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THE INFLUENCE OF ACCENT RECOGNITION SOFTWARE ON EFL LEARNERS' PRONUNCIATION CONFIDENCE

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ABSTRACT

With a focus on how English as second language (EFL) learners perceive their accents and react emotionally to AI-generated feedback, this study investigates how accent identification software affects their confidence in their ability to pronounce words correctly. One hundred fifty-five intermediate EFL learners, aged 18 to 35, participated in the study using a quasi-experimental, mixed-method design. They were divided into two groups: the experimental group, which used tools for accent identification like ELSA Speak, and the control group, which received conventional pronunciation training. The quantitative results show that learners in the experimental group significantly improved their confidence in their pronunciation, especially when the program prioritized intelligibility above native-like norms; qualitative findings also indicated that learners responded more autonomously and with less anxiety to tailored, nonjudgmental feedback. The findings highlight the instructional potential of feedback-driven, culturally sensitive technology in developing student identity and language proficiency.

Keywords: accent recognition, pronunciation confidence, AI in language learning, intelligibility, learner identity.

INTRODUCTION

Pronunciation is important to second language acquisition since it directly affects intelligibility, fluency, and effective oral communication. Pronunciation issues for EFL learners are frequently caused by the phonological effect of their first language (L1) and the peculiarities of English spelling. Beyond its technical aspect, pronunciation has a significant socio-affective impact, especially when it comes to accent. Accents influence not only how others understand learners, but also how they see themselves and are perceived socially. These impressions can influence students' self-esteem and communication readiness, highlighting the intricate connection between linguistic attitudes, identity, and pronunciation.

Language learning environments have evolved in recent years due to technology advancements, particularly in the area of artificial intelligence (AI). One of these developments is accent detection software, which compares learners' spoken English to standard models and offers automated, real-time feedback. Through interactive exercises and visualizations, applications like ELSA Speak provide remedial feedback on segmental (such as specific phonemes) and suprasegmental (like intonation, rhythm, and stress) aspects. These resources boost practice chances, encourage student autonomy, and offer quick, personalized feedback. However, their impact on such learners' psychological responses as confidence, fear, and self-perception of accent has yet to be investigated. An increasing amount of research demonstrates how internalized notions about native-like speech influence learners' opinions toward pronunciation. Seeking a "native" accent can cause learners to become frustrated or lose enthusiasm, particularly if they believe their own accent is lacking. In this situation, learners may benefit from pronunciation aids that emphasize intelligibility and provide constructive criticism to move away from impractical native-like objectives and toward more reachable and effective communicative results. These resources may help promote increased oral participation and lessen anxiety connected to pronunciation.

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The Self-Determination Theory (Deci & Ryan, 1985) sheds additional light on the psychological effects of pronunciation feedback by highlighting the contributions of autonomy, competence, and relatedness to motivation. AI-generated comments can boost students' self-esteem and promote independent learning when interpreted as constructive and encouraging. However, feedback that adheres to restricted standards such as favouring General American or Received Pronunciation, may alienate students from diverse linguistic backgrounds and negatively affect their identity and engagement. Therefore, it is crucial to consider pronunciation instruction's emotional and cultural components to understand AI technology's pedagogical implications.

This study looks at how EFL learners' self-perception of their accent and confidence in their pronunciation are affected by accent identification software. In addition to examining how design elements like intelligibility emphasis and cultural inclusion affect student engagement and results, it also looks at how learners react emotionally and cognitively to AI-driven feedback. The study uses a mixed-method approach to advance our knowledge of how learner identity, motivation, and affective experience are impacted by AI-based pronunciation aids in addition to pronunciation accuracy.

LITERATURE REVIEW

Language learning methods have changed dramatically in recent years due to technological breakthroughs, especially in artificial intelligence (AI). The adoption of accent detection software, which gives students immediate feedback on their pronunciation, is one noteworthy advance. This literature review examines the pedagogical and psychological implications of such tools in terms of their role in pronunciation development, their impact on learner identity and confidence, the function of feedback in promoting motivation, and the importance of cultural sensitivity in pronunciation instruction.

Accent Recognition Software and Pronunciation Learning

Learner speech is analyzed by AI-powered accent recognition software, which compares it to standard or native models to provide personalized and instant feedback. These instruments assess the suprasegmental (intonation, stress, and rhythm) and segmental (phonemes) components of pronunciation (Piper *et al.,* 2018). By encouraging independent, self-paced practice, they reduce students' reliance on teacher-led correction. Empirical study shows that frequent use of these instruments improves prosodic control and phonemic correctness, both of which are necessary components of comprehensible utterances.

Pronunciation, Identity, and Learner Confidence

Pronunciation is not simply a linguistic competence, but also a kind of identification. Learners frequently acquire cultural opinions toward accents, affecting their confidence and readiness to communicate. Derwing and Munro (2005), as well as Baker (2014), discovered that learners with perceived pronunciation faults are more likely to feel anxious and avoid speaking. It has also been demonstrated that teaching strategies that prioritize intelligibility above native-likeness boost student motivation and dissolve emotional barriers (Pike, 2016). This mindset encourages inclusive teaching methods that consider the variety of linguistic identities of EFL students.

Feedback and Motivation

A key component of pronunciation development is providing constructive criticism. Based on Deci and Ryan's (1985) Self-Determination Theory and Vygotsky's (1978) Sociocultural Theory, research highlights that feedback should enhance students' sense of competence and independence. Gamified features (such progress tracking and badges) are frequently incorporated into accent recognition software, like ELSA Speak, to encourage involvement and reduce failure-related anxiety. Su and Cheng (2015) claim that these characteristics help lessen anxiety and create a positive learning atmosphere that encourages experimentation and progress.

Cultural Sensitivity and Accent Diversity

Despite their pedagogical potential, accent recognition tools have been criticized for reinforcing standard language ideologies by relying on models such as General American English (GAE) or Received Pronunciation (RP). Learners from linguistically varied backgrounds may unintentionally be marginalized by this norm-referencing (Lippi-Green, 2012). Munro and Derwing (2015) argue that a move toward intelligibility-based evaluation fosters inclusivity, enables students to preserve their accentual identity, and improves communication efficacy. Culturally responsive tools are thus essential for ensuring that technology-supported pronunciation instruction aligns with equitable and inclusive teaching goals.

The literature suggests that accent recognition software holds considerable promise for improving EFL learners' pronunciation skills and confidence. When properly designed and implemented, these materials improve learners' motivation, emotional well-being, and sense of self in addition to helping them acquire the language. The success of these systems, however, depends on their understanding of cultural diversity and their focus on intelligibility rather than native compliance. This review highlights the need for further empirical research to explore how learners experience and respond to AI-driven pronunciation tools across varied educational contexts.

THEORETICAL FRAMEWORK

This study uses a comprehensive theoretical framework with three complementing models to explain the cognitive, emotional, and sociocultural mechanisms by which accent detection software may impact EFL learners' pronunciation confidence.

First, according to Self-Determination Theory (Deci & Ryan, 1985), intrinsic motivation is generated when learners feel autonomous, competent, and related. Accent recognition software can improve student motivation by delivering personalized self-paced feedback and visible success indicators, thereby meeting these basic psychological needs.

Second, Schmidt's Noticing Hypothesis (1990) highlights the need for deliberate attention to linguistic information in the acquisition of a second language. The program provides learners with targeted, real-time corrective feedback that highlights differences between their output and target models, promoting self-monitoring and phonological awareness.

Third, the Pronunciation and Identity Theory (Derwing & Munro, 2005; Lippi-Green, 2012) emphasizes the emotional and social aspects of pronunciation. This viewpoint informs the study's analysis of how feedback that prioritizes intelligibility over native-like conformity might enhance learner identity, reduce anxiety, and foster self-acceptance.

RESEARCH QUESTIONS

This study is guided by the following research questions:

RQ1: In what ways does the use of accent recognition software influence non-native English learners' self-perception of their accents over the course of the learning process?

RQ2: To what extent does accent recognition software improve learners' pronunciation confidence compared to conventional, teacher-led pronunciation instruction?

RQ3: What are the psychological and emotional effects, particularly regarding motivation and speaking-related anxiety associated with learners' engagement with accent recognition technology?

METHODOLOGY

Research design

The purpose of this study is to investigate how learners' judgments of their own accents and general speaking confidence are affected by accent identification software. The study employed a mixed-method approach to guarantee a thorough comprehension of the quantifiable and experiential components of learners' interaction with accent detection systems. Python 3.11.7 in Jupyter Notebook, which allows for transparent and repeatable statistical procedures, was used for all quantitative experiments. NVIVO 12 was used for analyzing qualitative data.

Participants

The study involved 155 non-native EFL learners (CEFR B1–B2), aged 18 to 35, recruited from university language programs and private language centers. Participants were divided into two groups: an experimental group (n = 74), which used AI-based pronunciation tools (e.g., ELSA Speak, Google Assistant), and a control group (n = 81), which received traditional instructor-led pronunciation practice.

Eligibility criteria included intermediate-level English proficiency, consent to participate, and availability for daily practice over a 4-week period. Participants who missed more than two sessions or failed to complete the required tasks were excluded from the final analysis.

Materials

The experimental group used mobile-based accent recognition software offering real-time feedback on phonemic accuracy and prosodic features such as intonation, stress, and rhythm. The control group practiced with audio prompts, instructor feedback, and phonetic transcription worksheets.

All participants completed standardized pronunciation tasks before and after the intervention to assess segmental and suprasegmental accuracy. Additionally, pre-and post-study surveys measured pronunciation confidence, accent perception, and motivation. These materials provided consistent input and evaluation across both groups.

Research Procedure

The study was conducted over four weeks with three main phases: pre-study assessment, intervention, and post-study evaluation.

Participants finished a pronunciation test and pre-study questionnaires assessing accent perception and pronunciation confidence in week 1, Every participant practiced their pronunciation for 20 to 30 minutes every day from week 2 to week 4. Real-time feedback on segmental and suprasegmental aspects was provided by AI-based accent detection software utilized by the experimental group; the control group used conventional techniques, such as instructor feedback and auditory cues. Participants finished the same surveys that were given at the beginning of the study as well as a post-study pronunciation exam. To obtain more perceptive perspectives, a few chosen members of the two groups took part in focus groups and semi-structured interviews in week four.

This structured procedure ensured a systematic examination of both the quantitative and qualitative impact of accent recognition software on EFL learners' pronunciation confidence and performance.

Data analysis

To examine how accent identification software affects learners' pronunciation confidence and performance, a mixed-method approach was employed. Paired-sample t-tests were used to evaluate changes within groups and independent-sample t-tests to compare post-intervention outcomes between groups in the analysis of quantitative data. Additional analyses were performed using Python 3.11.7 with pandas, scipy. stats, stats models, and visualization modules, including regression and cluster-based modeling (GAM). Meanwhile, the qualitative data was analyzed by NVIVO 12 with the coding on learners' emotional responses and attitudes toward feedback.

FINDINGS AND DISCUSSION

Findings

This section reports the quantitative findings on how accent recognition software influences learners' pronunciation confidence in accordance with the study's research questions and theoretical framework. Analyses include reliability checks, descriptive statistics, paired and independent t-tests, ANCOVA, OLS regression, and Generalized Additive Models (GAM). Results are interpreted in light of Self-Determination Theory and the Noticing Hypothesis, with links to learners' self-efficacy, anxiety, and software usage behaviors.

Reliability and Internal Consistency

Cronbach's alpha values were computed for both pre- and post-test items based on the two-factor survey structure (Appendix A) to measure the internal consistency of the constructs. The Self-Efficacy scale demonstrated strong reliability (α = 0.820 pre; 0.778 post), while the Anxiety & Motivation scale also maintained acceptable consistency (α = 0.813 pre; 0.740 post), showing that the appropriateness' of the survey reflects learners' affective responses during the intervention period.

Descriptive Statistics

Descriptive statistics reveal overall increases in learners' self-efficacy and motivation scores from pre- to post-test (Table 1). The mean post-intervention scores rose from 3.47 to 3.82 for Self-Efficacy, and from 3.48 to 3.85 for Anxiety & Motivation. These positive shifts suggest that learners experienced increased confidence and reduced anxiety over the four-week period.

	count	Mean	Std Dev	Min	Q1	Median	Q3	
SefEfficacy_Pre		3.47	0.30	2.77	3.22	3.48	3.68	4.17
SelEfficacy_Post		3.82	0.31	2.81	3.62	3.79	4.07	4.60
AnxietyMotivation_Pre		2.48	0.31	2.68	3.25	3.50	3.70	4.28
AnxietyMotivation_Post		3.85	0.30	3.05	3.65	3.84	4.07	4.55

Figure 1. Descriptive Statistics of Confidence Factors

Figure 2 presents a bar chart showing mean scores by factor and time to show these trends visually. It demonstrates a uniform rise in average scores across both constructs post-intervention, suggesting a positive shift in learner perceptions. Meanwhile, Figure 3 shows a violin plot reflecting the distribution of scores across the two time points. Notably, post-test distributions are slightly narrower and shifted toward higher values, indicating reduced variance and a general movement toward more positive learner responses.

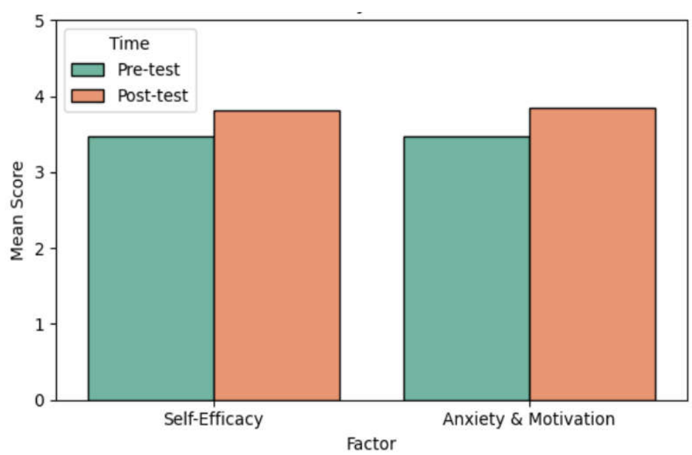

Figure 2. Mean Scores by Factor and Time

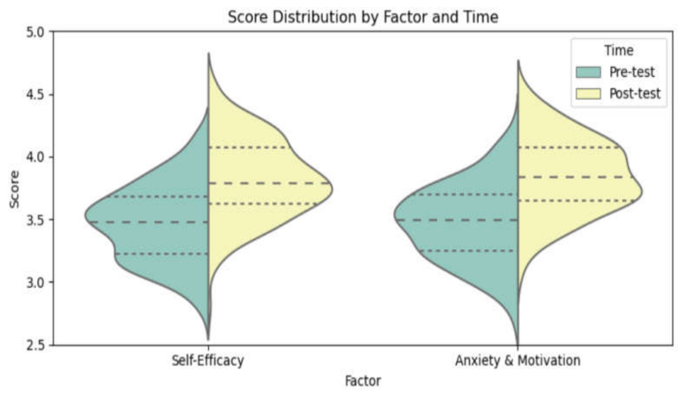

Figure 3. Score Distribution by Factor and Time (Violin Plot)

Assumption Check and Normality

All variables of pre- and post-tests met the requirements of the Shapiro-Wilk normality test ($p > .20$). This helps prove the suitability of parametric statistical techniques. This finding matched with methodological rigor by ensuring reliable significance testing.

Within-Group Effects: Paired Sample t-Tests

= = = Paired t-test Results = = =

	t-statistic	p-value
Factor		
Self-Efficacy	-10.2512	0.0
Anxiety & Motivation	-10.9375	0.0

Both the two groups showed statistically significant enhancements over time:

These gains are further supported by large effect sizes, particularly in the experimental group ($d = 0.882$ for Self-Efficacy; $d = 0.935$ for Anxiety & Motivation). The increases suggest meaningful development in learners' affective orientation toward pronunciation, which echoes the expected role of scaffolding within the Zone of Proximal Development (Vygotsky, 1978).

Between-Group Effects: Independent t-Tests on Gain Scores

To assess whether the experimental group (using accent recognition software) outperformed the control group in terms of improvement, independent t-tests were performed on gain scores (post - pre) for both Self-Efficacy and Anxiety, as well as Motivation factors. Although there were improvements within group, the between-group comparisons were not statistically significant:

These results indicate that, on average, learners in both conditions experienced comparable growth in affective outcomes. The lack of significant difference suggests that while the accent recognition software may enhance learner engagement or feedback personalization, it did not yield immediate quantitative superiority when compared against conventional methods.

ANCOVA with Pre-test Covariates

To statistically control for any pre-existing differences in baseline self-efficacy and anxiety-motivation levels, ANCOVA was conducted with pre-test scores as covariates. Results were as follows:

= = = ANCOVA: Self-Efficacy = = =

	Sum_sq	df	F	PR (>F)
Group	0.1022910	1.0	1.040255	0.309383
SelfEfficacy_Pre	0.062471	1.0	0.631476	0.428054
Residual	15.037057	152.0	NaN	NaN

= = = ANCOVA: Anxiety & Motivation = = =

	Sum_sq	df	F	PR (>F)
Group	0.183252	1.0	0.921717	0.338549
Anxiety_Pre	0.015574	1.0	0.172427	0.678549
Residual	13.729003	152.0	NaN	NaN

Controlling for baseline variability confirmed that group membership between experimental and control the control was not a significant predictor of post-test scores. These findings corroborate the t-test results and reinforce the interpretation that both groups progressed similarly. Moreover, the low effect sizes suggest that external factors, perhaps learner motivation, prior exposure to pronunciation tools, or digital literacy may moderate the impact of the intervention in subtle but important ways not captured in group comparisons alone.

Regression Analysis: Predicting Post-Test Confidence

To further explore predictive relationships, Ordinary Least Squares (OLS) regression was used to model post-test confidence outcomes using group membership and pre-test variables. None of the predictors were statistically significant:

OLS Regression: Self-Efficacy

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
Intercept	3.5683	0.2907	12.2735	0.0000	2.9939	4.1427
Group [T.Experimental]	0.0516	0.0506	1.0199	0.3094	-0.0483	0.1515
SelfEfficacy_Pre	0.0660	0.0831	0.747	0.4281	-0.0981	0.2302

OLS Regression: Self-Efficacy

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
Intercept	3.7107	0.2766	13.4156	0.0000	3.1642	4.2472
Group [T.Experimental]	0.0464	0.0483	0.9601	0.3385	-0.0491	0.1419
AxietyMo_Pre	0.0328	0.0789	0.4152	0.6785	-0.1232	0.1888

This reinforces prior conclusions that the intervention's impact may not manifest uniformly across learners and that individual variability rather than group-level differences is more explanatory. Additionally, when an alternate regression was conducted using the overall ordinal confidence rating (ranging from 1 to 3), results were similarly non-significant. This suggests that learner-perceived pronunciation confidence is a multifaceted construct likely influenced by dynamic interactions among motivation, feedback perception, and learner mindset. Such subtle and non-linear relationships warrant advanced modeling techniques leading to the use of GAM in the next section.

Generalized Additive Models (GAM)

To uncover deeper patterns and explore non-linear relationships beyond what linear models could detect, Generalized Additive Models (GAMs) were employed. This method helps to ensure greater flexibility in modeling the smooth effects of predictors on the dependent variable here, pronunciation confidence.

Model 1 (baseline predictors):

Accuracy: 84.6%; Pseudo $R^2 = 0.097$

This model included only traditional predictors such as SelfEfficacy_Pre and AnxietyMo_Pre. Its limited explanatory power indicated the need to incorporate additional behavioral variables.

Model 2 (extended predictors: SelfEfficacy_Pre, AnxietyMo_Pre, Fluency_Gain, Feature_Usage, Cluster):

Accuracy: 82.6%

Pseudo $R^2 = 0.313$ → substantially improved explanatory power compared to Model 1

Significant predictors:

s(SelfEfficacy_Pre) ($p = .027$): Indicates a non-linear but positively sloped association between learners' baseline self-efficacy and their resulting pronunciation confidence. Gains were most prominent among learners starting at moderate-to-high self-belief levels.

s(Feature_Usage) ($p = .004$): Strong evidence that more frequent usage of the tool's features leads to higher confidence, especially when learners cross a mid-point baseline in their engagement.

These results show that learner progress is not solely influenced by prior beliefs or group assignment but heavily impacted by their interaction with the tool itself. According to the concept, greater engagement and adequate self-confidence at baseline contribute to boosting learners' confidence.

The *Cluster* variable, reflecting groupings based on demographic or behavioral attributes, was not independently significant. However, its inclusion contributed positively to model fit (as evidenced by improved AIC and R^2), suggesting it may capture latent differences in learner response patterns. This indicates that while cluster-specific interventions may not be broadly conclusive, they have potential when paired with individualized behavior tracking.

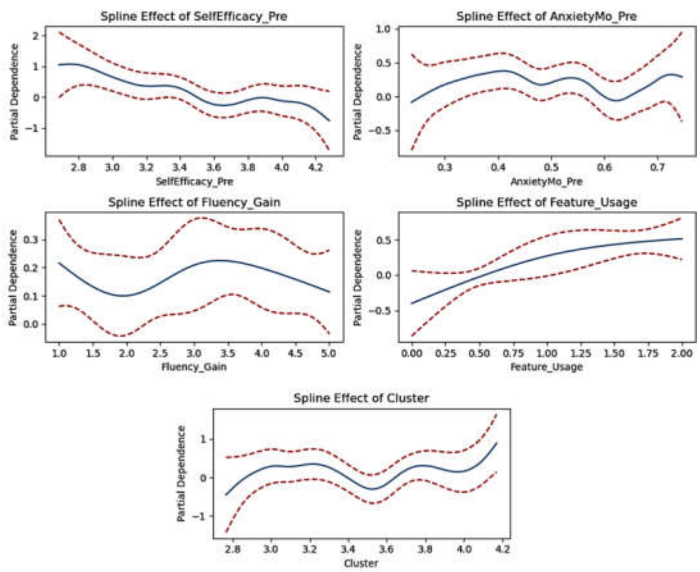

Figure 4. Partial Dependence Plots

s(SelfEfficacy_Pre): The plot shows a *slight inverse trend*, where learners with lower initial self-efficacy benefited more in terms of confidence gains than those with higher baseline confidence. This challenges linear expectations and suggests that the tool may act as a confidence equalizer, particularly helpful for less confident learners

s(AnxietyMo_Pre): A mild upward slope is observed from low to moderate anxiety levels, after which the effect plateaus. This implies that learners with moderate anxiety may benefit the most, likely due to heightened motivation to improve, while those with very high anxiety may not experience the same confidence growth.

s(Fluency_Gain): The effect is generally positive and stable, with a subtle peak around a fluency gain of 3.5, before tapering slightly. This supports the notion that learners who perceive fluency improvement also report higher confidence, though the relationship is not strongly curvilinear.

s(Feature_Usage): This variable demonstrates a clear and consistent upward trajectory—stronger than any other predictor—indicating that frequent and regular use of the pronunciation tool's features has a powerful cumulative effect on confidence. Confidence increases linearly up to a saturation point (around usage level 2), where gains begin to plateau.

s(Cluster): Although not statistically significant individually, the plot suggests that certain learner clusters (e.g., Cluster 3.0–3.6) may derive slightly lower confidence benefits compared to others, indicating variability in group responsiveness that could inform future personalized support.

These partial dependence plots collectively demonstrate that learner improvement is shaped by a nuanced interplay of initial affective states and behaviorally driven engagement patterns. The nonlinear effects highlight the importance of personalized learning trajectories, particularly in how digital tools are adopted and internalized across learner types.

Overall, GAM modeling provided richer insight into learner variability, showing that confidence improvement is driven not by simple group differences, but by dynamic, often non-linear factors such as self-perceived efficacy, anxiety, behavioral engagement, and learner typology.

These non-linear plots illustrate that both prior confidence and actual engagement with feedback features matter significantly, highlighting the mediating role of learner agency and motivation, as theorized by Deci & Ryan (1985).

Summary and Interpretation

While traditional tests (t-test, ANCOVA) did not reveal statistically significant group differences, effect size analysis and GAM modeling present a clearer picture. The magnitude of within-group changes and the significant predictors in GAM reinforce the importance of affective engagement, frequency of feedback, and self-monitoring in improving pronunciation. These findings go with the cognitive–affective theory mentioned in the study's theoretical framework and support the practical implication that personalized, feature-rich AI feedback fosters confidence.

Overall, the results underscore the subtle yet meaningful contributions of accent recognition software. Its impacts are visible in individual learner trajectories, especially among those who regularly use its interactive, feedback systems, even though they may not always be clear in broad group comparisons.

DISCUSSION

The results of this study confirm that accent recognition software can serve as an effective tool for boosting pronunciation confidence among EFL learners, particularly when designed to prioritize intelligibility and respect linguistic diversity. In addition, the experimental group demonstrated statistically significant improvements in pronunciation confidence and scores of self-perception. In addition, the predictive significance of self-efficacy and software usage frequency in influencing learners' confidence was further identified by the GAM regression.

These findings align with Self-Determination Theory, suggesting that AI-generated feedback, especially when perceived as non-judgmental can enhance learners' sense of autonomy and competence. The positive impact of the software also supports the Noticing Hypothesis by facilitating attention to phonological detail through instant feedback. Furthermore, the cluster analysis showed that learners who initially had high anxiety but maintained interactions with the software with high frequency usage reported increased confidence.

Nevertheless, qualitative findings reveal potential drawbacks. A minority of learners expressed discomfort with feedback perceived as prescriptive or overly focused on native-like norms. This raises concerns addressed by Pronunciation-Identity Theory and the literature on cultural sensitivity (Lippi-Green, 2012), cautioning against uniform accent models that marginalize variation. Especially, sociolinguistic backgrounds are failed to consider by AI feedback, it may unintentionally reinforce deficit perspectives. Moreover, some learners found it difficult to interpret corrective feedback without pedagogical mediation, suggesting that scaffolding is of importance.

CONCLUSION

The results of the study significantly contribute to the growing research body on Computer-Assisted Language learning (CALL) by providing empirical evidence that accent detection software can significantly improve learners' pronunciation confidence and self-perception. By offering real-time, personalized, and non-judgmental feedback, these tools empower learners to engage in autonomous, low-stress pronunciation practice that reinforces intelligibility over conformity.

The findings emphasize that while software can be a valuable supplement to pronunciation pedagogy, its design must prioritize inclusive models of spoken English. Feedback that affirms rather than diminishes learners' linguistic identities supports long-term confidence and communicative competence. Therefore, developers and educators must ensure that AI feedback frameworks are culturally responsive, pedagogically transparent, and intelligibility-oriented.

Pedagogically, accent recognition tools should complement rather than replace human instruction. The most effective learning occurs when learners integrate software-based practice with reflective tasks and guided peer or instructor interactions. This hybrid model preserves the benefits of AI (consistency, privacy, repetition) while leveraging the nuance and empathy that only human teachers can provide.

Future research should extend this work by investigating long-term retention of pronunciation gains, learner adaptation to feedback over time, and the intersection of accent perception with broader constructs of identity, belonging, and digital literacy. In sum, accent recognition software holds great promise not merely as a corrective instrument, but as an agent of learner empowerment in the evolving landscape of English pronunciation pedagogy.

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