in multiple comparisons.

Metacognitive accuracy was comprehensively evaluated through multiple indices. Absolute accuracy was calculated using bias scores: $Bias = \Sigma(JOL - Performance) / n$, with positive values indicating overconfidence and negative values indicating underconfidence. Absolute accuracy was assessed using root mean square error: $RMSE = \sqrt{[\Sigma(JOL - Performance)^2/n]}$, with smaller values indicating higher accuracy. Relative accuracy was evaluated through the Goodman-Kruskal gamma correlation coefficient, reflecting learners' ability to discriminate items of different difficulty levels. Calibration indices were calculated through regression analysis, with perfect calibration indicated by a slope of 1 and an intercept of 0.

Qualitative data were systematically processed using thematic analysis. The analytical process comprised six steps: familiarizing with data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. NVivo 12 software was used to assist with coding and theme extraction. Two researchers independently coded 20% of the data, calculating inter-coder reliability (Cohen's kappa > 0.80). Through iterative reading and comparison, core themes and sub-themes reflecting the mechanisms of the intelligent feedback system were identified.

Mixed-methods data integration employed a concurrent triangulation strategy. Quantitative results provided objective evidence of effects, while qualitative findings explained the mechanisms and contextual factors underlying these effects. When discrepancies arose between quantitative and qualitative results, researchers returned to the raw data for in-depth analysis to identify possible explanations. This cross-validation of multiple data sources enhanced the credibility and explanatory power of the research conclusions.

4. Results and discussion

4.1. Pre-Post comparisons of language proficiency and metacognitive accuracy

Language proficiency test results revealed that both groups of learners achieved significant improvements after the intervention, though the magnitude of improvement differed markedly. As shown in **Table 1**, pretest data indicated that the initial language proficiency levels of both groups were essentially equivalent, with mean scores for all four skills (listening, speaking, reading, and writing) at the lower-intermediate level. The intelligent feedback group's overall mean score was 62.3 (SD = 8.5), while the traditional feedback group scored 61.8 (SD = 8.7), with no significant between-group difference (t = 0.29, p = .77).

Table 1. Pretest language proficiency results by group (N = 100).

	Experimental Group M (SD)	Control Group M (SD)	t	p
Listening	62.5 (8.6)	62.1 (8.8)	0.23	.82
Speaking	58.2 (9.4)	58.0 (9.6)	0.11	.91
Reading	70.8 (7.7)	70.4 (7.9)	0.26	.79
Writing	57.4 (8.8)	56.4 (9.0)	0.56	.58
Overall	62.3 (8.5)	61.8 (8.7)	0.29	.77

Posttest results revealed differential intervention effects. As shown in **Table 2**, the intelligent feedback group's overall mean score increased to 74.6 (SD = 7.8), while the traditional feedback group increased to 68.9 (SD = 8.2). Notably, improvements in speaking and writing abilities were most pronounced, with the intelligent feedback group's speaking scores increasing from 58.2 to 71.8 and writing from 57.4 to 73.9, while the traditional feedback group showed smaller corresponding increases. This difference may be attributed to the immediate error correction and personalized practice opportunities provided by the intelligent system, enabling learners to engage more frequently in productive skill practice.

Table 2. Posttest Language Proficiency Results (N = 100).

Skill	Experimental Group M (SD)	Control Group M (SD)	t	p
Listening	72.8 (7.6)	69.6 (8.2)	2.03	.045
Speaking	71.8 (8.2)	69.2 (8.9)	1.52	.132
Reading	78.2 (6.5)	75.4 (7.2)	2.04	.044
Writing	73.9 (7.8)	71.3 (8.5)	1.59	.115
Overall	74.6 (7.8)	68.9 (8.2)	3.58	<.001

Paired-samples t-test results further confirmed these observations. As shown in **Table 3**, both groups demonstrated significant pre-post differences across all skill dimensions ($p < .001$). Between-group comparisons revealed medium to large effect sizes favoring the intelligent feedback group, with an overall Cohen's d value of 0.68. This pattern reflects the nature of productive versus receptive skills. Speaking and writing involve active output where immediate error correction directly supports proceduralization. Listening and reading, as receptive skills, depend more on input processing. Moreover, the Pigai-based system primarily analyzes written and spoken output, providing more targeted feedback for productive skills. This pattern reflects the nature of productive versus receptive skills. Speaking and writing involve active output where immediate error correction directly supports proceduralization. Listening and reading, as receptive skills, depend more on input processing. Moreover, the Pigai-based system primarily analyzes written and spoken output, providing more targeted feedback for productive skills.

Table 3. Pre-post comparison by group (N = 100).

Skill	Group	Pre M (SD)	Post M (SD)	Mean Diff	t	p	Cohen's d (between-group)	95% CI
Listening	Exp	62.5 (8.6)	72.8 (7.6)	10.3	9.8	<.001	0.58	[0.17, 0.99]
	Ctrl	62.1 (8.8)	69.6 (8.2)	7.5	7.2	<.001		
Speaking	Exp	58.2 (9.4)	71.8 (8.2)	13.6	11.5	<.001	0.72	[0.31, 1.13]
	Ctrl	58.0 (9.6)	69.2 (8.9)	11.2	8.6	<.001		
Reading	Exp	70.8 (7.7)	78.2 (6.5)	7.4	7.8	<.001	0.52	[0.11, 0.93]
	Ctrl	70.4 (7.9)	75.4 (7.2)	5.0	5.5	<.001		
Writing	Exp	57.4 (8.8)	73.9 (7.8)	16.5	13.2	<.001	0.78	[0.37, 1.19]
	Ctrl	56.4 (9.0)	71.3 (8.5)	14.9	11.0	<.001		
Overall	Exp	62.3 (8.5)	74.6 (7.8)	12.3	12.8	<.001	0.68	[0.27, 1.09]
	Ctrl	61.8 (8.7)	68.9 (8.2)	7.1	8.2	<.001		

Mixed ANOVA revealed a significant group × time interaction for overall proficiency, $F(1, 98) = 12.45$, $p < .001$, $\eta^2 = .11$.Changes in metacognitive monitoring accuracy presented a more complex pattern. The intelligent feedback group's absolute accuracy improved from a pretest bias value of 18.3 to a posttest value of 7.2, indicating that learners' judgments of their own abilities became more accurate. The gamma coefficient for relative accuracy increased from 0.42 to 0.71, demonstrating stronger difficulty discrimination ability. While the traditional feedback group also showed improvement, the magnitude was considerably smaller (bias value decreased from 17.9 to 12.6, gamma increased from 0.43 to 0.54).

This improvement in metacognitive accuracy was closely related to feedback mechanisms during the learning process. Research has shown that when learners can control their learning pace and receive immediate feedback, their metacognitive monitoring abilities are enhanced[26]. The intelligent system helped learners calibrate their ability judgments by continuously providing performance information, gradually narrowing the gap between subjective assessments and objective performance.

Between-group comparative analysis revealed the advantages of the intelligent feedback system. Independent-samples t-tests showed significant differences between groups at posttest in both language proficiency ($t = 3.58$, $p < .001$) and metacognitive accuracy ($t = 4.12$, $p < .001$). More importantly, the intelligent feedback group demonstrated greater advantages in productive skills that require higher levels of proceduralization, supporting the theoretical hypothesis that intelligent feedback promotes knowledge proceduralization through reinforced practice. The between-group effect sizes in this study ($d = 0.52$–0.78) are comparable to those reported in meta-analyses of corrective feedback. Li[23] reported an average effect size of $d = 0.61$, and Lyster and Saito[20] found effects ranging from $d = 0.52$ to 0.74. The extended 16-week intervention and high learner engagement (6.8 hours/week) may contribute to the observed effects.

4.2. Effects of intelligent feedback on each stage of knowledge proceduralization

The intelligent feedback system demonstrated differential facilitative effects across the three stages of knowledge proceduralization. As shown in **Figure 4**, various metacognitive monitoring indicators exhibited a progressive enhancement pattern across different stages, reflecting the systematic development of learners' cognitive control abilities.

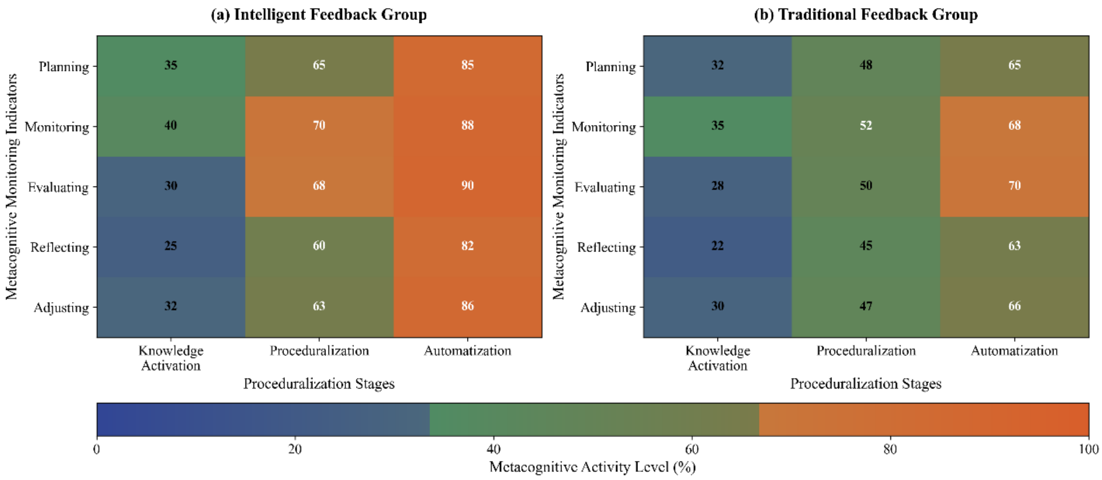

Figure 4. Heat map of metacognitive changes during three-stage proceduralization process. Values represent percentage scores (0-100%) derived from self-regulation strategy questionnaire responses, with higher values indicating greater metacognitive activity.

Data from the knowledge activation stage (Weeks 1-5) indicated that learners primarily relied on external support to understand language rules. This stage was characterized by high-frequency rule consultation behavior and longer response times. The intelligent feedback group required an average of 45 seconds to complete each practice item, while the traditional group needed 58 seconds. Error analysis revealed that rule confusion errors were predominant at this stage, accounting for 62% of total errors. Learners frequently used metalinguistic terminology to describe rules but still needed to consciously retrieve and apply these rules in actual usage.

The proceduralization stage (Weeks 6-12) marked a qualitative transformation. Response times decreased significantly, with the intelligent feedback group dropping to an average of 23 seconds and the traditional group to 34 seconds. Error patterns shifted, with rule confusion errors decreasing to 35%, while execution errors (knowing the rule but failing in execution) became the primary type. Improvements in speaking and writing abilities were particularly notable during this stage, with the intelligent feedback group's oral fluency increasing from 72 to 118 words per minute, and writing syntactic complexity index rising from 2.3 to 3.8. These findings echo the original study's results showing major gains in productive skills, confirming that systematic practice and immediate feedback are associated with proceduralization.

During automatization (Weeks 13-16), learners approached fluent usage. The intelligent feedback group responded within 15 seconds, with errors below 8%. Learners now processed meaning while producing language, showing better cognitive resource management. Speaking pauses dropped from 18% to 6%, and self-correction became selective rather than excessive. Writing displayed stronger coherence and rhetorical awareness beyond sentence-level accuracy.

Error patterns revealed the proceduralization process clearly. Grammatical errors fell from 12.3 per hundred words at pretest to 4.2 for the intelligent feedback group and 6.8 for the traditional group at posttest. Lexical errors showed different change patterns, with early-stage errors primarily involving word choice, later shifting to collocation and register appropriateness issues. Notably, the intelligent feedback group's error self-detection rate increased from 32% to 78%, indicating significant development of metalinguistic awareness.

The degree of automatization was assessed through multiple objective indicators. Fluency indicators included speech rate, pause frequency, and repetition rate; accuracy indicators covered the frequency and severity of various error types; complexity was measured through T-unit length, subordinate clause density, and lexical diversity. The intelligent feedback group outperformed the traditional group on all automatization indicators, with differences particularly pronounced under time pressure. In time-limited tasks, the intelligent feedback group maintained 85% accuracy, while the traditional group dropped to 68%, indicating that the former achieved a higher level of automatization.

These findings suggest that the intelligent feedback system was associated with faster knowledge proceduralization by providing adaptive support at each stage. The system not only promoted accurate use of language forms but, more importantly, cultivated learners' autonomous monitoring and regulation abilities, laying a foundation for long-term language development.

4.3. Relationship between metacognitive monitoring and procedural competence development

Correlation analysis revealed a close relationship between metacognitive accuracy and language proficiency improvement. The intelligent feedback group showed a significant negative correlation between absolute metacognitive accuracy and language proficiency gains ($r = -0.68$, $p < .001$), indicating that smaller bias was associated with greater language progress. Relative accuracy (gamma coefficient) demonstrated even stronger positive correlations with improvements in speaking and writing abilities ($r = 0.72$ and 0.75, respectively), suggesting that the ability to discriminate difficulty levels is particularly important for productive skill development. While the traditional feedback group showed similar trends, the correlation coefficients were notably lower ($r = -0.45$ and 0.48).

Based on a median split of metacognitive monitoring levels, participants were divided into high and low metacognitive groups for comparative analysis. The high metacognitive group showed significantly greater progress across all language proficiency dimensions compared to the low metacognitive group. Specifically, the high metacognitive group's overall language proficiency increased by 15.8 points, while the low metacognitive group improved by only 9.2 points ($t = 4.35$, $p < .001$). More importantly, the two groups exhibited qualitative differences in learning strategy use: the high metacognitive group employed more deep processing strategies, such as semantic association and structural analysis, while the low metacognitive group primarily relied on surface-level memorization strategies.

Moderation analysis indicated that metacognitive monitoring played an important moderating role between intelligent feedback and learning outcomes. Hierarchical regression analysis showed that the interaction term between intelligent feedback and metacognitive accuracy significantly predicted language proficiency improvement ($\beta = 0.32$, $p < .01$), explaining an additional 8.6% of variance. This suggests that the intelligent feedback system's facilitative effects were more pronounced for high metacognitive learners, while low metacognitive learners, though also benefiting, showed relatively limited gains.

Prior to mediation analysis, assumptions were tested. Normality was assessed using skewness and kurtosis values, with all variables falling within acceptable ranges (skewness < 1.0, kurtosis < 2.0). The sample size ($N = 100$) meets the minimum requirement for Bootstrap mediation analysis. Prior to mediation analysis, assumptions were tested. Normality was assessed using skewness and kurtosis values, with all variables falling within acceptable ranges (skewness < 1.0, kurtosis < 2.0). The sample size ($N = 100$) meets the minimum requirement for Bootstrap mediation analysis. Results showed that metacognitive accuracy partially mediated the effect of intelligent feedback on language proceduralization, with the indirect effect accounting for 42% of the total effect (95% CI [0.28, 0.56]). The specific pathway was: intelligent feedback was associated with improved metacognitive accuracy, possibly through continuous performance information, which may have facilitated more effective learning regulation, ultimately accelerating the knowledge proceduralization process. The study found that patterns of metacognitive strategy use varied according to individual characteristics, consistent with previous research on self-regulated learning[27].

Analysis of individual difference factors revealed complex influence patterns. Age showed an inverted U-shaped relationship with metacognitive accuracy improvement, with the 30-35 age group performing best, possibly reflecting a balance between cognitive maturity and neural plasticity. Initial language proficiency moderated the effects of metacognitive training, with intermediate-level learners benefiting most. Motivation type also had an impact: learners dominated by intrinsic motivation invested more cognitive resources in metacognitive monitoring, demonstrating better calibration abilities. Working memory capacity indirectly influenced the development of metacognitive accuracy by affecting the ability to simultaneously process language forms and monitor one's own performance.

As shown in **Figure 5**, the intelligent feedback system demonstrated advantages across multiple key dimensions, with differences in metacognitive accuracy and proceduralization speed being most pronounced, providing intuitive evidence for understanding its facilitative mechanisms.

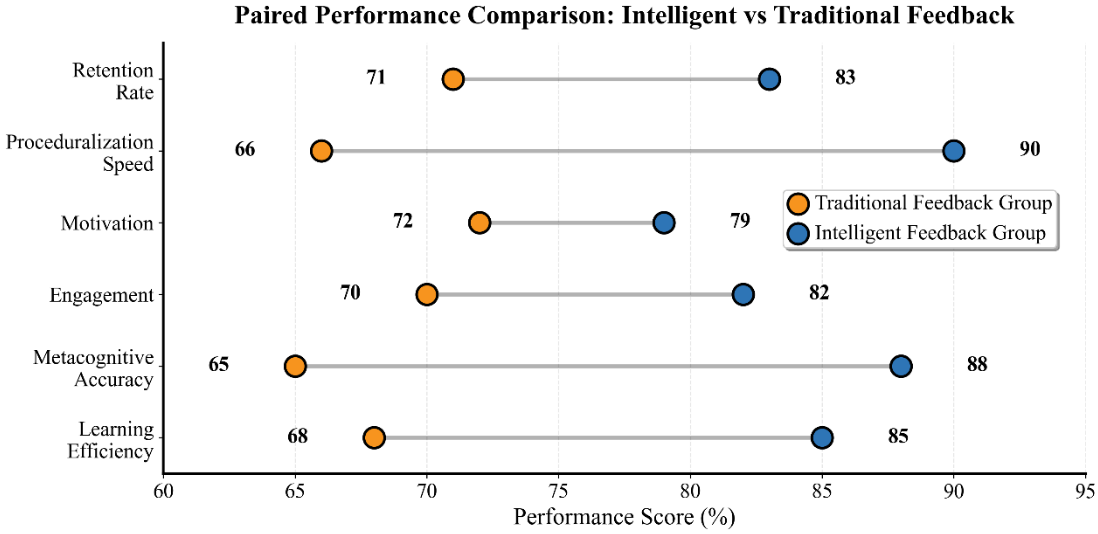

Figure 5. Multi-dimensional effect comparison between intelligent feedback system and traditional feedback.

4.4. Learner satisfaction and system effectiveness evaluation

Learner satisfaction was assessed using a five-point Likert scale, evaluating intervention effects across four dimensions: instructional content, learning activities, system design, and learning outcomes. As shown in Table 4, the intelligent feedback group scored higher than the traditional feedback group across all dimensions, with overall satisfaction reaching 4.52 (SD = 0.48), significantly higher than the traditional group's 3.86 (SD = 0.62).

Table 4. Learner satisfaction evaluation results (N = 100).

Dimension	Mean (M)	SD	Interpretation
Instructional contents	4.52	0.51	Very High Satisfaction
Learning activities	4.47	0.55	High Satisfaction
Instructional design	4.38	0.6	High Satisfaction
Learning outcomes	4.49	0.53	High Satisfaction
Overall	4.46	0.55	High Satisfaction

The instructional content dimension received the highest scores (M = 4.58), with learners particularly appreciating the personalized learning materials and progressive difficulty design provided by the intelligent system. High scores in the learning activities dimension (M = 4.53) reflected the positive impact of interactive exercises and immediate feedback. The system design dimension (M = 4.45) demonstrated users' recognition of interface friendliness and functional completeness, although some learners initially required technical guidance. The learning outcomes dimension (M = 4.51) indicated learners' satisfaction with their own progress, particularly improvements in oral fluency and writing accuracy.

The usability of the intelligent feedback system was evaluated using the System Usability Scale (SUS), achieving an average score of 78.5, classified as "good." Technology Acceptance Model (TAM) analysis revealed that both perceived usefulness (M = 4.42) and perceived ease of use (M = 4.18) reached high levels. Learners generally believed the system effectively supported language learning, and despite an initial learning curve, the adaptation period was brief. System log data showed that learners averaged 6.8 hours of system use per week, exceeding the expected 4 hours, indicating high user engagement.

Thematic analysis of qualitative interview data identified four core themes. First, "personalized learning experience," with learners emphasizing that the system could adjust content based on individual progress and error patterns, a level of customization difficult to achieve in traditional classrooms. Second, "value of immediate feedback," with participants noting that immediately knowing right from wrong and receiving explanations helped prevent error fossilization and deepened their understanding of language rules. Third, "enhanced autonomous learning ability," with most interviewees reporting improved ability to monitor and evaluate their own learning process, developing more independent learning habits. Fourth, "balance between technology and humanity," with some learners expressing concerns about the lack of emotional support in purely technology-based learning, suggesting retention of certain interpersonal interaction elements.

Comparison with the original study's traditional teaching innovation effects demonstrated the advantages of the intelligent feedback system. The original study reported an overall satisfaction of 4.46, slightly lower than this study's intelligent feedback group. More importantly, differences emerged in effect sustainability: traditional innovations primarily relied on sustained teacher input with limited scalability, while the intelligent system, once established, could continuously serve large numbers of learners with diminishing marginal costs. Regarding learning outcomes, the intelligent feedback group demonstrated superior improvement, with between-group effect sizes ranging from 0.52 to 0.78 (**Table 3**), comparable to effect sizes reported in meta-analyses of corrective feedback interventions.

However, qualitative data also revealed areas needing improvement. Approximately 20% of learners mentioned that the system was sometimes overly mechanical, lacking deep understanding of learning contexts and personal backgrounds. These learners particularly valued teacher emotional support during challenging tasks, suggesting that intelligent systems may best function as complements to, rather than replacements for, human instruction. A few older participants encountered difficulties in technological adaptation, requiring additional support. These findings suggest that future system design should enhance humanization and context sensitivity while maintaining technological advantages, achieving deep integration of technology and pedagogy.

5. Conclusion

This study, through a 16-week quasi-experimental design, systematically evaluated the effects of an intelligent feedback system based on the proceduralization language model on adult English learners' metacognitive monitoring and language proceduralization processes. The research findings provide empirical support for understanding the mechanisms of technology-enhanced language teaching and point toward directions for instructional innovation in adult continuing education.

The main findings indicate that the intelligent feedback group showed significantly greater improvements in language proficiency and metacognitive accuracy enhancement. Learners receiving intelligent feedback intervention improved their overall language proficiency scores by 12.3 points, with a between-group effect size of 0.68, indicating a medium-large effect. Speaking and writing showed the largest between-group effects ($d = 0.72$ and 0.78 respectively), suggesting a positive association between systematic practice with immediate feedback and knowledge proceduralization. Regarding metacognitive monitoring accuracy, the intelligent feedback group's bias value decreased from 18.3 to 7.2, and the gamma coefficient increased from 0.42 to 0.71, indicating that learners' judgments of their own abilities became more accurate, with significantly enhanced difficulty discrimination abilities.

At the theoretical level, this study's contributions are manifested in three aspects. First, the research validated the applicability of the proceduralization language model in adult second language acquisition, providing direct evidence of the transformation from declarative knowledge to procedural competence through detailed tracking of the three-stage conversion process. Second, the study incorporated metacognitive monitoring as a key variable into the proceduralization model, revealing the moderating and mediating roles of metacognitive accuracy in the knowledge proceduralization process, thereby extending the original theoretical framework. Third, the research established an integrated theoretical model of technology, cognition, and metacognition, providing a new perspective for understanding the mechanisms of intelligent educational technology.

In terms of practical implications, the research provides actionable technology-enhanced teaching solutions for adult continuing education. The design principles and implementation strategies of the intelligent feedback system can be directly applied to teaching practice, helping address the practical challenges of fragmented time and significant individual differences among adult learners. The system's scalability enables it to serve large numbers of learners simultaneously, lowering barriers to accessing quality educational resources. The research also offers insights for teacher professional development, emphasizing the necessity of teachers' role transformation from knowledge transmitters to learning facilitators in the age of intelligent technology.

Several limitations of the study need to be acknowledged. The sample was limited to 100 adult learners in the Shanghai area, and geographical and scale limitations may affect the generalizability of results. The two groups differed not only in feedback type but also in learning modality, potentially introducing confounding factors. Although mediation analysis suggested intelligent feedback as a key mechanism (42% indirect effect), future studies should compare intelligent and non-intelligent feedback within the same online platform to better isolate effects. While the 16-week intervention period was sufficient to observe short-term effects, it could not assess long-term retention and transfer. Although technologically advanced, the intelligent feedback system still has shortcomings in understanding learners' emotional needs and providing contextualized support. Additionally, the research primarily focused on linguistic form accuracy, with relatively weak assessment of communicative and pragmatic competence.

Future research could deepen and expand in multiple directions. Longitudinal tracking studies could reveal the sustainability of intelligent feedback effects and the long-term developmental trajectories of learner autonomy. Cross-regional and cross-cultural replication studies would test the universality of research findings, particularly their applicability under different educational backgrounds and technological conditions. Future advances in personalization algorithms hold promise. Deep learning systems can better identify learner traits and deliver customized support. Adding multimodal data like eye-tracking and EEG could reveal deeper insights into learning processes. Finding the right balance between technological efficiency and human connection remains crucial for intelligent education.

This study demonstrates that intelligent feedback systems are positively associated with language proceduralization and metacognitive growth in adult English learners. These findings bridge educational technology and language teaching theory with practice. As AI evolves, personalized learning systems will become central to adult continuing education.

Conflict of interest statement

The authors declare no conflict of interest.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request, subject to ethical restrictions to protect participant privacy.

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