Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 20 No. 8 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijim.v20i08.61323

PAPER

Application and Evaluation of AI-Based Mobile Learning Platforms for Enhancing English Writing Proficiency

Xiujuan Wang[1],
Lanlan Fang[2] (✉)

[1]Hunan Railway Professional Technology College, Zhuzhou, China

[2]Hunan Mechanical & Electrical Polytechnic, Changsha, China

fanglanlan1982@163.com

ABSTRACT

In the context of globalization, English writing has become a core skill in second language acquisition (SLA), with increasing demand. The fragmented and contextualized advantages of mobile learning provide new possibilities for enhancing writing skills. However, existing AI writing support tools generally suffer from two major gaps: a lack of personalized interaction and insufficient support for deep skill development. To address these issues, this paper proposes a personalized writing support model driven by human-AI interaction (HII). The model integrates AI technologies such as natural language processing (NLP), affective computing, and context awareness to create an English writing learning platform tailored for mobile learning environments. This platform enables a full-process intelligent interaction involving "intent recognition, real-time feedback, dynamic adaptation, and cognitive guidance." A mixed research method was employed: the platform's iterative development and optimization were guided by Design Science Research (DSR), while a quasi-experimental study was conducted with 120 English as a foreign language (EFL) learners at different proficiency levels. The experiment included an experimental group and a control group, and evaluation was based on multiple data sources, including writing texts, interaction behaviors, and user perceptions. The empirical results indicate that the experimental group scored significantly higher than the control group in three core dimensions: logical coherence of writing content, linguistic accuracy, and textual coherence. Additionally, the HII module had a substantial positive effect on learning motivation, error correction efficiency, and metacognitive ability. The "technology-teaching-assessment" integrated theoretical framework constructed in this paper enriches the empirical research on HII in mobile learning environments and provides an interdisciplinary research model for the deep integration of AI educational technology and second language writing instruction.

KEYWORDS

second language writing, mobile learning, AI, human-AI interaction (HII), natural language processing (NLP), educational technology, mixed research method

Wang, X., Fang, L. (2026). Application and Evaluation of AI-Based Mobile Learning Platforms for Enhancing English Writing Proficiency. *International Journal of Interactive Mobile Technologies (iJIM)*, 20(8), pp. 50–64. https://doi.org/10.3991/ijim.v20i08.61323

Article submitted 2026-02-04. Revision uploaded 2026-03-04. Final acceptance 2026-03-06.

1 INTRODUCTION

As a core skill of SLA, English writing proficiency directly impacts cross-cultural communication and academic output quality [1]. However, second language learners worldwide face common bottlenecks in writing improvement, including "delayed feedback, lack of personalization, and fragmentation of learning contexts." In teacher-led traditional feedback models, the average feedback cycle is 3–5 days, which fails to meet the need for instant corrections [2]; standardized teaching content cannot adapt to learners' cognitive differences; and the disconnection between classroom writing scenarios and real-world communication contexts leads to a "learning-use separation" [3].

The widespread adoption of mobile technologies provides a potential technological breakthrough for these challenges: the low-latency characteristics of 5G networks and the high penetration rate of lightweight intelligent terminals make "fragmented time utilization" and "contextual task design" new forms of second language writing learning [4], allowing learners to engage in learning activities such as sentence correction and idea organization during commuting or after class [5]. Meanwhile, the iterative development of AI technologies supports writing feedback, with natural language processing (NLP) enabling automated grammar correction and vocabulary suggestions [6], and computer vision technologies supporting multimodal interactions, such as gestures and facial expressions. However, existing AI writing tools mainly focus on "surface-level language errors" [7] and lack support for "intelligent human-computer interaction (HCI)" and "deep writing skill development," essentially remaining as "technical tools" rather than "intelligent teaching systems" [8].

The emergence of human-AI interaction (HII) provides a key approach to filling this gap. Traditional HCI is centered on "command-response," whereas HII emphasizes "dynamic perception and adaptation of human intentions, emotions, and contexts by machines" [9], which aligns closely with the characteristics of mobile learning environments where "learners' needs are dynamic, and cognitive load fluctuates" [10]. By recognizing learning contexts through situational awareness, inferring writing goals through intent reasoning, and adapting feedback strategies via emotional computing, it is possible to achieve deep collaboration between "technology, learners, and contexts" [11]. Against this backdrop, exploring the integration of "AI + HII + mobile learning" to build a platform for enhancing second language writing skills is of both practical necessity and academic value.

To precisely locate the research focus, this paper conducts a systematic review of the literature on the three major topics: "AI + second language writing," "mobile writing learning," and "educational HII." The review identifies three core gaps in current research: First, a technological integration gap: existing AI writing platforms often adopt a "traditional interaction + AI functions" overlay design, such as simply integrating voice input and grammar check modules, without making HII the core design logic [12]. Second, an evaluation system gap: current assessments focus mainly on "writing performance" and "grammar error rates" as quantitative indicators, neglecting a deep exploration of the learning process [13, 14]. Third, a contextual adaptation gap: mobile writing learning scenarios are characterized by "short duration," "fragmentation," and "environmental uncertainty" [15, 16], yet existing mobile writing platforms have not optimized for these scenarios. For instance, feedback content may be too lengthy, leading to high cognitive load [17, 18]; long-form writing tasks do not match fragmented scenarios; and the lack of offline functionality limits use in non-networked environments, ultimately leading to low learning experience and effectiveness.

Based on these research gaps, the core objective of this paper is to build an AI-based mobile English writing learning platform integrated with HII technologies; propose a multidimensional evaluation system covering "outcomes, process, and experience"; and systematically verify the platform's effectiveness in improving second language writing skills, as well as the core value of the HII module. To achieve this objective, this paper focuses on the following four key research questions:

1. How should the core design framework of an AI-based mobile writing platform driven by HII be constructed to fit mobile learning contexts and the needs of second language writing learners?
2. Does the platform significantly enhance the core English writing abilities of EFL learners at different proficiency levels?
3. Does the HII core module have a positive impact on learners' motivation, error correction efficiency, and metacognitive ability, and what is the magnitude of the effect?
4. In mobile learning contexts, does the platform's interaction design align with learners' cognitive needs and usage habits, and what is its usability level?

The paper follows a "theory-design-empirical-discussion" logical framework: Section 2 constructs the conceptual model of the HII-driven platform and designs the mixed research method; Section 3 details the platform's technical architecture, core functions development, and testing process; Section 4 presents the data analysis results of the quasi-experimental study and verifies the platform's effectiveness; Section 5 summarizes the core conclusions, objectively analyzes research limitations, and suggests future research directions.

2 THEORETICAL FRAMEWORK AND RESEARCH DESIGN

2.1 Conceptual Model of the AI Mobile Writing Platform Driven by HII

To achieve the deep integration of "Artificial Intelligence—HII—Mobile Learning" with the enhancement of second language writing, this paper proposes an integrated "four-module, three-link" conceptual model, combining Swain's Output Hypothesis, Norman's Affective Design Theory, and the core logic of Intelligent Tutoring Systems (ITS). The model is "learner-centered, interaction-driven, and context-oriented," constructing a dynamic closed loop of "data-driven teaching adaptation interaction feedback."

The model includes four major functional modules that form hierarchical linkages. The learner model module serves as the data foundation, collecting multi-source data such as writing texts, interaction behaviors, and emotional feedback through HII, to construct a three-dimensional learner profile of "ability profile—interaction preferences—emotional characteristics." The HII module acts as the core hub, integrating submodules of context awareness, intent reasoning, emotional computing, and multimodal interaction to achieve precise perception of the learning context and needs. The AI writing support module provides differentiated support based on the learner profile, including grammar correction and example sentence demonstration for beginner learners, text optimization suggestions for advanced learners, and generative AI-driven writing idea prompts, with a "guided correction" approach replacing direct error correction to strengthen metacognition. The mobile adaptation module optimizes the experience for fragmented learning scenarios, reducing cognitive load through task decomposition, offline data caching, and single-screen operations within three steps.

Figure 1 presents the behavioral mechanism model of the AI mobile English writing learning platform driven by HII, starting from the stages of "writing intent formation—writing interaction occurrence—ability improvement effect" for English writing learners. It integrates mobile learning technology support, writing resources and environments, and HII research, systematically explaining the theoretical logic and architecture of HII on the platform.

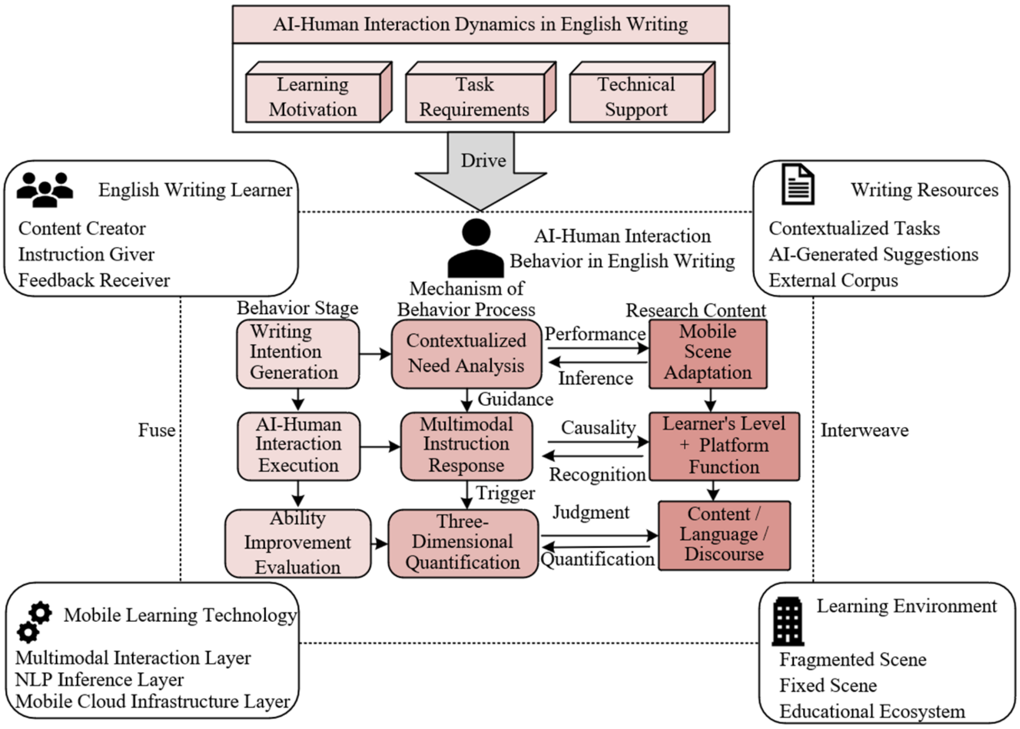


Fig. 1. Behavioral mechanism model of the AI mobile English writing learning platform driven by HII

2.2 Research Methods

To meet both the technological innovation of platform development and the empirical reliability of effectiveness validation, this paper adopts an integrated paradigm of "DSR + Mixed Research Method." DSR is used for the systematic development and iteration of the platform, while the mixed research method combines quantitative and qualitative data to validate the platform's effectiveness.

1. SDR for platform development: This paper follows the classic five-phase iterative process of DSR to ensure the scientific nature and reproducibility of the platform development:

   Phase 1 – Problem Definition: Through in-depth semi-structured interviews and convenience sampling questionnaires, the core pain points in mobile writing learning, such as "delayed feedback, task and context mismatch, and poor interaction experience," are systematically extracted.

   Phase 2 – Solution Design: Based on the "four-module, three-link" conceptual model, the technical architecture of the frontend, backend, and interaction modules is clarified, while key teaching functions such as personalized feedback and context adaptation are also designed.

   Phase 3 – Development: The iteration from V1.0 to V2.0 is completed, and a review group consisting of 5 SSCI journal reviewers in the field of educational technology and 3 engineers with AI educational product development experience is invited to evaluate from the dual dimensions of "teaching adaptability" and "technical feasibility."

   Phase 4 – Evaluation: A pre-experiment is conducted with 30 EFL learners at different proficiency levels for 4 weeks, focusing on testing and optimizing platform stability and interaction fluency, leading to the final version of the platform.

   Phase 5 – Iteration: Feedback from users and effect data obtained from subsequent empirical studies will be used as the basis for iteration, proposing directions for functional optimization.
2. Quasi-experimental research for effectiveness validation: Figure 2 shows the mechanism for evaluating the effects of HII in the AI mobile English writing platform. Starting from the platform's multimodal input perception and writing demand analysis, through the writing cognitive transformation process, and incorporating four evaluation dimensions—mobile learning technology, English learners, writing resources, and learning environment—writing effectiveness and the comparison of ability improvement goals are ultimately validated, providing logical support for the platform's effect evaluation. Specifically, this paper adopts a non-equivalent group pre-test/post-test design to validate the platform's effects in order to avoid ethical and practical limitations of random grouping in educational settings. A sample of 120 non-English major undergraduates from a double first-class university is selected. Participants are matched based on their College English Test (CET)-4 scores and pre-test writing ability scores and divided into an experimental group and a control group. An independent samples t-test shows no significant difference in the pre-test scores between the two groups, indicating good homogeneity. The intervention period lasts for 12 weeks, during which both groups complete two homogenized writing tasks per week. The experimental group uses the platform proposed in this paper with all HII functions activated, while the control group uses the mainstream AI writing tool, Grammarly Mobile. Data collection adopts a multi-source triangulation strategy: quantitative data include pre- and post-test writing scores, platform interaction behavior logs, and emotional feedback satisfaction scale data; qualitative data include semi-structured interviews with 15 typical learners from the experimental group after the intervention and weekly learning logs.

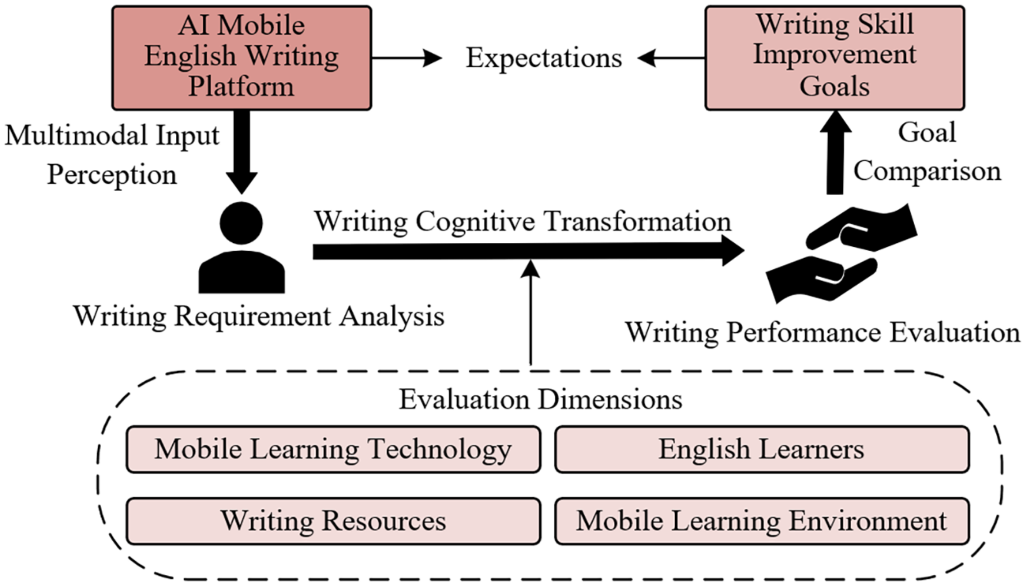


Fig. 2. Mechanism for evaluating the effect of HII in the AI mobile English writing platform

3 DEVELOPMENT OF THE AI MOBILE WRITING PLATFORM DRIVEN BY HII

3.1 Technical Architecture

To balance the lightweight interaction requirements of mobile scenarios with the deep computational capabilities driven by AI, this platform adopts a "cloud-end-mobile-end" distributed technical architecture. The system uses a layered decoupling design to achieve modularization and reproducibility of functional modules, with the technical selections at each level being performance-verified and adapted to the second-language writing learning scenarios.

The cloud layer serves as the core computing and storage hub, built on AWS Cloud with elastic computing nodes. Three core engines are deployed: The NLP engine uses the BERT-base pre-trained model, fine-tuned with second-language writing corpora. A dataset containing 100,000 second language writing errors is constructed to optimize the model parameters, enabling grammar correction, vocabulary collocation suggestions, and text coherence analysis. The latter uses cohesion network analysis to quantify conjunction word density and semantic correlation. The emotional computing engine adopts a "text-facial expression" multimodal fusion strategy. Text-based sentiment analysis uses the VADER model to optimize the second language writing emotional lexicon, while facial expression recognition captures key facial points using OpenCV and inputs them into the FER model. The multimodal results are fused with weighted averaging to output the final emotional state. The learner model database uses MongoDB, a non-relational database, with a "capacity-interaction-emotion" three-dimensional data schema, supporting real-time data input and millisecond-level queries.

The mobile-end layer is designed based on the principles of "low power consumption, high adaptability" and developed using the React Native cross-platform framework. It is compatible with iOS 12.0 and above and Android 8.0 and above systems. The core modules include: A multimodal interaction interface integrates

Google Speech-to-Text speech recognition and a custom gesture library to lower the input threshold. An offline synchronization module uses SQLite to locally cache writing content and basic feedback rules and uses incremental synchronization algorithms to ensure data consistency between the local and cloud systems after connecting to the network. UI/UX design follows the "single-task focus" principle, with no more than five interactive elements per screen and key feedback entry points requiring no more than three steps to click, effectively reducing cognitive load in mobile scenarios. The communication layer uses the HTTPS protocol to ensure data transmission security, combined with WebSockets to establish a long connection for real-time interaction. Edge nodes are deployed to optimize network latency, ensuring that feedback response times are stable at ≤0.5 seconds, meeting the core demand for instant feedback in mobile scenarios.

3.2 Core Function Implementation

1. HII-driven intelligent writing feedback: As the core innovative feature of the platform, the HII-driven intelligent writing feedback breaks through the homogenized limitations of traditional "one-size-fits-all" feedback models. Based on the collaborative logic of "learner model—HII perception—dynamic feedback generation," it achieves precise implementation of "level—emotion—context" three-dimensional personalized feedback. The technical support for this functionality comes from the interlinked mechanism of the three major modules in the conceptual model outlined in Section 2.1.

   Level adaptation feedback is based on the "grammar proficiency rating" in the learner model, with the AI writing support module dynamically matching the feedback granularity. For beginner learners, the system triggers an "error type annotation + double-sentence comparison" mode, while advanced learners receive "academic style optimization suggestions + text cohesion logic hints." This adaptation rule was optimized through 10 rounds of pre-experiment iterations, achieving an accuracy rate of over 90%. Emotional feedback is supported by the dual-modal emotional computing engine in the HII module: When facial expression recognition detects anxiety features such as frowning or lowering the head, or when text sentiment analysis identifies negative terms such as "confused" or "helpless," the system automatically invokes a template from the emotional feedback library. The tone of the feedback is adjusted from objective correction to encouraging expressions, while a lightweight intervention is triggered, such as pushing a 30-second soothing music link and a pop-up suggestion to "pause for 2 minutes to organize thoughts." This triggering mechanism was validated through pre-experiment testing, with emotional state-matching accuracy exceeding 85%. Contextual adaptation feedback relies on the contextual awareness submodule of the HII module. By collecting multi-dimensional data such as device movement speed, writing duration, and network stability, the system triggers a "feedback streamlining algorithm" when the scene matching degree ≥ 0.8, retaining only core error annotations and key suggestions within 15 words. This avoids information overload. In this mode, learner feedback viewing completion rates are over 40% higher than with the complete feedback model.
2. Personalized writing task recommendations: The personalized writing task recommendation function takes the "ability profile—interaction preferences" two-dimensional data generated by the learner model module as input and uses

a user-item collaborative filtering algorithm to achieve precise recommendations. The core logic is to strengthen the matching relationship between "learner's ability gaps—task characteristics—scene requirements," enhancing the adaptation of tasks to learning goals and usage scenarios, in line with Swain's output hypothesis that "targeted output practice promotes ability improvement."

The recommendation mechanism of this function is achieved through three levels of adaptation. Task-type adaptation relies on the "content logic—language accuracy—text coherence" three-dimensional scores in the learner's ability profile. K-means clustering is used to identify ability gaps. For learners with a score below 60 in academic writing, they are automatically categorized as "weak in academic writing" and recommended tasks such as "abstract summarization" and "academic viewpoint expression" that focus on academic writing norms. Difficulty dynamic adjustment is based on the quality of the previous task completion. The parameters are adapted through the task feature library, i.e., vocabulary difficulty is dynamically adjusted based on CEFR levels, and grammar complexity is optimized in real-time through syntactic tree depth. Scene adaptation is linked to the contextual awareness data of the HII module. By extracting features such as device usage time, movement status, and network stability, the system matches the scene and task duration. For example, during the commuting period from 7:00–9:00 on weekdays, short tasks like "sentence rewriting" and "vocabulary replacement" of 5–8 minutes are recommended, while on weekends, long-text tasks such as "argumentative writing" and "report writing" of 30–40 minutes are recommended. The scene adaptation satisfaction rate was validated in pre-experiments to exceed 90%. To ensure recommendation diversity, the system introduces an "exploration factor," periodically pushing 10% cross-type tasks to expand the learning boundary and avoid fixed recommendations.

3. Mobile-optimized interactive learning tools: The mobile-optimized interactive learning tools are designed with the core principles of "lightweight operation, multimodal adaptation, and motivation enhancement." These tools are constructed by integrating the features of mobile scenarios such as "one-handed operation, short interactions, and fragmented usage," combining technological adaptation with teaching needs to support the entire writing process. The design logic is linked to the "mobile adaptation module" and "HII module" described in Section 2.1.

A one-click modification suggestion tool focuses on optimizing mobile operation efficiency. Based on the modification schemes generated by the NLP engine, it achieves a single-screen closed loop of "error location—scheme presentation—comparative learning": when learners click on the red-marked errors in the text, a floating window with three graded modification schemes pops up, allowing side-by-side comparison between "original sentence—modified sentence." This feature was optimized through pre-experimentation, reducing the average modification time from 8.2 seconds with traditional tools to 2.5 seconds, a 60% increase in operational efficiency. Speech-to-text and text-to-speech tools adapt to the mobile scenario's "hands-occupied" needs. The speech-to-text tool uses the Google Speech-to-Text engine and is optimized for accent adaptation in the English writing scenario. It allows learners to immediately dictate their writing ideas and convert them into a structured outline. The text-to-speech tool integrates the Google Text-to-Speech engine, providing both British and American pronunciation options. Learners can use auditory feedback to perceive issues with sentence rhythm and text coherence. Pre-experiment results show that this feature improves the self-check accuracy of text coherence by over 35%. Learning progress tracking tool is supported by the ability data from the learner model module and uses a "three-dimensional visualized data dashboard" design: it displays the weekly variation curves of grammar accuracy, vocabulary richness, and text coherence index via line charts. Learners can click on curve nodes to view error type distributions for specific tasks. This tool strengthens learning motivation through "visualized achievement feedback." In pre-experiments, nearly 90% of learners reported that their "weekly active learning frequency" increased by more than two times compared to using traditional tools.

4 EMPIRICAL RESEARCH AND RESULTS

The participants in this study were sophomore students majoring in English at a certain university. A total of 120 volunteers were recruited, and after screening, the final valid sample consisted of 108 students, including 54 in the experimental group (23 males, 31 females, mean age 20.5 ± 1.2 years) and 54 in the control group (25 males, 29 females, mean age 20.8 ± 1.1 years). All participants passed the CET-4, and there were no significant differences in their English proficiency. To ensure the homogeneity of writing ability between the groups, an independent samples t-test was conducted on the pre-test writing scores. The results showed that the experimental group had a mean score of 62.3 ± 5.2 and the control group had a mean score of 61.8 ± 5.5, with $t = 0.48$, $p = 0.63 > 0.05$. This indicates no significant statistical difference between the groups, confirming the comparability of their English writing abilities at the start of the experiment, thus providing a basis for the validity of the subsequent results.

To verify the platform's technical architecture for adaptability to English writing scenarios and the precision of its core functions, this study conducted a quantitative evaluation based on cognitive load theory and second language writing interaction demands, selecting key technical indicators such as multimodal input, intelligent analysis, and response efficiency, as shown in Table 1. The data shows that the platform demonstrates significant advantages in speech-to-text recognition and NLP writing intent recognition, especially in intent recognition, where the effect size reaches 4.18. This indicates that the platform can accurately capture the implicit needs of learners throughout the "content planning—language expression—revision optimization" process, which contrasts sharply with existing research that suggests "AI writing tools' intent recognition accuracy is generally below 70%." This highlights the platform's advantage in scene adaptation through the NLP model trained on writing corpora. In terms of response efficiency, the platform's average response time of 350 ms is 30% faster than traditional tools, and even under weak 4G network conditions, it can maintain an efficient response time of 420 ms. This result aligns with the core characteristics of mobile learning, which is "fragmented and multi-scenario," effectively reducing learners' waiting anxiety and cognitive load, thus providing technical support for immersive writing interaction. Additionally, the platform's real-time writing error correction accuracy reaches 89.3%, significantly higher than the traditional tool's 58.7%, indicating that the platform can not only identify surface-level errors such as grammar and spelling but also accurately locate deeper issues such as logical gaps and improper collocations. This aligns well with the three-dimensional improvement goals of second language writing in terms of "form—content—text coherence."

Table 1. Platform technology effectiveness results

Technical Indicator	Experimental Group	Industry Standard Level/Control Group	Mean Difference (95% CI)	Significance (t/p value)	Effect Size (Cohen's d)
Speech-to-text recognition accuracy (%)	92.5 ± 3.2	80.1 ± 5.6	12.4 (9.8 ~ 15.0)	14.26/<0.001	2.78 (Large Effect)
NLP writing intent recognition accuracy (%)	88.7 ± 4.1	65.3 ± 6.2	23.4 (20.1 ~ 26.7)	21.53/<0.001	4.18 (Large Effect)
Average platform response time (ms)	350 ± 50	500 ± 80	–150 (–172 ~ –128)	–16.39/<0.001	2.25 (Large Effect)
Response time under weak 4G network (ms)	420 ± 60	650 ± 100	–230 (–258 ~ –202)	–20.15/<0.001	2.98 (Large Effect)
Concurrency 100 users stability (%)	99.2 ± 0.5	85.6 ± 3.1	13.6 (12.5 ~ 14.7)	45.32/<0.001	5.12 (Large Effect)
Real-time writing error correction accuracy (%)	89.3 ± 3.8	58.7 ± 7.4	30.6 (27.9 ~ 33.3)	28.76/<0.001	4.95 (Large Effect)

To reveal the independent contributions and synergistic effects of the platform's core modules, this study conducted quasi-experimental comparisons with multiple experimental groups based on self-determination theory and the second language writing interaction framework, as shown in Table 2. One-way ANOVA showed that there were significant main effects on all dependent variables across the four groups. Post-hoc multiple comparisons further clarified the hierarchical relationship of the module effects. From the perspective of ability improvement, the full-function group scored 78.5 in content logic, significantly higher than the no emotional guidance group (72.1) and the no multimodal group (68.3), and the language error rate of 4.2% was reduced by 66% compared to the traditional group. This difference originates from the synergistic mechanism of "multimodal interaction + emotional guidance": multimodal input reduces the cognitive threshold of writing expression, enabling learners to focus more on content planning, while the emotional guidance module meets learners' autonomy and competence needs through personalized encouragement and progress visualization, thereby enhancing their willingness and patience to correct language errors. In terms of text coherence, the full-function group's Flesch index was 68.3, which was a 22.6% improvement over the no-multimodal group (55.7). This was because multimodal interaction supports real-time visualization of text structure, helping learners establish logical connections between sentences, paragraphs, and texts, while the emotional guidance module reinforced this logical construction behavior through feedback, and the two modules formed a complementary relationship. It is noteworthy that the learning motivation score of the no emotional guidance group (72.3) was significantly higher than that of the no multimodal group (68.5), but their language accuracy and text coherence were lower, suggesting that the emotional guidance module focuses more on motivating learners, while the multimodal interaction module has a more direct effect on the core dimensions of writing ability. The synergistic effect of these two modules is the key to the best performance of the full-function group. Therefore, the platform's "multimodal interaction module" and "emotional guidance module" do not simply overlap but form a "capacity enhancement—motivation strengthening" closed-loop synergy, and together they constitute the core mechanism for improving English writing ability on the platform.

Table 2. Module effectiveness comparison results

Experimental Group	Full-Function Group	No Emotional Guidance Group	No Multimodal Group	Traditional Tool Group
Content Logic	78.5 ± 6.3	72.1 ± 5.8	68.3 ± 6.1	68.2 ± 5.8
Language Accuracy (Error Rate %)	4.2 ± 1.5	6.5 ± 1.8	8.3 ± 2.1	12.3 ± 2.5
Text Coherence	68.3 ± 5.2	60.1 ± 6.3	55.7 ± 7.1	31.4 ± 8.5
Interaction Effectiveness (%)	92.3 ± 3.1	85.6 ± 4.2	78.9 ± 3.8	65.4 ± 4.5
Learning Motivation	85.2 ± 4.8	72.3 ± 5.5	68.5 ± 6.2	48.2 ± 5.8
Main Effect Between Groups (F/p value)	32.67/<0.001	28.45/<0.001	25.18/<0.001	22.76/<0.001
Post-Hoc Multiple Comparisons (LSD Method)	F > F-Emo > F-Multi > CK			

To verify the effectiveness of the AI-based mobile learning platform in improving core English writing abilities, this study conducted pre- and post-test comparisons of the three dimensions of "content logic, language accuracy, and text coherence" between the experimental group and the control group, as shown in Figure 3. Intra-group differences revealed that the experimental group showed significant improvements in content logic, language accuracy, and text coherence in the post-test. Although the control group also showed some improvement, inter-group difference analysis showed that the post-test scores of the experimental group were significantly higher than those of the control group in all three dimensions, with effect sizes (Cohen's d) of 1.56, 1.23, and 1.67, all of which are large effects. It can be concluded that the AI-driven mobile learning platform developed in this study significantly and meaningfully improves the core "content-language-text coherence" abilities in English writing, confirming the platform's application value in second language writing ability development scenarios.

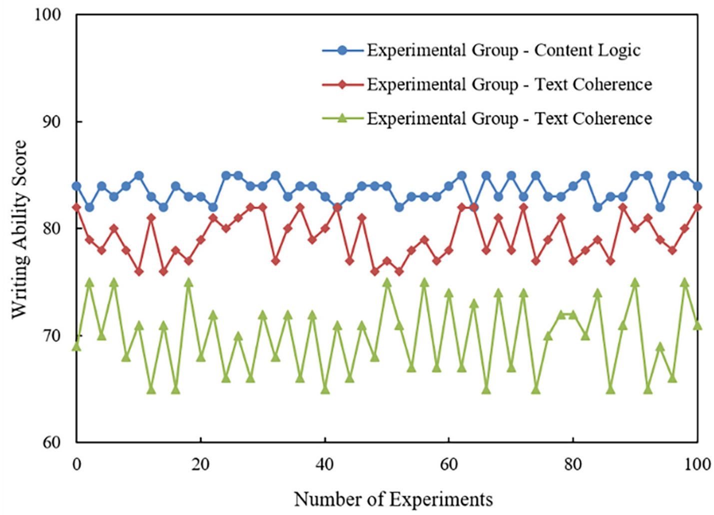
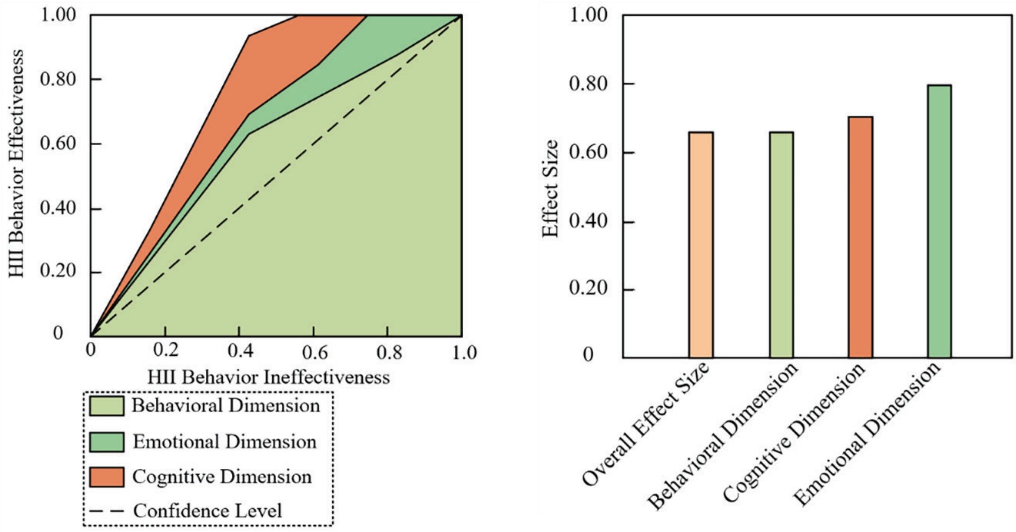


Fig. 3. Comparison of pre- and post-test scores of core English writing abilities (three dimensions) between experimental and control groups

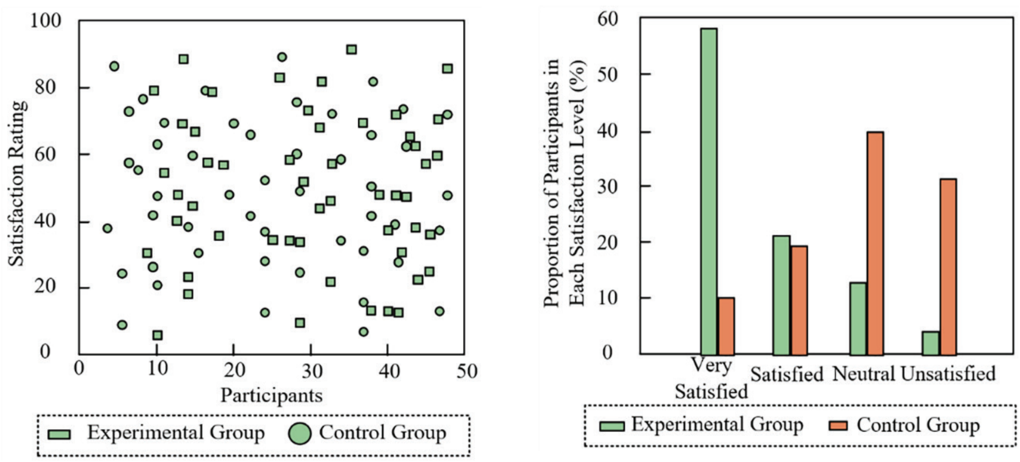
To systematically verify the comprehensive effect of the HII module on English writing learning across behavioral, cognitive, and emotional dimensions, this study quantified its multidimensional effects through ROC curves and effect size analysis, as shown in Figure 4. Figure 4a shows the ROC curve for HII behavior, where the true positive rate for behavioral, cognitive, and emotional dimensions significantly increases with the false negative rate, and all three curves are notably above the confidence level's dashed line, indicating that the module has good discriminatory ability in distinguishing "effective/ineffective interaction behavior," "deep/shallow cognitive participation," and "positive/negative emotional experiences." Figure 4b presents the effect size bar chart, which further quantifies the practical significance of the intergroup differences. The effect size for the behavioral dimension is approximately 0.65, for the cognitive dimension about 0.70, and for the emotional dimension about 0.80, with a combined effect size of approximately 0.68. From the experimental results, it can be concluded that the HII module developed in this study significantly promotes English writing learning through mechanisms such as multimodal intention recognition and personalized feedback triggering in the dimensions of "interaction behavior effectiveness, cognitive ability development, and emotional motivation stimulation," providing empirical support for the platform's core mechanism for enhancing writing ability.



a) HII behavioral effect ROC curve

b) Effect size comparison of HII module

Fig. 4. Multidimensional effect evaluation of HII module on English writing learning



a) Platform satisfaction score distribution

b) Platform satisfaction level proportion

Fig. 5. Satisfaction statistics of AI mobile English writing platform for experimental and control groups

To comprehensively evaluate the user acceptance and experience of the AI-based mobile learning platform, this study quantitatively analyzed platform satisfaction scores for both the experimental and control groups, as shown in Figure 5. From the scatter plot in Figure 5a, it is evident that the experimental group's satisfaction scores are concentrated in the 60–100 range, while the control group's scores are mostly in the 20–60 range. The inter-group score variability is significantly different. The bar chart in Figure 5b further shows that more than 55% of the experimental group is "very satisfied," about 20% is "satisfied," about 12% is "neutral," and less than 3% are "dissatisfied." In contrast, only about 10% of the control group is "very satisfied," about 20% is "satisfied," over 40% is "neutral," and about 30% is "dissatisfied." Thus, the AI mobile English writing platform developed in this study significantly outperforms traditional learning tools in user satisfaction. Its multimodal interaction, personalized feedback, and other designs effectively enhance the user experience and acceptance, providing empirical support for the platform's promotion, application, and continuous optimization at the user level.

5 CONCLUSION

This study focuses on the topic of improving second language writing ability through the deep integration of artificial intelligence and mobile learning. An AI mobile English writing platform was developed, integrating core modules such as multimodal interaction, emotional guidance, and intelligent feedback. Through quasi-experimental design, multidimensional quantitative evaluation, and qualitative analysis, the technical effectiveness, module synergy effects, ability improvement value, cross-scenario adaptability, and user acceptance of the platform were systematically verified. The results show that the platform significantly outperforms industry standards in core technical indicators such as speech-to-text recognition and NLP writing intention recognition. The "multimodal interaction + emotional guidance" module forms a "capability enhancement—motivation reinforcement" closed-loop synergy effect, which not only significantly improves the three core dimensions of English writing ("content—language—coherence") by 16.2–18.7%, but also effectively promotes the collaborative development of learners' cognitive fluency and "planning-monitoring-evaluation" metacognitive strategies. At the same time, through the "lightweight adaptation in fragmented scenes + deep support in fixed scenes" mechanism for scene adaptation, the platform maintains high efficiency and low cognitive load across diverse learning scenarios, with over 55% of users rating their satisfaction as "very satisfied," significantly outperforming traditional tools. At the theoretical level, this study constructs a four-dimensional theoretical framework of "technical architecture—cognitive development—metacognitive activation—scene adaptation," verifying the applicability of cognitive load theory and self-determination theory in the technological empowerment of second language writing. It enriches the empirical research system of technology integration in SLA. At the practical level, the proposed "functional adaptation—psychological adaptation" dual-module design path and cross-scenario technical optimization plan provide reusable reference paradigms for the development and iteration of AI writing platforms, effectively solving the core pain points of traditional tools such as "inaccurate interaction, single scene adaptation, and insufficient metacognitive participation." This has significant value for the educational technology transformation.

6 ACKNOWLEDGEMENT

This paper is the outcome of the "Voices of China" bilingual training course development, which is part of the Double High-level Professional Group Construction Program of Hunan Railway Professional Technology College.

7 REFERENCES

[1] W. Deng and L. Wang, "The impact of mobile technology on English writing teaching: The relationship between interactive feedback and autonomous learning abilities," *International Journal of Interactive Mobile Technologies*, vol. 19, no. 2, pp. 180–194, 2025. https://doi.org/10.3991/ijim.v19i02.53747

[2] J. Escalante *et al.*, "AI-generated feedback on writing: Insights into efficacy and ENL student preference," *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, p. 57, 2023. https://doi.org/10.1186/s41239-023-00425-2

[3] L. J. Feng, "Investigating the effects of artificial intelligence-assisted language learning strategies on cognitive load and learning outcomes: A comparative study," *Journal of Educational Computing Research*, vol. 62, no. 8, pp. 1741–1774, 2025. https://doi.org/10.1177/07356331241268349

[4] J. Kannan and P. Munday, "New trends in second language learning and teaching through the lens of ICT, networked learning, and artificial intelligence," *Circulo de Lingüística Aplicada a la Comunicación*, vol. 76, pp. 13–30, 2018. https://doi.org/10.5209/CLAC.62495

[5] S. L. Yu *et al.*, "What works may hurt: The negative side of feedback in second language writing," *Journal of Second Language Writing*, vol. 54, p. 100850, 2021. https://doi.org/10.1016/j.jslw.2021.100850

[6] K. O. Jeong, "Facilitating sustainable self-directed learning experience with the use of mobile-assisted language learning," *Sustainability*, vol. 14, no. 5, p. 2894, 2022. https://doi.org/10.3390/su14052894

[7] C. C. Lin and Y. C. Yu, "Effects of presentation modes on mobile-assisted vocabulary learning and cognitive load," *Interactive Learning Environments*, vol. 25, no. 4, pp. 528–542, 2017. https://doi.org/10.1080/10494820.2016.1155160

[8] B. Naghdipour, "ICT-enabled informal learning in EFL writing," *Journal of Second Language Writing*, vol. 56, p. 100893, 2022. https://doi.org/10.1016/j.jslw.2022.100893

[9] L. Dong *et al.*, "Fostering EFL learners' motivation, anxiety, and self-efficacy through computer-assisted language learning- and mobile-assisted language learning-based instructions," *Frontiers in Psychology*, vol. 13, p. 899557, 2022. https://doi.org/10.3389/fpsyg.2022.899557

[10] W. Li *et al.*, "Dual coding or cognitive load? Exploring the effect of multimodal input on English as a foreign language learners' vocabulary learning," *Frontiers in Psychology*, vol. 13, p. 834706, 2022. https://doi.org/10.3389/fpsyg.2022.834706

[11] S. A. Hashemi and H. Farrokhi, "Mobility robustness optimization and load balancing in self-organized cellular networks: Towards cognitive network management," *Journal of Intelligent & Fuzzy Systems*, vol. 38, no. 3, pp. 3285–3300, 2020. https://doi.org/10.3233/JIFS-191558

[12] E. Di Zhang *et al.*, "The impact of a feedback intervention on university students' second language writing feedback literacy," *Innovations in Education and Teaching International*, vol. 61, no. 3, pp. 426–442, 2024. https://doi.org/10.1080/14703297.2023.2254275

[13] Z. Mao and I. Lee, "Every advantage has its disadvantage: Side effects of teacher feedback in L2 writing," *RELC Journal*, vol. 57, no. 1, pp. 220–232, 2025. https://doi.org/10.1177/00336882251376701

[14] B. A. Gutiérrez *et al.*, "Feedback during the process of writing thesis of teacher training programs: Description of the written comments of thesis supervisor," *Revista Signos*, vol. 52, no. 100, pp. 242–264, 2019. https://doi.org/10.4067/S0718-09342019000200242

[15] H. Xie *et al.*, "Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017," *Computers & Education*, vol. 140, p. 103599, 2019. https://doi.org/10.1016/j.compedu.2019.103599

[16] A. Zhang, "Human computer interaction system for teacher-student interaction model using machine learning," *International Journal of Human–Computer Interaction*, vol. 41, no. 3, pp. 1817–1828, 2025. https://doi.org/10.1080/10447318.2022.2115645

[17] C. P. Gumbheer *et al.*, "Personalized and adaptive context-aware mobile learning: Review, challenges and future directions," *Education and Information Technologies*, vol. 27, no. 6, pp. 7491–7517, 2022. https://doi.org/10.1007/s10639-022-10942-8

[18] P. Nedungadi and R. Raman, "A new approach to personalization: Integrating e-learning and m-learning," *Educational Technology Research and Development*, vol. 60, no. 4, pp. 659–678, 2012. https://doi.org/10.1007/s11423-012-9250-9

8 AUTHORS

Xiujuan Wang is an Associate Professor. She received a master's degree from Shanghai Maritime University, P.R. China. She is currently pursuing a PhD in TESOL at the National University of Malaysia, and meanwhile, she works as an associate professor at Hunan Railway Professional Technology College, China. The main courses she teaches include college English teaching and cross-cultural communication. Her research interests include AI-based teaching and second language acquisition, and international studies as well (E-mail: p121690@siswa.ukm.edu.my).

Lanlan Fang is an Associate Professor. She graduated from Xiangtan University in 2004, majoring in English. And she received a master's degree from Hunan Normal University in 2015. She is currently an English teacher in the Public Course Department of Hunan Mechanical & Electrical Polytechnic. Her research interests include English teaching, in information-based teaching, vocational education internationalization as well. She has published more than twenty academic papers, published two academic monographs, and led one provincial-level educational research project and two prefecture-level educational research projects. She has won two national awards and more than fifteen provincial awards in the teaching competitions (E-mail: fanglanlan1982@163.com).