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PAPER

Strategies for Enhancing Linguistic Teaching Effectiveness Based on Interactive Technologies in Mobile Learning Environments

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ABSTRACT

The digital transformation of education and the widespread adoption of mobile devices have propelled mobile learning to become the core setting for linguistic teaching, with extensive applications in fields such as second language acquisition and intercultural communication. However, current practices reveal issues such as a disconnect between interactive technology applications and the intrinsic laws of language acquisition, as well as imbalanced cognitive load for learners, which severely hinder the improvement of teaching quality. This study is grounded in the input hypothesis and interaction hypothesis of applied linguistics, the theory of ubiquitous mobile learning in educational technology, and cognitive load theory in cognitive psychology. By using a mixed research method that combines surveys, classroom observations, and quasi-experimental research, the study systematically analyzes the current application of interactive technologies in mobile linguistic teaching, identifies key pain points, and constructs a "technology-teaching-cognition" three-dimensional collaborative strategy system to enhance teaching effectiveness. The empirical findings show that targeted interactive technology designs, such as AR-based situational interaction, AI-driven feedback, and cross-cultural collaborative interaction, can effectively improve the comprehensibility of input, the depth of knowledge internalization, and the authenticity of language output in mobile linguistic teaching. This research provides a reliable reference model for the theoretical refinement and practical optimization of global digital linguistic education.

KEYWORDS

mobile learning, interactive technology, linguistic teaching, teaching effectiveness, cognitive load, applied linguistics

1 INTRODUCTION

The global process of educational digital transformation is accelerating, and the widespread adoption of mobile devices has driven mobile learning to become an

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important form of education [1–3]. According to the *Global Education Monitoring Report 2023: Digital Transformation in Education* published by UNESCO, the usage rate of mobile learning in K-12 and higher education has exceeded 65%. This trend is particularly significant in the field of linguistic teaching, where core teaching scenarios such as second language acquisition and intercultural communication have widely integrated mobile learning models. Linguistics, as a discipline emphasizing practice and interaction, has an inherent demand for immediate interaction and contextualized experiences. The portability and connectivity of mobile devices provide the technological foundation for these needs. However, significant contradictions in current practices hinder the improvement of teaching effectiveness: technology applications often remain at a superficial level of resource distribution [4, 5], lacking interactive designs that stimulate deep thinking, and failing to align with the core input-interaction-output loop of language acquisition. This results in the failure to meet expectations for improving deeper competencies such as pragmatic ability. In this context, synchronous interaction technologies such as real-time video conferencing and AI chatbots, asynchronous interaction technologies like forum collaboration and intelligent grading systems [6, 7], and multimodal interaction technologies such as AR/VR situational simulations [8, 9] not only offer solutions to the fragmentation of mobile learning time and space but can also activate the intrinsic mechanisms of language acquisition through precise design.

A review of related research published in SCI/SSCI journals between 2019 and 2024 shows that mobile learning in linguistic teaching has made initial progress. In second language acquisition, it has been shown to enhance vocabulary retention efficiency through short, frequent learning sessions, with memory retention rates improving by 15%–20% compared to traditional classroom settings. In intercultural linguistics and English for specific purposes teaching, its ability to connect across time and space has made cultural comparisons and professional context simulations possible. However, existing studies have notable limitations. Most focus on the effectiveness of single technologies, such as specific vocabulary learning apps, and lack systematic exploration of multi-technology integration. Additionally, they neglect the analysis of the adaptability between technology and teaching processes, failing to establish precise correspondence between technology and teaching objectives. Existing research on interactive technologies has formed a classification system based on synchronous, asynchronous, and multimodal categories. Synchronous technologies rely on immediacy to achieve meaning negotiation, asynchronous technologies adapt to fragmented learning scenarios to provide delayed feedback, and multimodal technologies enhance experience through multi-sensory stimulation. According to the interaction hypothesis in literature [10], it has been confirmed that meaning negotiation during interaction can transform incomprehensible input into comprehensible input, significantly promoting language internalization. However, studies based on cognitive load theory [11] simultaneously point out that the misuse of technology, leading to excessive multimodal information redundancy and cumbersome processes, can cause excessive extraneous cognitive load, which in turn inhibits learning effectiveness. In terms of teaching effectiveness evaluation, existing research has identified three core dimensions: language ability, learning behavior, and learning attitude [12]. However, the evaluation systems are imbalanced, with more than 70% of studies focusing on quantifying behavioral indicators such as click frequency and speaking rates, lacking effective evaluation tools for deeper language ability improvements. In particular, they neglect the correlation between cognitive load balance and language ability development, making it difficult to fully reflect the essence of teaching effectiveness.

From the above review, it can be seen that there are three core gaps in the field: On the theoretical level, there is insufficient interdisciplinary integration between applied linguistics, educational technology, and cognitive psychology, and no unified framework exists to guide the precise design of interactive technologies, resulting in a lack of scientific theoretical support for technology applications. On the practical level, there is no established system for matching interactive technologies with teaching processes such as linguistic input, internalization, and output. The unclear adaptation logic leads to a disconnection between technology and teaching objectives. On the empirical level, most studies use small sample sizes (less than 100 participants) and short cycles (less than four weeks), lacking long-term tracking of strategy effectiveness. Moreover, sample coverage is narrow, and group differences among learners with different language levels and cultural backgrounds are not considered, which limits the generalizability of research conclusions.

To fill these research gaps, this study sets three core objectives: to construct a strategy system for enhancing linguistic teaching effectiveness based on interactive technologies in mobile learning environments, grounded in interdisciplinary theoretical integration; to empirically verify the impact of this system on language ability, learning motivation, and cognitive load through quasi-experimental research; and to propose guidelines for applying interactive technologies in core scenarios such as second language vocabulary acquisition and intercultural pragmatics. This study poses three core research questions: What is the current application status, core pain points, and causes of interactive technologies in mobile linguistic teaching? How can interactive technology strategies be designed based on the laws of language acquisition and cognitive load theory while ensuring theoretical adaptability and practical feasibility? To what extent does the constructed strategy system improve linguistic teaching effectiveness, and what dimensions are most affected?

The significance of this study lies in both theoretical and practical aspects: Theoretically, it expands the boundaries of the interaction hypothesis in mobile ubiquitous learning environments, establishing an integrated model of technology empowerment, language acquisition, and cognitive optimization. It reveals the intrinsic mechanisms by which interactive technologies influence language acquisition and fills the interdisciplinary gap between educational technology and applied linguistics, providing a theoretical framework for digital language education that combines both discipline-specific and technological perspectives. Practically, the teaching process-technology matching strategies and interactive task design methods proposed in this study can directly guide teachers' teaching practices, improving the accuracy of technology applications. The identified functional requirements, such as AI feedback modules and AR situational interactions, will also provide optimization directions for developers of mobile education platforms, promoting deep integration between technology products and teaching needs.

2 CURRENT STATUS AND PROBLEM DIAGNOSIS OF INTERACTIVE TECHNOLOGY APPLICATIONS IN LINGUISTIC TEACHING IN MOBILE LEARNING ENVIRONMENTS

2.1 Application methods

This study adopts a mixed research method combining quantitative and qualitative approaches. A three-dimensional research framework of "macro survey—micro verification—platform profiling" is constructed, integrating platform function analysis to ensure the comprehensiveness and credibility of the research conclusions. The quantitative research covers 30 universities in 15 countries across three major regions: Asia, Europe, and North America. A structured questionnaire survey on the current status of interactive technology applications was conducted, and a total of 1,286 valid questionnaires were returned, including 324 from teachers and 962 from students. Descriptive statistics and bivariate correlation analysis were performed using SPSS 26.0 software. The qualitative research selected 6 representative universities and conducted in-depth interviews with 12 linguistics teachers for 45–60 minutes. In addition, 24 mobile linguistic classrooms were observed participatorily. After transcription of the interview recordings and observation notes, a three-level coding analysis was carried out using Nvivo 12.0. Furthermore, 10 mainstream global mobile linguistic teaching platforms, such as Duolingo, Babbel, and Coursera language courses, were selected. Quantitative rating criteria were established from three dimensions: interaction types, feedback mechanisms, and contextualization levels, to create an objective profile of platform technology applications.

2.2 Application status

Regarding the distribution of interactive technology types, current mobile linguistic teaching presents a significant structural imbalance. The actual usage rate of synchronous interactive technologies is low, with only one-third of classrooms adopting synchronous interactive forms such as real-time video collaboration and AI instant conversation, while asynchronous interactive technologies dominate, with more than three-quarters of classrooms relying on asynchronous methods such as forum discussions and peer reviews. The application of multimodal interactive technologies is even more limited, with fewer than one-fifth of the surveyed platforms providing AR/VR and other multimodal functions. Moreover, existing applications are highly concentrated in vocabulary teaching scenarios, such as using AR technology for physical object labeling to assist vocabulary memory. However, multimodal interactive technologies are almost absent in core teaching processes such as grammar rule explanations and pragmatic scenario simulations, with their technical advantages not fully exploited.

The overall compatibility of interactive technologies with core linguistic teaching processes is relatively low, and different processes present differentiated adaptation issues. In the input phase, over 80% of teaching practices involve interactive technologies only performing resource-pushing functions, such as sending learning materials (texts, videos, etc.) to learners via mobile devices. There is a lack of scene-based deep interactive designs, such as AR scenario simulations to assist contextualized input. In the internalization phase, more than 75% of technological feedback is limited to simple answer checking, merely informing learners whether their answers are correct or incorrect, with a lack of personalized explanations and guidance, such as AI-based grammar error analysis, which makes it difficult to meet the demands of language knowledge internalization. In the output phase, there is a severe shortage of real interactive scenarios. Only one-third of platforms provide simulated output functions such as virtual dialogues. In most cases, learners can only complete tasks through solo recordings or offline writing, lacking the meaning negotiation process found in real communication. Data on learners' and teachers' cognitive attitudes further confirms the severity of the adaptability issue: more than 45% of students reported experiencing information overload in mobile interactive tasks, with multiple sources of information (texts, videos, pop-up windows) displayed simultaneously, causing attention fragmentation. Over 60% of teachers believe that technical operations are complicated, and additional time spent on technical explanations affects teaching progress. Correlation analysis shows that learning motivation is significantly positively correlated with the authenticity of interactive technologies. The absence of highly authentic interactive scenarios directly suppresses learners' initiative in learning.

2.3 Core issues and causes

The most fundamental issue is the disconnection between interactive technology applications and the laws of language acquisition. The essence of this problem is the misalignment between the logic of technology design and the logic of language learning. The core of language acquisition is the closed-loop process of input-interaction-output, yet existing technology designs generally ignore this principle. For example, some platforms only design simple interactive question-and-answer activities in the input phase but fail to match corresponding feedback and correction mechanisms for the output phase, which prevents learners from completing meaning negotiation and knowledge internalization through interaction. The root cause of this issue lies in the fact that most mobile education platform developers come from a technical background and lack expertise in applied linguistics. As a result, the core of their technology design focuses on enhancing user engagement, such as task check-ins and points exchange, rather than constructing a complete interactive chain to improve language abilities.

Another key issue is the cognitive load imbalance caused by improper technology design, which restricts teaching effectiveness. According to cognitive load theory, effective learning requires balancing intrinsic, extraneous, and relevant cognitive loads. However, current practices show a dual imbalance: on the one hand, extraneous cognitive load is too high, caused by the piling up of technological functions and multimodal information redundancy. For instance, some platforms blindly embed AR/VR modules without optimizing interface design, leading to complicated operations and conflicting information presentation. On the other hand, relevant cognitive load is insufficient. Current interactive tasks are mostly low-level memory-based question-and-answer activities, lacking deep thinking tasks such as cross-cultural pragmatic decision-making and grammar rule transfer, which fail to stimulate cognitive engagement. This imbalance directly results from the lack of guidance from cognitive load theory in technology design. Developers prioritize feature richness as their core competitive advantage and ignore the adaptability of learning scenarios and adherence to cognitive rules.

The incomplete interactive effect evaluation system prevents the scientific measurement of technology application effectiveness, thus hindering technological optimization and teaching improvement. Current evaluations show a clear tendency toward focusing on behavior rather than ability. Most teaching and platforms only focus on surface behavior indicators such as click frequency and speaking turns, while assessments of deep language abilities such as pragmatic accuracy and grammar internalization are seriously inadequate. A deeper problem is the lack of tools for analyzing the correlation between interactive behaviors and language ability. Existing data collection is limited to single-dimensional quantitative statistics, which cannot accurately identify the causal relationship between different interactive technologies, tasks, and language ability improvements. As a result, the effectiveness of technology applications is difficult to quantify, and there is no targeted basis for technological optimization.

3 CONSTRUCTION OF STRATEGIES FOR ENHANCING LINGUISTIC TEACHING EFFECTIVENESS BASED ON INTERACTIVE TECHNOLOGIES

3.1 Guiding principles

To ensure the scientific nature and feasibility of the strategy system, this study establishes four core guiding principles, forming an organic whole. The language acquisition-oriented principle is the core, requiring that all interactive technology designs focus on the three key aspects of input comprehensibility, interaction meaning negotiation, and output authenticity, ensuring that the technology serves the intrinsic laws of language acquisition. The cognitive load balance principle serves as a safeguard, reducing extraneous cognitive load through simplified interfaces, phased tasks, and multimodal collaboration, while enhancing relevant cognitive load through deep interactive tasks to achieve efficient allocation of cognitive resources. The contextualization and personalization principle serves as the foundation for adaptation, designing interactive scenarios based on learners' language proficiency (beginner, intermediate, advanced) and cultural background differences, ensuring the targeted application of technology. The closed-loop feedback principle acts as a supporting mechanism, constructing a complete chain of input-interaction-output-feedback-correction, ensuring that each interactive link receives precise feedback to facilitate optimization.

3.2 Strategic system construction

Table 1. Interactive technology matching strategies for core teaching processes

Teaching Process	Core Goal	Matching Interactive Technology	Implementation Path
Input Phase	Enhance input comprehensibility, activate existing language knowledge	AR situational interaction technology, adaptive push technology	Teachers upload AR markers for real-world scenes such as campuses and business districts; the platform uses pre-test data to locate learners' levels and push i + 1 level resources. Learners scan the markers to receive contextualized input.
Internalization Phase	Promote meaning negotiation, and strengthen internalization of grammar/pragmatics rules	AI smart feedback technology, structured peer review technology	After completing exercises, AI generates error analysis reports based on NLP technology (including error types, rule explanations, and example sentences); teachers assign peer review tasks, with the platform providing a 5-level pragmatic appropriateness rating scale and evaluation dimension explanation.
Output Phase	Create authentic output scenarios, enhance language use ability	Virtual simulation interaction technology, cross-cultural collaboration interaction technology	The platform pre-sets 12 scenarios, such as airport check-in and business negotiations. AI dialogue robots dynamically adjust the conversation difficulty based on learners' responses; teachers organize international learning groups, and learners complete cross-cultural communication projects via the platform's shared task board.

Based on the above principles, this study constructs a "teaching process adaptation—cognitive load optimization—effectiveness evaluation regulation" three-dimensional collaborative strategy system. Teaching process adaptation, as the core dimension, matches exclusive interactive technologies and implementation paths for the input, internalization, and output phases based on their target differences (refer to Table 1). The cognitive load optimization dimension provides cognitive protection for technology applications, designing phased tasks to form a developmental path of cognition from shallow to deep. Beginner tasks (5–10 minutes) use a single-modal interaction to reduce extraneous load, intermediate tasks (15–20 minutes) use dual-modal collaboration to gradually enhance cognitive participation, and advanced tasks (25–30 minutes) use multimodal collaboration to deepen cognitive involvement, while adhering to Sweller's redundancy principle to integrate multimodal information. Audio-visual collaborative modes are prioritized to avoid information repetition, with adaptive interface designs supporting learners' custom elements and intelligent break reminders. The effectiveness evaluation regulation dimension forms a dynamic optimization mechanism, establishing a multidimensional indicator system covering language ability (vocabulary, grammatical accuracy, pragmatic ability), cognitive load (NASA-TLX scale, task completion time), and learning behavior (interaction frequency, task persistence). The platform's embedded analysis module collects data in real time and builds a prediction model based on the random forest algorithm. When the predicted effectiveness value falls below the threshold, it automatically adjusts task difficulty and technology type.

3.3 Strategy implementation path

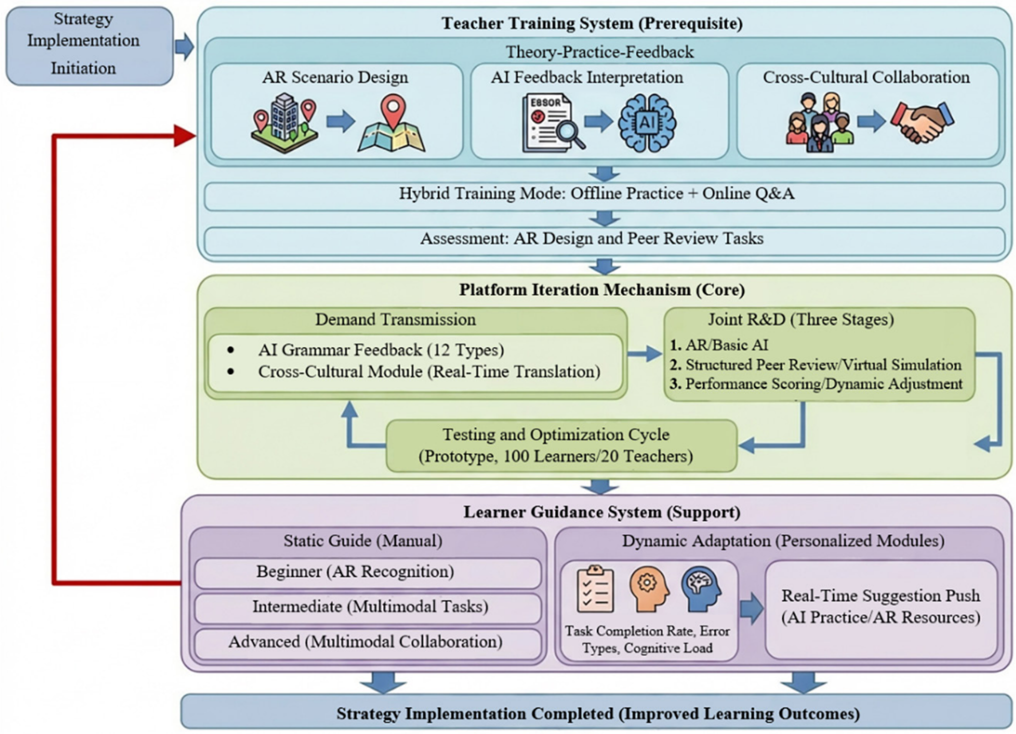

Fig. 1. Strategy implementation path for enhancing linguistic teaching effectiveness based on interactive technologies

Teacher training is a key prerequisite for the strategy's implementation, requiring the establishment of a "theory-practice-feedback" integrated training system. The training content focuses on three core modules: the AR situational design module, which covers practical skills such as marker point creation and scene resource development; the AI feedback interpretation module, which emphasizes the teaching transformation of error analysis reports and personalized guidance strategies; and the cross-cultural collaboration task design module, which includes methods such as group division design and cultural conflict mediation. The training adopts a hybrid model of "offline practical training + online Q&A," with 40 hours of practical training held offline and case breakdowns of teaching examples from six pilot universities; an online Q&A community is established where experts in applied linguistics and educational technology provide continuous guidance. After the training, practical assessments, such as AR scene design and peer review task development, are conducted to ensure teachers have mastered core skills (see Figure 1).

Platform iteration requires the establishment of a closed-loop mechanism for "demand transmission-joint research and development-testing and optimization" to achieve deep adaptation between technical functions and teaching needs. First, based on the previous survey conclusions and strategy requirements, a demand list is formed, detailing functional points, such as the AI grammar feedback module needing to support automatic classification of 12 common grammatical errors, provide hierarchical explanations of error rules, and include a personalized error collection function. The cross-cultural collaboration module needs to integrate core features such as real-time subtitle translation, cultural custom tips, and multi-version task document sharing. Then, a research and development team is formed by collaborating with three mainstream mobile education platforms, turning strategy requirements into technical parameters, and completing prototype development in three phases: Phase 1 implements AR situational interaction and basic AI feedback functions, Phase 2 develops structured peer review and virtual simulation dialogue modules, and Phase 3 integrates effect analysis and dynamic adjustment functions. At each development stage, 100 learners and 20 teachers are selected for prototype testing. Feedback is collected through user experience surveys and focus group interviews, and functionality optimization is completed based on the feedback data.

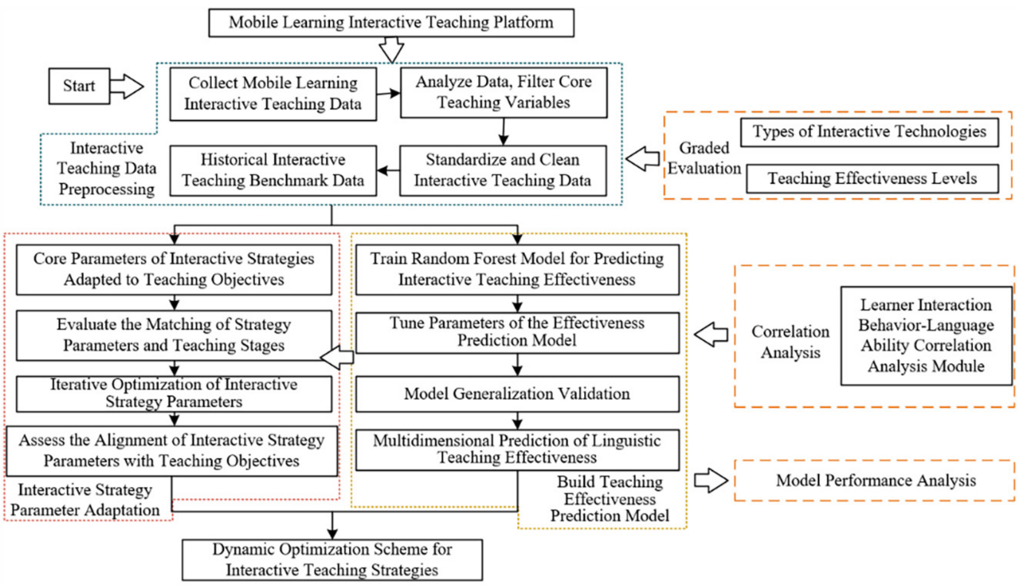

Fig. 2. Implementation and dynamic optimization process of mobile linguistic teaching interactive technology strategies

Learner guidance requires the construction of a "static guide + dynamic adaptation" support system to enhance the autonomy and accuracy of strategy application. A "Mobile Interactive Learning Guide" is compiled for learners of different levels, clarifying core tasks and key technology usage at each stage: beginner learners mainly focus on single-modal tasks such as AR vocabulary recognition and short dialogue simulations, emphasizing mastering basic technology operations; intermediate learners focus on dual-modal interactive tasks, such as completing grammar exercises with AR scenarios combined with text annotations, participating in peer reviews, and learning how to write feedback; advanced learners focus on multimodal collaboration tasks, enhancing pragmatic ability through cross-cultural projects and complex scenario simulations. At the same time, a personalized guidance module is embedded in the mobile platform, which provides real-time adaptation suggestions based on learners' task completion rates, error types, and cognitive load data. For example, if learners' grammatical errors are concentrated in tense issues, the platform will automatically recommend AI-based tense exercises and related AR contextual input resources. If cognitive load scores exceed a threshold, a suggestion to switch to low-load single-modal tasks will be prompted.

Figure 2 visually presents the full process management logic of the interactive technology teaching strategy, which covers three major modules: 1) Mobile learning interactive teaching data processing; 2) Strategy optimization closed loop; 3) Implementation support system. It intuitively shows the complete logical chain of the strategy from design and validation to dynamic adjustment.

4 EXPERIMENTAL RESULTS AND ANALYSIS

To accurately verify the effect of the interactive technology strategy on the improvement of core dimensions of language ability, this study conducted pre-test and post-test comparison experiments across four sub-dimensions: vocabulary, grammar, pragmatics, and speaking. The results in Table 2 show that the experimental group significantly outperformed the control group in all post-test dimensions, with notable differences in improvement rates: grammar error rate and speaking fluency improved by over 50%, pragmatic appropriateness score improved by 52.8%, and vocabulary retention rate improved by 41.7%. In contrast, the control group showed a maximum improvement rate of only 29.7%, with the lowest being 13.0%. This result indicates that the interactive technology strategy developed can comprehensively enhance various sub-dimensions of language ability, with particularly notable improvements in deeper competencies such as grammar proficiency, speaking expression, and pragmatic adaptation, validating the effectiveness of the strategy's design focused on "input contextualization, internalization depth, and output authenticity."

To explore the long-term impact of the interactive technology strategy on the learning experience, this study dynamically tracked learning motivation and cognitive load over an 8-week experimental period. The results in Table 3 show that the experimental group demonstrated a positive trend of "sustained motivation increase and continuous cognitive load decrease": learning motivation increased from 3.2 points in Week 1 to 4.3 points in Week 8, while cognitive load decreased from 6.8 points to 3.7 points, with significant changes observed by Week 4. In contrast, the control group showed "slight fluctuations in motivation followed by a decline and a slight decrease in cognitive load followed by stability": at Week 8, the motivation score of 3.2 points was close to the initial level, and the cognitive load remained high at 5.9 points. These results suggest that the developed strategy not only enhances language ability but also improves the learning experience by optimizing interactive design. Phased tasks and multimodal collaboration effectively reduce cognitive burden, while authentic interactive scenarios continuously stimulate learning motivation, creating a virtuous cycle of "ability improvement—experience optimization."

Table 2. Comparison of improvement in sub-dimensions of language ability

Group	Language Ability Dimension	Pre-Test Mean ± Standard Deviation	Post-Test Mean ± Standard Deviation	Improvement (%)	Inter-Group Significance (p-Value)
Experimental Group	Vocabulary Retention Rate (%)	58.2 ± 6.3	82.5 ± 5.1	41.7	<0.001
Control Group	Vocabulary Retention Rate (%)	57.8 ± 6.5	65.3 ± 5.8	13.0	<0.001
Experimental Group	Grammar Error Rate (%)	18.5 ± 3.2	7.2 ± 2.1	61.1	<0.001
Control Group	Grammar Error Rate (%)	18.2 ± 3.1	12.8 ± 2.5	29.7	<0.001
Experimental Group	Pragmatic Appropriateness Score (10-point scale)	5.3 ± 0.8	8.1 ± 0.6	52.8	<0.001
Control Group	Pragmatic Appropriateness Score (10-point scale)	5.2 ± 0.9	6.4 ± 0.7	23.1	<0.001
Experimental Group	Speaking Fluency (words/minute)	82.3 ± 10.5	125.6 ± 9.8	52.6	<0.001
Control Group	Speaking Fluency (words/minute)	81.9 ± 10.2	98.4 ± 10.1	20.1	<0.001

Table 3. Dynamic changes in learning motivation and cognitive load

Group	Time Point	Learning Motivation Scale Score (1–5)	NASA-TLX Cognitive Load Score (1–10)	Motivation Change Trend	Cognitive Load Change Trend
Experimental Group	Week 1	3.2 ± 0.5	6.8 ± 1.2	–	–
Experimental Group	Week 4	3.8 ± 0.4	4.5 ± 1.0	Increase	Decrease
Experimental Group	Week 8	4.3 ± 0.3	3.7 ± 0.8	Continuously Increasing	Continuously Decreasing
Control Group	Week 1	3.1 ± 0.5	6.7 ± 1.1	–	–
Control Group	Week 4	3.3 ± 0.4	6.2 ± 1.0	Slight Increase	Slight Decrease
Control Group	Week 8	3.2 ± 0.5	5.9 ± 1.2	Slight Decrease	Mostly Stable

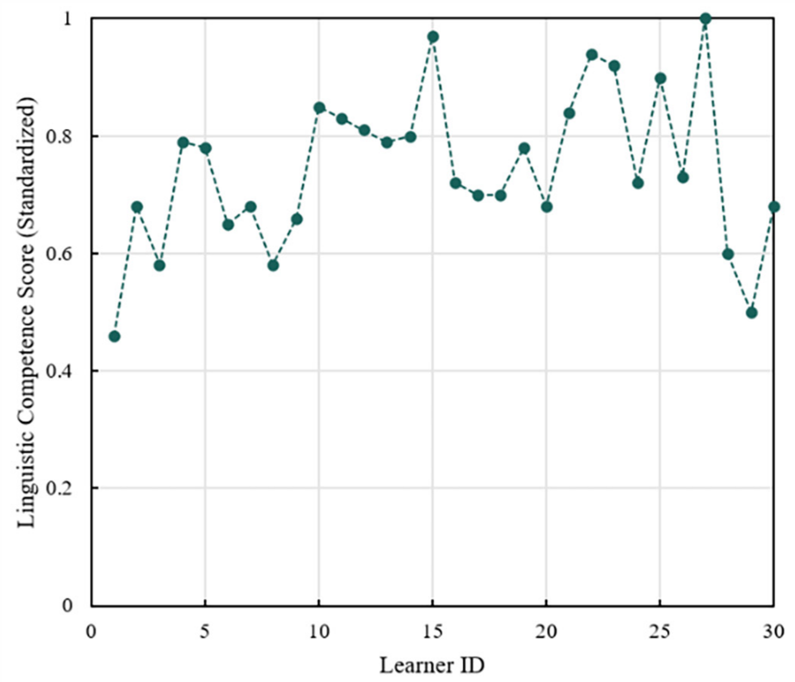

Fig. 3. Standardized scores of linguistic comprehensive ability for different learners

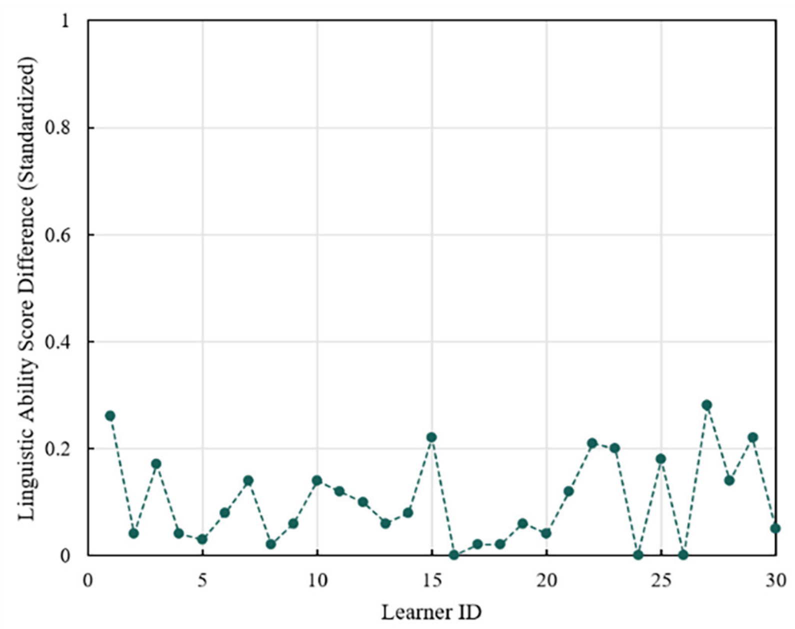

Fig. 4. Ability difference between the interactive technology strategy group and the traditional mobile teaching group

To clarify the effect of the interactive technology strategy on the improvement of comprehensive linguistic ability and individual performance differences among learners, this study conducted ability scoring and inter-group difference analysis for 30 learners who participated in the experiment. Figure 3 presents the standardized scores for the linguistic comprehensive ability of different learners. It is evident that most learners scored above 0.6, with some learners' scores close to 1.0, showing a high level of language ability overall. However, scores fluctuated according to learner number, reflecting differences in individual learning backgrounds and strategy adaptability. Figure 4 shows the ability differences between the interactive technology strategy group and the traditional mobile teaching group. Most learners' differences were concentrated above 0.2, with some learners' differences exceeding 0.8, and only a few learners had differences close to 0. This indicates that the interactive technology strategy significantly improved the linguistic comprehensive ability of the majority of learners, while the effect was limited for a small number of learners with lower learning foundations or lower acceptance of technology. This result not only verifies the overall effectiveness of the developed interactive technology strategy but also suggests that future practices should optimize strategy adaptability based on individual learner characteristics to further reduce individual differences in ability improvement.

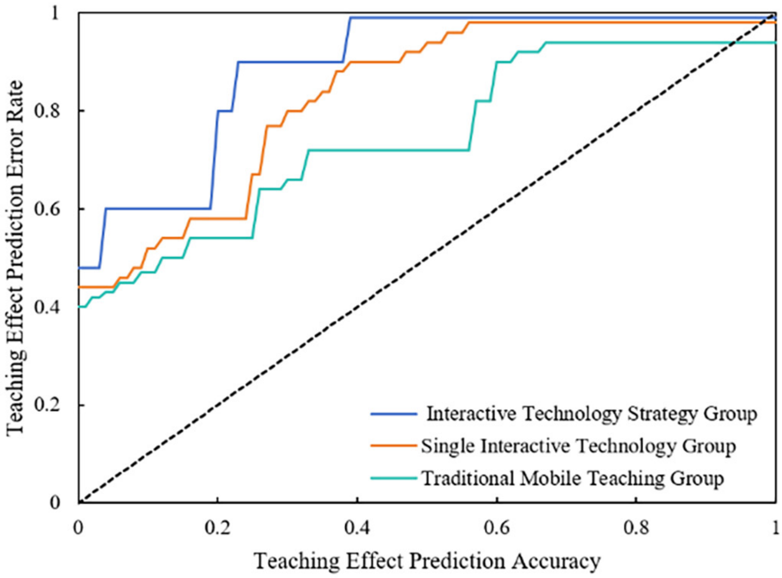

Fig. 5. ROC curve comparison of interactive effect prediction models for different teaching modes

To quantify the performance differences of interactive effect prediction models for different teaching modes and to verify the accuracy of the interactive technology strategy in identifying teaching effectiveness, this study conducted an ROC curve comparison experiment. Figure 5 presents the ROC curves for the teaching effect prediction models of the interactive technology strategy group, the single-interactive technology group, and the traditional mobile teaching group. The vertical axis represents teaching effect prediction accuracy, while the horizontal axis represents teaching effect prediction error rate. The results show that the interactive technology strategy group's curve is closest to the upper-left corner of the coordinate graph, with its area under the curve significantly higher than the other two groups. The single-interactive technology group's curve lies between the interactive technology strategy group and the traditional mobile teaching group, while the traditional mobile teaching group's curve is closest to the random prediction baseline, showing the weakest prediction performance. These results suggest that the prediction model based on the proposed interactive technology strategy has the best accuracy in identifying and predicting teaching effectiveness. It can more accurately capture the correlation between interactive design and teaching outcomes, indirectly validating the stability and superiority of the interactive technology strategy in enhancing mobile linguistic teaching effectiveness and providing quantifiable model performance support for its application in practical scenarios.

To verify the general applicability of the interactive technology strategy, this study divided the learners into groups based on language proficiency and learning styles and compared the improvement effects across groups. The results in Table 4 show that the improvement in the experimental group was significantly higher than that in the control group across all groups, with group differences observed: in terms of language proficiency, beginner learners showed the highest improvement in vocabulary and grammar, with increases of 52.3% and 68.2%, respectively. Intermediate learners showed the most significant improvement in pragmatics, while advanced learners exhibited relatively lower but still significant improvement across all dimensions. In terms of learning style, visual learners showed higher improvement in speaking fluency than auditory learners. This result indicates that the strategy is adaptable to different groups, with particularly notable improvement for beginner learners with weaker foundations. It also reflects that the visualized interactive designs, such as AR contexts, are more suited to visual learners, providing a clear direction for optimizing strategy details for different groups in future research.

Table 4. Strategy adaptation effect results for different learner groups

Learner Group	Language Ability Dimension	Experimental Group Improvement (%)	Control Group Improvement (%)	In-group Significance (p-Value)
Beginner Level	Vocabulary Retention Rate	52.3	18.5	<0.001
Beginner Level	Grammar Error Rate	68.2	35.7	<0.001
Beginner Level	Pragmatic Appropriateness Score	45.1	19.3	<0.001
Intermediate Level	Vocabulary Retention Rate	40.8	12.7	<0.001
Intermediate Level	Grammar Error Rate	60.5	28.9	<0.001
Intermediate Level	Pragmatic Appropriateness Score	56.4	24.8	<0.001
Advanced Level	Vocabulary Retention Rate	29.7	8.3	<0.01
Advanced Level	Grammar Error Rate	38.2	15.6	<0.01
Advanced Level	Pragmatic Appropriateness Score	42.9	18.5	<0.01
Visual Learners	Speaking Fluency	58.3	22.4	<0.001
Auditory Learners	Speaking Fluency	47.2	17.9	<0.001

5 CONCLUSION

This paper focuses on the core challenges of linguistic teaching in mobile learning environments, supported by interdisciplinary theories from applied linguistics, educational technology, and cognitive psychology. Through a mixed research method, the study systematically completed three core tasks: current situation diagnosis, strategy construction, and empirical validation. The research first identified key issues in current mobile linguistic teaching, such as the superficial application of interactive technologies, disconnection from language acquisition principles, cognitive load imbalance, and incomplete evaluation systems. Then, a three-dimensional interactive technology strategy system was developed, focusing on "teaching segment adaptation—cognitive load optimization—effect evaluation control," and matching exclusive interactive technologies for input, internalization, and output segments. Finally, multi-dimensional experiments were conducted to verify the effectiveness of the strategy. The results showed that the experimental group achieved much greater improvement than the control group in key language ability dimensions such as vocabulary retention rate and grammar error rate, with a 61.1% improvement in grammar error rate. The strategy also fostered a positive cycle of sustained increases in learning motivation and steady decreases in cognitive load. The adaptation effect for beginner-level learners was especially prominent, and the prediction model based on this strategy had the best teaching effect identification accuracy. The core value of this study lies in its theoretical contribution, expanding the application boundary of the interaction hypothesis in ubiquitous mobile environments and constructing an integrative theoretical framework for technology-enabled language acquisition, filling a gap in interdisciplinary research. On a practical level, it provides an operable strategy encompassing technology selection, task design, and group adaptation, offering direct reference for linguistic teachers' teaching practices and the optimization of mobile education platform functions.

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