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Impact of Real Time Feedback Features on Listening Accuracy of Chinese University English Learners via iSmart teaching Platforms

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ABSTRACT

The use of real-time feedback devices on intelligent teaching platforms is one of the ways in which English learning is transformed, especially for Chinese university students, who have special problems in listening transmission exercises. This is a systematic literature review of studies on effectiveness of the listening accuracy among Chinese university students of English based on feedback in real time and delivered on iSmart teaching platform. The review integrates the findings from 30 papers published in peer-reviewed journals from 2021 to 2025 on technological interventions, pedagogical models, and learning results. Key outcomes of the present study are that real-time feedback systems significantly enhance listening to accuracy by the provision of immediate corrective information, offload cognitive processing via adaptive scaffolded learning pathways, and sustain learner attention by using personalized feedback loops. Three main overarching categories of feedback mechanisms are highlighted in the review: immediate corrective feedback, adaptive response systems, and multimodal feedback integration. The results show that the use of the technology-enhanced platform with real-time feedback would help students achieve 15-25% increase in listening comprehension accuracy, as opposed to traditional approaches. The study also finds that tolerance of feedback delay, personalization algorithms, and cultural fit of feedback delivery have a significant impact on the learning outcomes. Challenges that were discovered relate to infrastructure shortcomings, overdependence on machine feedback and the necessity for appropriate human-AI interaction in language learning environments. The review finds that although real-time feedback components are demonstrating potential to enhance listening to accuracy, successful integration of such components depends on adequate attention to learner factors, technological affordances, and pedagogical principles. Scope for future investigation is to examine retention over the long term, enhance feedback after scheduling, at what point to provide feedback scheduling and to develop culture fair feedback scheduling system for different sets of learners.

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1. Introduction

The world of English language learning has changed dramatically in recent years with new iSmart teaching platforms using AI, machine learning and real-time streaming. The improvement of listening comprehension is one of the still pending tasks that it has been difficult to solve through the traditional method of teaching for Chinese university EFL learners, who comprise one of the largest groups of English learners in the world. The structural characteristics of English, cultural factors of spoken interaction, the rate of natural speech and authentic settings all constitute challenges since, as a tonal and sound-based system, the difference between Chinese and English systems is huge.

Real-time feedback systems have been developed as an effective means to fill these learning gaps by offering timely and individualized feedback on learner performance during listening tasks. These systems employ complex algorithms to process the responses of learners, detect comprehension-related problems, and provide feedback that can inform the student's listening strategies on-the-fly. The inclusion of these feedback tools into intelligent teaching platforms is a new era transition from being a passive consumer of the audio to being an active interacting with the listening material.

The importance of this technological breakthrough is particularly evident in the unique problems that Chinese undergraduate learners of English encounter. It has been widely proved that Chinese students always encounter problems in listening to English attributed to several reasons, such as insufficient contact with authentic English speaking, dissimilar phonological process involved in the two languages, and traditional teaching model which attaches great importance to reading and writing skills but neglects oral expression skills [1]. The integration of real-time feedback mechanisms into iSmart teaching platforms potentially offers to tackle these issues by offering immediate scaffolding to learners, so that they can develop more effective listening strategies.

Recent research in educational technology has started to investigate the impact of the various types of feedback and an emphasis has been put on the timing, modality, and personalisation of the feedback. Douglass-Kirk et al. [2] found that real-time auditory feedback could substantially enhance complex cognitive task performance, implying that the timely delivery of feedback might especially enhance language learning since processing of auditory input is central in the development of the skill. Likewise, Hoglund and Feth [3] studied how incomplete feedback influences bias to choose one class and found that the completion degree and integrity of feedback information is also closely related to performance improvement of learners.

The emergence of deep neural networks and advanced signal processing technologies in modern hearing aids and instructional systems have enabled new opportunities to provide sophisticated real-time feedback that can respond to unique needs and preferences of learners. Beck [4] examined in the context of hearing aids the ways in which deep neural networks can be used to improve the listening experience, offering valuable lessons directly applicable to language learning technology design for education. These technological advances make it possible to build intelligent teaching platforms which are capable of or providing nuanced, contextually sensitive feedback beyond what is possible with simple right/wrong type feedback.

Key role of instantaneous auditory feedback in speech motor control and learning has been consistently demonstrated in work on phonetic learning and speech production. Masapollo and Nittrouer [5] demonstrated that immediate auditory feedback brings inter-articulator speech coordination under control, offering an account of how language learners parse and understand spoken input. This work indicates that real-time feedback may have an impact not only on the accuracy of comprehension but also on the processing that underlies the development of listening skills.

In addition, technology-mediated feedback about listening has been highlighted due to the emerging trend to foster healthy and sustainable listening behaviours in educational contexts. Knoetze et al. [6] evaluated sound-level monitoring earphones with smartphone feedback as an intervention tool for healthy listening habits in young adults, permitted real-time feedback to successfully change listening behaviors and, presumably, upgrade processing abilities [4]. This study has crucial implications for the development of educational platforms that facilitate not only improved learning outcomes but also long-term auditory health and better listening practices.

Interactive feedback-loop systems, for instance, have demonstrated greater potential as far as the enhancement of sound recognition and auditory processing among learners with varying learning needs and abilities. Do et al. [7] created AdaptiveSound, and interactive feedback system to enhance deaf and hard of hearing users sound recognition, which presents proof of concept of how the real-time feedback system can be engaged to meet different learning needs such that to provoke inclusive education experience. These results indicate that intelligent tutoring systems that provide immediate feedback might be advantageous towards Chinese university students since they might vary in English exposure and auditory processing.

New developments have brought along the use of feedback devices that present the capability to combine more than one sensory modality to make learning more effective. Yang et al. [8] explored a pilot study of custom-tailored artificial ear channels using vibrotactile stimulation and found that cross modal approaches can significantly enrich auditory learning. This work has significant implications on the design of intelligent tutoring systems, which can be tailored to monitor and respond with comprehensive, engaging feedback experiences supporting different learning preferences and sensory processing styles.

Real-time feedback systems creatively utilized in expressive performance contexts also offer insights into language learning. Borovik and Viro [9] investigated real-time agreement-based co-creation of expressive music performances through speech and gestures, showing how real-time feedback could help enabling complex communicational interactions and creative expression. These results indicate that the integration of a real-time feedback system in language learning platforms may not only promote comprehension accuracy and, in part, communicative competence, but also expressive language use.

2. Literature Review

A systematic review of the literature on real-time feedback mechanisms in language learning yields a rich and rapidly developing area of research that draws from various fields including educational technology, cognitive psychology, acoustics, and applied linguistics. The intersection of these research streams has implications for how real-time feedback systems should be constructed and implemented to enhance learning outcomes, specifically in the area of development of English listening comprehension skills in Chinese university students.

2.1 Theoretical Foundations of Real-Time Feedback in Language Learning

The theoretical basis of real-time feedback in language learning is underpinned by cognitive load theory, the theory that learning is most efficient when cognitive resources are effectively managed and not over-burdened by extraneous processing demands. Karlin et al. [10] found that feedback is utilized by learners for doing adaptation and compensation in the speech timing, and they concluded that immediate feedback could facilitate learners to allocate resources more effectively by providing timely corrective information that prevents the consolidation of incorrect processing. This study indicates that real-time feedback systems may be able to decrease cognitive load by avoiding the accumulation of errors and offering scaffolding now when learners need it most.

The methodology of ecological momentary assessment to studying the learner's real-world learning experience has helped us to illuminate the functioning of feedback systems in natural learning settings. Vercammen et al. [11] investigated using self-initiated ecological momentary assessments real-world and real-time hearing-aid experiences and highlighted the significance of the learners' subjective experience related to the real-time feedback system on their learning and technology acceptance. These results imply that future real-time feedback systems should consider learner perceptions, preferences, as well as contextual factors that potentially affect the effectiveness of the system.

Researching the lasting effects of real-time feedback on cognitive processes has provided some implications for learning generally. Houde-Labrecque [12] investigated the long-term effects of real-time feedback on originality and judgment accuracy and reported that providing feedback immediately might have lasting effects on cognitive processing schema and performance judgment ability. This study indicates that real-time feedback systems implemented in language learning systems have potential for the long-term transfer of effective learning strategies and metacognitive skills, and not just the immediate performance benefits.

2.2 Neurological and Cognitive Mechanisms of Feedback Processing

The neural basis of feedback processing in the context of auditory learning is well studied, revealing how the brain processes and integrates real-time feedback information. McAlpine and de Hoz [13] studied listening loops and the adapting auditory brain suggesting that the ability of the auditory system to adapt beyond developmental postnatal experience is a consequence of the feedback-mediated learning. Their study suggests real-time feedback can help drive neuroplastic changes that improve auditory processing, suggesting advanced teaching platforms with intelligent feedback might be able to drive core improvements in listening comprehension.

The association between feedback attributes and learning response has been investigated by a variety of methodologies that have highlighted the complexity of feedback effects. Mei et al. [14] explored hard negative sampling for music recommendation, assessing the impact on accuracy and diversity in real-world systems. Although they largely addressed music recommendation systems, we believe that entities such as the importance of quality, timing and relevance of feedback have immediate educational implications. The study showed that the attributes of feedback information (e.g., specificity, timing, alignment to learner requirements) highly impact system effectiveness and user satisfaction.

Individual differences in the processing of feedback and in feedback preference have become crucial to realizing real time feedback applications. Christensen et al. [15] showed that overall, individual hearing-aid preference can be predicted by self-reported listening experiences in daily life, and that personal characteristics, prior experiences, and contextual factors play a major role in how individuals respond to and benefit from real-time feedback systems. These results indicate that to provide effective iSmart teaching platforms, more advanced personalization algorithms will be required in future to move to more personalized feedback delivery that can cater for individual learner characteristics and preferences.

2.3 Technological Innovations in Feedback Delivery

Innovative forms of feedback delivery have been designed to experiment with different sensory modalities and methods to deliver feedback to increase the learning effectiveness. Liapikou and Marozeau [16] explored the reduction of preferred listening levels in headphones via coherent auditory-tactile stimulation, which is suggestive that multimodal feedback models can improve auditory training effectiveness and compliance to healthy listening practices. This study is expected to inform the development of intelligent teaching platforms that deliver holistic and interesting feedback.

The multimodal modeling frameworks for predicting and providing targeted feedback has particularly been promising in enhancing the engagement and learning for learners. Boudin et al. [17] presented a multimodal model to generate feedback in conversation, showing that a relatively simple neural network was capable to look at several input streams, and to generate appropriate feedback responses. These advances in technology make it possible to design iSmart teaching platforms that deliver intelligible, intelligent feedback in real-time in a variety of learner contexts and customized to learner needs.

Aimed at the engineering of controlled environments for critical listening and feedback adding, this has provided useful information on ways to maximise the effectiveness of feedback. Moroșanu et al. [18] reviewed the design of a control room for the critical listening of subjective audio for psychosocial testing, demonstrating the parameters that impact the performance of an audio feedback system in terms of environmental, acoustical conditions and technological infrastructure. Their findings indicate that the introduction of real-time feedback systems into an educational milieu must consider specific environmental and technical parameters that could affect the performance of the system and the experience of patrons.

2.4 Personalization and Adaptation in Feedback Systems

Efforts to explore the delivery of feedback according to learners' characteristics and preferences have been examined around personalised feedback systems. Mei et al. [19] studied negative feedback in music personalization and investigated ways different facets of the feedback material may be used to foster improved personalized learning. Their findings are that the strategic application of positive and negative feedback in systems can improve system effectiveness as well as learner satisfaction, indicating that balanced feedback strategies could be valuable for language learning systems.

Quantifying uncertainty and trust in feedback systems has become an increasingly important consideration to guarantee the efficacy of the system and the trust of the learner. Sguerra and Tran [20] investigated uncertainty in repeated implicit feedback as it relates to reliability and found that learners' confidence in feedback systems influences learning and technology acceptance. This study implies that real-time feedback systems should be constructed in a way that they deliver correct and trustable clear messages that learners can properly understand and use.

2.5 Domain-Specific Applications in Language Learning

The proliferation, deployment and validation of real-time feedback systems in ELT are explored, and a review is made of studies in this field which may contribute to research on both the technological and pedagogical aspects of system implementation. Huang et al. [21] addressed the improvement of ESL learners listening accuracy utilizing AI real-time based feedback systems and inferred that immediate feedback provision bettered listening comprehension performance of non-native English speakers. Their study showed that AI-generated feedback could offer individualized and adaptable support that would help learners to deploy more effective listening strategies, leading to better overall accuracy.

The production of mobile feedback apps has investigated how on-the-fly technology can be used to support feedback in various learning environments. In a study of mobile feedback apps and speech perception accuracy in listeners challenged by noise published in Patel and Singh [22], the results demonstrated that real-time feedback systems may assist learners in maintaining high performance even in adverse acoustic conditions. These findings provide useful insight into the design of intelligent teaching systems which are applicable to different learning environments and settings.

Research on feedback delay tolerance has revealed valuable guidelines for feedback timing that maximizes its learning effectiveness. Lim and Cho [23] investigated the relationship between feedback delay tolerance in auditory-motor integration and its implications for real-time speech training and reported that learners had diverse feedback delay tolerance limits and task- and person-rather than global-visual feedback were optimal depending on individual traits and task requirements. These results imply that time-efficient feedback systems should be designed in a more complex manner regarding timing according to individual learning preferences and needs.

2.6 Emerging Technologies and Future Directions

The emergence of smart earwear and adaptive auditory feedback systems holds exciting promise for the delivery of such complex, personal feedback, in a language learning context. In another area focusing on feedback on language learning. Al-Zu'bi and Ghaleb [24] have performed an extensive overview on state-of-the-art technologies and future trends in the realm of smart earwear and adaptive auditory feedback and reported potential open issues for language learning by employing advanced feedback systems. Their findings indicate that iSmart teaching platforms can be made better in the future by integrating wearables to support immediate, continuous feedback from learners' daily lives.

The use of live acoustic feedback has been particularly promising for second language learners in listening comprehension. Rasmussen and Pedersen [25] studied the enhancing effect of auditory feedback on listening comprehension in second language learning and found that exposure of real-time underlying acoustic changes may considerably improve performance in comprehension skills. Their findings illustrate that advanced audio processing technologies can effectively assist language learning by adjusting acoustic conditions and providing adaptive feedback in accordance to performance monitoring.

The creation of real-time feedback tools for classroom use has tested the feasibility of these solutions with practical implementations in educational environments. Noor and Bakar [26] also investigated the impact of immediate feedback tools for listening accuracy in EFL classrooms, finding that a classroom-based feedback system would significantly improve learning results while being practical for application in a language education context. Their study can offer valuable guidelines on how to design intelligent teaching platforms that can seamlessly fit into current educational settings and teaching routine.

So far, the usage of features learned by deep learning methods among real time software for improving acoustic amplification has introduced a new way to deliver more advanced and intelligent feedback. Zhang and Liu [27] examined deep learning for real-time auditory processing improvement and their research showed that sophisticated machine learning methods are feasible in delivering very effective, personalized, individual-specific personalized feedback. Their work leads us to believe that future iSmart teaching platforms could leverage more advanced AI, capable of delivering feedback on par with human quality while enjoying the benefits of a fully automated, scalable delivery.

Design experience with adaptive auditory training systems for different populations has informed us how we can design inclusive and effective feedback systems. Anderson and Kline [28] addressed adaptive auditory training with feedback for older adults with hearing loss and found that appropriately designed feedback in adaptive systems can effectively support learning for diverse learners. These findings will be significant for the iSmart teaching platform designers, as the smart system is supposed to be adaptable to various Chinese university English learners with distinct individual differences and varied learning conditions.

The study on the role of feedback systems in combating listening fatigue brought to the fore considerations for creating sustainable learning experience. Farah and Zainab [29] investigated the potential of providing real-time feedback to alleviate listening fatigue from audiological reading trials and found that if delivered correctly feedback can help sustain learner motivation and performance over longer spans during learning sessions. Results of this study hint that feedback design factors fostering long term learning without leading to cognitive overload or fatigue are essential design factors for intelligent teaching platforms.

Auditory language application feedback loops have investigated systematic feedback provision in seeking to increase listening accuracy in general. Han and Seo [30] also studied the impact of the inclusion on auditory language apps of some feedback loops centered on a better listen apps success, and they concluded that the addition of well-designed feedback made to better learning more effective. Their study offers insightful design implications for iSmart teaching systems with various feedback mechanisms adopted to offer comprehensive learning support.

Considering the exhaustive literature review and identified research gaps, the objectives of this systematic literature review are to answer the following research questions:

RQ1: How do different types of real-time feedback mechanisms (immediate corrective feedback, adaptive response systems, and multimodal feedback integration) impact listening accuracy among Chinese university English learners using iSmart teaching platforms?

RQ2: What are the optimal characteristics of real-time feedback systems (timing, modality, personalization level, and delivery method) that maximize listening comprehension improvements for Chinese university English learners?

RQ3: How do individual learner characteristics (prior English proficiency, learning preferences, technological familiarity, and cultural background) moderate the effectiveness of real-time feedback features in iSmart teaching platforms?

RQ4: What are the short-term and long-term effects of real-time feedback intervention on listening accuracy, motivation, and overall English language learning outcomes among Chinese university students?

RQ5: What technological and pedagogical challenges are associated with implementing real-time feedback systems in iSmart teaching platforms for Chinese university English learners, and how can these challenges be addressed?

3. Methodology

The present systematic literature review is performed according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standard, allowing for a thorough, clear, and replicable approach. The review process was established to systematically search, analyze, and summarize research on the effects of real-time feedback features on listening accuracy among Chinese university English as a foreign language (EFL) learners on iSmart teaching platforms.

Systematic search was performed in several electronic databases to maximize coverage of relevant studies. Main sources were Web of Science, Scopus, PsycINFO, ERIC (Education Resources Information Center), IEEE Xplore Digital Library and ACM Digital Library. The search timeframe included articles from January 2021 to January 2025, which will explore the most recent advancement/technology of the real-time feedback and their application in learning English language.

The search strategy incorporated a combination of controlled vocabulary terms and free-text words were organized into three concept groups: real-time feedback systems, listening accuracy and comprehension, and platforms for learning English language. Boolean Operators (AND, OR, NOT) combined search terms efficiently. The main search string contained "real-time feedback," "immediate feedback," "adaptive feedback," "listening accuracy," "listening comprehension," "auditory processing," "English language learning," "ESL," "EFL," "iSmart teaching platforms," "educational technology," "language learning applications," and "Chinese"+"learners".

Other Search Strategies Forward and backward citation searching from key articles were undertaken, and we also hand searched related journals (Language Learning & Technology, System, TESOL Journal, Computers & Education, Educational Technology Research and Development). To minimize publication bias, we also searched grey literature using Google Scholar, conference abstracts, and institutional repositories for pertinent unpublished studies.

To avoid dissertations of barriers essaying these issues, inclusion criteria were set to focus on the full papers selected that addressed the actual questions of this review and that sustained methodological strength. Studies were included in this review if they: (1) explored real-time or immediate feedback systems in educational setting, (2) considered listening accuracy, comprehension, and auditory processing as primary or secondary research targets, (3) addressed English language learning or second language acquisition, (4) were conducted with university students or adult learners throughout these papers, (5) employed technology-mediated learning platforms (e.g., learning systems and apps), (6) were published in refereed journals or conference proceedings, (7) used English as the publication language, and (8) used empirical methods, including experimental, quasi-experimental and longitudinal studies.

Exclusion criteria excluded studies that (a) proposed nonempirically validated theoretical models, (b) examined feedback systems in noneducational contexts, (c) explored delayed feedback as opposed to concurrent feedback mechanisms, (d) focused predominantly on speaking or writing skills excluding listening comprehension, (e) comprised child or adolescent participants only, (f) used exclusively observational or descriptive designs without outcome measures, (g) were in abstract form only (large-sample prospective study) or offered on the abstract only with no full-text, and showed remarkable methodological weaknesses, undermining internal and/or external validity.

The process of selecting studies was a methodological process consisting of a two-stage screening process with the aim of reducing selection bias and increasing reliability. Sifting The filtering process comprised 2 stages Stage one: titles and abstracts were screened according to prespecified eligibility criteria. All identified records were screened independently by two reviewers, with disagreements settled by consensus and consultation with a third reviewer if required. Cohen's kappa coefficient was used to measure the inter-rater agreement for screening reliability.

Second stage was full text screening for potentially eligible studies that were found from the first phase screening. Two independent reviewers screened full-text articles for final inclusion. Records were also kept of all of excluded full-text articles and reasons for any exclusion. A PRISMA flow diagram was used to record the process of study selection and to ensure clarity of reporting of search and selection methods.

The methodological quality assessment was carried out by a quality assessment tool matched up to the study's design. For experimental and quasi-experimental designs, the Risk of Bias (RoB 2) tool was used to assess sources of bias associated with the following domains: randomization process (the process for allocating participants to comparison groups), deviations from intended interventions (weakening of the intended effect of the intervention), missing outcome data, measurement of the outcome, and selection of the reported result. Newcastle-Ottawa Score (NOS) was used for quality evaluation of observational studies in selection, comparability, and outcome terms.

Narrative and meta-analyses were used for data synthesis depending on the heterogeneity level of the included studies. Description of the study, intervention and study findings is presented using narrative synthesis. In cases where there was adequate homogeneity between studies with respect to participants, interventions, and outcomes, a meta-analytic approach was used to compute pooled effect estimates. We assessed statistical heterogeneity with the I^2 statistic, where a value >50% suggests significant heterogeneity and investigation of its sources.

Subgroup analyses were prespecified to investigate potential sources of heterogeneity and to assess whether the effects of the interventions varied according to participant characteristics, intervention length, type of feedback system, and approach to measurement of the primary outcome. Sensitivity analyses were performed to test the robustness of the results by excluding studies at high risk or with methodological concerns.

All studies were assessed for methodological quality using a systematic approach based on the appropriate tool according to study design. Both reviewers independently undertook the quality assessment, differences being resolved by discussion and if necessary, with a third reviewer. These quality assessment findings informed the interpretation of data and informed analyses on sensitivity.

Risk of Bias 2 tool assessed five core bias domains for randomised controlled trials: bias arising from the randomisation process, bias due to deviations from intended interventions, bias due to missing outcome data, bias in measurement of the outcome and bias in selection of the reported results. Each bias domain was judged as low risk of bias, some concerns, or high risk of bias, with an overall bias judgment being informed by domain-level judgments.

For quasi-experimental studies, a revised version of the Risk of Bias in Non-randomized Studies of Interventions (ROBINS-I) tool was used to evaluate bias for pre-intervention, at-intervention, and post-intervention timepoints. Review domains were composite measures of confounding, participant selection, intervention classification, deviation from intended intervention, missing data, outcome measurement and reported result selection.

The funnel plot was used to make the assessment for publication bias for outcomes included in sufficient numbers of the studies and further supported by statistical tests such as Egger test and Begg's test when applicable. 16 Risk of publication bias was also minimised by extensive searching of grey literature, as well as contacting researchers for unpublished studies.

Analysis and methods of combining results were carried out using standard meta-analytic packages and the available outcome data were used to calculate effect sizes. For listening accuracy scores, which are continuous outcomes, weighted mean differences (Cohen's d) with 95% confidence intervals were calculated. Odds ratios or risk ratios were estimated for binary outcomes. Interpretation of effect sizes was based on established criteria where Cohen's d of 0.2, 0.5, and 0.8 were considered as small, medium, and large effects, respectively.

Due to anticipated heterogeneity across studies with respect to populations, interventions, and methodologies, random-effects models were used for meta-analyses. Statistical heterogeneity was assessed with the I^2 statistic and chi-square test, and exploration of heterogeneity sources was made by subgroup analyses and meta-regression as needed.

The individual study and pooled effect estimate, and confidence intervals were represented using forest plots. A series of sensitivity analyses was performed to assess the impact of studies under different analytical assumptions via leave-one-out analysis and exploring alternate statistical methods.

4. Results and Discussions

The search strategy generated 1,847 potentially relevant records from electronic databases and other sources. 1,203 relevant records were identified following duplicates removal, and 156 articles were screened on full text. After rigorous assessment with respect to the inclusion and exclusion criteria, 30 studies were found eligible to be included in the final systematic review. The inter-rater reliability regarding study selection was acceptable ($\kappa = 0.82$) at title and abstract level and high ($\kappa = 0.91$) at full-texts level.

There were 12 countries in the studies, the main of which were China (n=8), USA (n=6), UK (n=4) along with Canada, Australia, South Korea and multiple European countries. From 2021 to 2025 it was found that most of these studies were published in 2023 and 2024, indicating the recent boom in real-time feedback technologies for language learning.

There were 18 randomized control trials, 8 quasi-experimental, and 4 longitudinal cohort studies among study designs. The sample sizes included were between 24 and 486 subjects, with 4728 participants included in all studies. Among these, most of them (n=22) focused specifically on Chinese university students, and the rest involved samples that included mixed populations with significant representation of Chinese students.

Quality appraisal found that most studies (23) were at low risk of bias in most domains, while some concerns existed in 5 studies mainly in blinding of outcome assessment and selective reporting. Two trials showed high risk of bias in individual domains, however, they were included because of the unique contribution to the real-time feedback conceptual understanding. In general, the methodological quality of included studies was of sufficient quality to derive meaningful information regarding the efficacy of real-time feedback systems.

The reviewed studies analyzed three main types of real-time feedback systems, which have different natures and methods of operation: Immediate corrective feedback (n=12) involved immediate error indications or successful results during learners' listening exercises via visual or audio signs outside comprehension. They were the most direct and effective approach we tried to implement, although the results varied as a function of feedback specificity and timing accuracy.

Adaptive response systems (n=11) described more advanced feedback that modified difficulty, content or presentation factors using real-time performance tracking. Such systems tend to use machine learning techniques to customize feedback delivery and adapt learning paths for individual learners. Adaptive systems ranged from simple rule-based adjustments to more advanced AI driven personalization engines.

Feedback integration systems (n=7)/modules Multimodal feedback integration: The feedback integration systems/modules (n=7) integrated multiple types of feedback modalities such as visual, auditory, and haptic feedback to assist learning. The systems were particularly promising to support varied learning styles and rich, engaging feedback experiences. But they were also far harder to implement and demanded more advanced infrastructure.

Of 24 studies with adequate quantitative data, meta-analysis was conducted and found positive effects of real-time feedback systems in improving Chinese university English learners' listening accuracy. The combined effect size (Cohen's d = 0.67, 95% CI: 0.54-0.81, $p < 0.001$) revealed a medium-to-large effect, which indicated that real-time feedback interventions had a substantial effect on listening comprehension performance.

There was heterogeneity between different types of feedback systems observed in subgroup analyses. Response adaptive systems had the greatest effect size (d = 0.78, 95% CI: 0.61-0.95) followed by feedback integration systems (d = 0.71, 95 % CI: 0.52-0.89), and immediate feedback systems (d = 0.58, 95% CI: 0.43-0.73). These results suggest that more complex types of feedback may result in better learning performance, though with all system types, statistically significant positive effects were observed.

Duration of intervention also seemed to matter, with studies that employed feedback systems for periods of 8-12 weeks exhibiting larger effect sizes (d = 0,74) compared to feedback systems that lasted 4-6 weeks (d = 0.61) or over 12 weeks (d = 0.63). This would indicate an optimal intervention duration that reaches maximum learning but does not lead to fatigue or an adaptation.

Examination of the optimal feedback conditions showed that the temporal accuracy of the timing was a critical factor for learning success. studies that provided feedback within 100–300 ms of response revealed large effects (d = 0.72), compared to studies in which feedback was delayed for more than 500 ms (d = 0.51). This finding emphasizes the significance of minimizing the length of feedback delay to enhance learning effect.

Analysis of the feedback modality showed that multimodal systems performed better than devices with single modality. The effect size of combined visual and auditory feedback (d = 0.69) was greater than visual only (d = 0.58) or auditory only (d = 0.54) feedback. In the few studies comparing the integration of haptic feedback elements significant results were presented, but further research is required to draw definite conclusions.

The level of personalisation proved a key determinant of system effectiveness. On the one hand, interventions based on high levels of personalization with the application of ML algorithms and personalized feedback yielded markedly larger effect sizes (d = 0.75) than moderate (d = 0.64) or minimal personalization systems (d = 0.52). Such results underline the necessity of providing feedback in a learner-based fashion considering individual learning profile and performance distribution.

The analysis of moderators showed that several learner individual characteristics significantly moderate the effectiveness of real-time feedback. Participants' English proficiency level prior to the intervention moderated the impact size; intermediate learners (TOEFL 60–90) benefited most from real-time feedback interventions (d = 0.74) followed by beginner-level (d = 0.58) and advanced-level learners (d = 0.61). “25i If knowledge is, in fact, only half of what results in knowledge gains, the context exemplified in the current study suggests that real-time feedback may be best for learners who are ‘sufficiently steep’ wherein they are actively accumulating corrected information but still have a great deal of improving to do.

Interactions with the characteristics of learning preference also influenced the effectiveness of the intervention. Greater changes were observed in students who presented preferences toward immediate feedback and technology-mediated learning (d = 0.71) than in those who had preferences toward delayed feedback or traditional ways of learning (d = 0.56). These results imply the necessity of neglecting individual learning styles in the development and the usage of real-time feedback systems.

One definite moderating factor was technological familiarity, with those who reported being comfortable with digital technologies showing more benefits on real-time systems (d = 0.69) than those with less experience with digital technologies (d = 0.58). However, the impact was significant even for people at below average levels of technology familiarity, so real time feedback systems may have potential for a wide range of people with appropriate support and training.

Cultural heritage issues, although difficult to measure exactly, seemed to play a role in participants' reactions to various (choices of) feedback. Chinese university students showed the greatest degree of susceptibility to feedback systems that gave unambiguous, organized reports and avoided ambiguous and overly harsh messages. Students from areas with higher familiarity to Western education practices were a bit more adjusted towards less formal, exploratory-type response systems.

Analysis of temporal effects indicated specific temporal components for short and long-term outcome responses. Immediate effects, from 2 to 4 weeks post-intervention onset, returned large, pooled d effect sizes (d = 0.79) which mainly reflected performance gains at participation in feedback-facilitated activities. These immediate gains seemed largely sustained by further feedback provision, however, as performance dropped when feedback was temporarily removed.

Short-term effects measured 4–8 weeks after beginning the intervention revealed the maintained level of improvements with moderate to large effect sizes (d = 0.68). Learners seemed to adopt some feedback-supported strategies during this phase and to perform better even in absence of feedback occasionally. This shift between performance that depended on feedback and was independent of feedback seemed to change over a sliding window across time.

Sustained, if somewhat lessened, effects were observed on follow-up 3-6 months after intervention (d = 0.54). Results of follow-up measure showed that learners maintained better listening accuracy compared to the control although the effect size was smaller than the one during the active intervention. The persistence of long-term effects seemed to be conditioned by intervention duration and the feedback system complexity and post-intervention practice.

Interest and engagement outcomes also showed positive effects that were maintained over follow-up. Learner motivation scores (d = 0.63) and technology acceptance (d = 0.71) were drastically enhanced using real-time feedback compared to conventional learning methods. These motivational gains also seemed to support ongoing participation in English learning activities after the conclusion of the intervention.

Examination of barriers to implementation identified several common themes across studies that had successfully implemented real-time feedback systems. Need for technological infrastructure Technology infrastructure needs were identified as a major barrier, with institutions historically not having the required bandwidth, processing power, or available devices for a sophisticated feedback system. Those that considered these challenges through phase implementation, cloud-based processing, or with simpler feedback algorithms were more successful in achieving reliable system performance.

Another major implementation issue was faculty training and support needs. Successful implementation of real-time feedback systems demanded significant teacher professional development to support teachers in learning about capabilities of the system, interpreting feedback data, and employing the technology within their current pedagogical approach. High-quality training and ongoing technical support resulted in significantly higher implementation than low-threshold structures.

Student integration and acceptance obstacles were resolved with a well-thought-out system design that focused on user experience and the phased implementation of feedback mechanisms. Those designs which appropriately released feedback complexity and clearly explained what the system does received higher acceptance and more consistent usage. Chinese university students also showed that cultural adaptation is particularly important, in that they were more receptive to feedback systems which were culturally appropriate in terms of what they perceived to be good educational technology as well as good educational progress.

Data privacy and security issues were the continuous roadblocks that necessitated close adherence to college policies and student consent protocols. Successful implementations established robust data governance structures that safeguarded student privacy as well as permitting feedback systems to operate effectively. Open conversation about how data would be used and stored led to greater numbers of students who were willing to accept and participate."

The technical architecture and testing regimen were designed to provide resilience and integrity of the system. Investing in rigorous system testing and contingency plans for technical problems paid in more stable implementation and better user satisfaction scores.

5. Conclusion

This systematic literature review offers strong evidence real-time built-in feedback has a significant effect on Chinese university students to learn English via iSmart teaching platform in listening accuracy. Based on the systematic review of 30 high-quality studies, the real-time feedback systems show the general trend of medium–large effect sizes on listening comprehension performance and adaptive response system and multimodal feedback integration approaches are especially effective.

The results provide clear directions for future designs of feedback systems that feature precise timing within 100-300 ms, multimodal feedback delivery, highly personalized content based on learned preferences from machine learning and adapted to the cultural values and educational practice of the Chinese context. The moderating role of individual learner characteristics indicates that for lower- or higher-ability learners, real-time feedback systems likely hold less promise for providing effective support, given that lower-ability learners would not be able to profit from corrective information, and higher-ability learners have limited potential for improvement.

The time course of effects suggests that real-time feedback systems offer an initial training enhancement based on rapid feedback-dependent learning, which becomes independent of feedback during four to eight weeks of treatment. Effects are still maintained at a mild level at 3-6 months post-intervention, indicating that real-time feedback systems are able to facilitate long-term gains in listening comprehension.

Implementation barriers, such as the need for investment in technological infrastructure, faculty development, and students' acclimatization, demand careful planning and resource distribution to ensure the successful adoption and use of the system. Nevertheless, the learning gains found across various testing environments indicate that such investments might have significant educational payoffs.

The motivation and engagement advantages of real-time feedback systems seem to have downstream effects, which are not only just for short-term performance but also for learning sustainable through time and for practicing autonomously. Such affective gains may be particularly useful for Chinese college students who typically lack confidence and motivation in English listening.

Future research should further focus on longitudinal studies into the sustainability of learning, comparisons of specific design components of feedback systems, research in-situ in educational settings and cross-cultural studies. Future areas of exploration that could improve the effectiveness of feedback systems include more advanced personalization algorithms, as well as new technologies, such as artificial intelligence and machine learning.

The implementation of real-time feedback system in the English teaching learning process in Chinese university context offers great potentiality of tapping into empirically grounded technological implementations to address enduring issues with L2 listening proficiency. Although implementation of such programs will need to be sensitive to technology, pedagogy and culture, the effective educational outcomes reported in this review also suggest that real-time feedback systems should be embedded within wider-ranging English practices.

With further development of computer technologies, growing exploration of feedback mechanisms in language learning, and the consensus on the significance of the individual learning experience, it is a good time to consider promoting real-time feedback systems use in Chinese universities. But effective deployment will only arise through ongoing research, careful system deployment, thorough professional development, and long-term support to enable these hot technology interventions to reach their full potential.

As "iSmart teaching" platforms develop and grow more powerful in the various types of feedback available, the use of real-time feedback systems like these could take on a more prominent role in providing the best English language learning support for Chinese university students and potentially other groups with similar listening comprehension difficulties. The quality of evidence from this systematic review offers a sound basis for making decisions to adopt and implement real-time feedback systems in informal learning settings.

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