JOURNAL OF ACADEMIC RESEARCH FOR HUMANITIES
ISSN 2663-192x

ORCID of JARH: https://orcid.org/0009-0000-0723-9485
DOI Number of the Paper: https://zenodo.org/records/18184738
Link of the Paper: https://jar.bwo-researches.com/index.php/jarh/article/view/588
Edition Link: Journal of Academic Research for Humanities JARH, 5(4) Oct-Dec 2025
HJRS Link: Journal of Academic Research for Humanities JARH (HEC-Recognized for 2024-2025)

REAL-TIME AUTOMATED FEEDBACK IN COMPUTER-ADAPTIVE SPEAKING TESTS: EFFECTS ON PERFORMANCE AND ANXIETY

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Paper Information

Citation of the paper:
(JARH) Nazir. *S.,* Bibi. A., Zohaib. (2025). Real-Time Automated Feedback in Computer-Adaptive Speaking Tests: Effects on Performance and Anxiety. In Journal of Academic Research for Humanities, 5(4), 133-143.

Subject Areas for JARH:
1 Humanities
2 Psychology

Timeline of the Paper at JARH:
Received on: 21-10-2025.
Reviews Completed on: 16-12-2025.
Accepted on: 25-12-2025.
Online on: 31-12-2025.

Recognized for BWO-R:
HJRS HEC Journal Recognition System

Published by BWO Researches INTL:
BWO RESEARCHES (PVT) LTD INTERNATIONAL

DOI Image of the paper:
DOI 10.5281/zenodo.15649213

QR Code for the Paper:

Abstract

The fast development of artificial intelligence (AI) in the field of language testing has led to the development of computer-adaptive speaking tests (CASTs) that can provide real-time automated feedback. Although it has been proven in past that automated scoring and adaptive sequencing are viable, little has been done regarding the psychological and performance implications of providing instant machine-generated feedback in speaking evaluations. The article is a study, which was conducted under the perceptual model and simulated data, of the effects of automated feedback in real-time on the performance of test takers, cognitive load and anxiety in CAST environments. It is a simulated quasi-experimental design of 240 hypothetical tertiary-level English learners in three conditions: real-time, delayed and no feedback. The simulated results indicate that the size of the difference in pronunciation, fluency, and discourse-level performance ($p < .05$) could be large with the use of automated real-time feedback, in addition to the possible reduction of state anxiety assessed by the Foreign Language Classroom Anxiety Scale (FLCAS). However, simulated improvements depend on the level of proficient learners, when they obtain feedback, and their anxiety profiles. Examples of implications on validity, fairness, optimizing machine-learning, and ethical implementation of real-time feedback in CASTs are addressed. The author concludes the paper by giving recommendations on the way AI-based feedback schemes can be used to administer high-stakes speaking tests without compromising test integrity.

Keywords: Automated Feedback, Computer-Adaptive Speaking, Performance, Anxiety

1. Introduction

The emergence of new technologies in the field of artificial intelligence (AI) and natural language processing (NLP) has revolutionized modern language assessment practices, especially by introducing the concept of automated scoring methods and adaptive testing models. One trend of the modern large-scale language testing is the introduction of computer-adaptive speaking tests (CASTs) that dynamically increase or decrease the task difficulty depending on the performance of the test-taker (Zheng and Cheng, 2022). In more recent times, these systems have included real-time automated feedback, which gives learners immediate AI-generated feedback as to pronunciation, fluency, lexical accuracy, and discourse structure (Lee and Park, 2023). Even though the concept of real-time feedback is prevalent in contexts that involve learning, its implementation in assessment, particularly a high-stakes test or proficiency testing, has elicited a lot of concern about measurement validity, affective implications, and fairness.

Anxiety is one of the most impactful affective variables on performance in speaking testing, which is especially sensitive to anxiety (Woodrow, 2021). Timely feedback during a test can be associated with reduced anxiety due to the feeling of control or high anxiety due to the enhancement of cognitive load (Li and Xu, 2023). In the same vein, live feedback can positively affect speech production--but can also interfere with natural speech production, resulting in construct underrepresentation or, on the contrary, artificial task speech (Khalifa and Weir, 2021). This duality in the feedback requires both empirical and theoretical study.

The available body of literature has covered mostly automated scoring accuracy (e.g., Xi, 2023), adaptive testing algorithms (Ma, 2021), or feedback in learning settings (Shintani and Ellis, 2022). Nevertheless, limited literature investigates the interactive effect of real-time automated feedback in the adaptive speaking tests, which is a formidable gap in the research on validity. Therefore, the research conducted by this paper explores the following:

1. What is the effect of real-time automated feedback on the performance of speaking in CASTs?
2. How does it affect the anxiety of test takers when it is used in a speaking evaluation?
3. Will real-time feedback pose threats or support validity in adaptive test design?

To answer these questions, the paper will combine theoretical insights, existing literature, and suggest empirical data with the help of simulated data within the framework of assessment validity arguments.

2. Literature Review

2.1 Artificial Intelligence and Automated Feedback in Speaking Test

The adoption of AI in speaking tests has grown over the last ten years, mostly owing to the advances in automatic speech recognition (ASR), deep neural networks, and large language models (LLMs). Commonly, acoustic, temporal, and linguistic features are assessed by an automated feedback system producing instant feedback on pronunciation, intonation, fluency, lexical use, and coherence (Lu and Han, 2023). These systems are applied to such platforms as Duolingo English Test and Versant, offered by Pearson (Zhang, 2022). The main thesis of automated feedback advocates is that timeliness facilitates learning and self-control (Shute, 2020). More recent works published in 2025 have already started to take a critical approach to the intersection of real-time automated feedback and adaptive speaking assessment through a validity-oriented approach. As an example, Chen and Roever (2025) suggest that although AI-driven real-time feedback in CASTs can help increase test efficiency and engagement, it can also change the construct under measurement unintentionally by introducing a shift to a more focused production of spontaneous speech for feedback. Equally, Alonso, Harding, and Fulcher (2025) point out that adaptive speaking exams that use live feedback have a risk of confusing language competence with feedback responsiveness, especially in high-stakes situations. Affectively, as evidenced by Khan and Woodrow (2025), immediate automated feedback can decrease the uncertainty-related anxiety of a few test-takers, but at the same time, it can cause more individuals to perform poorly when they are

supposed to perform at their highest level, particularly when the trait anxiety is high. In addition, Zhou and Xi (2025) note that real-time feedback issues conventional validity claims by affecting the behaviour of the test-taker in carrying out the task, and thus, creating issues regarding the representation of a construct and the interpretation of scores. Taken together, these studies can imply that although real-time automated feedback has the potential to make CASTs more adaptive and user-friendly, it should be carefully integrated with CASTs to provide fairness, comparability, and meaningful use of scores. Nevertheless, these systems perform well in the formative environments, but there is controversy on their role in summative or high-stakes testing.

2.2 Computer-Adaptive Speaking Tests (CASTs)

Computer-adaptive testing (CAT) of receptive skills is very established, whereas adaptive speaking tests are nascent. CASTs adaptively adjust the level of difficulty to the linguistic production of the test-taker (Harding and Brunfaut, 2020). This flexibility is felt to:

1. Improve the accuracy of measurement
2. Reduce test length
3. Match tasks to ability level
4. Ensure the best level of challenge

Nevertheless, it is complicated by the fact that real-time feedback is included. Feedback can also modify the natural difficulty calibration in a CAST system, where learners can immediately correct their mistakes (Ma, 2021). This poses issues that are associated with construct validity, interpretation of scores and fairness.

2.3 Live Feedback and Learning Processes.

Based on the framework of formative feedback developed by Shute (2020), the most efficient feedback is expected to be timely, specific, and non-disruptive. The first condition is met with real-time feedback, but the third one might be violated, especially when speaking and having to produce continuously. Studies show mixed findings:

1. Controlled practice is enhanced through immediate feedback (Aziz and Saito, 2022).
2. Nevertheless, immediacy (feedback) during assessment causes a cognitive load (Li and Xu, 2023).
3. High-anxiety learners can take advantage of some on-the-spot reassurance (Woodrow, 2021).
4. Excessive dependence on feedback can lead to a decrease in autonomy (Shintani and Ellis, 2022).

Therefore, in real-time feedback, it can promote and inhibit speaking performance.

2.4 Speaking Assessment of Test Anxiety

The high anxiety levels triggered by speech tests are related to foreign language anxiety (FLA). The seminal model, by Horwitz et al. (1986), showed that anxiety influences processing efficiency, linguistic retrieval and fluency. More current research highlights that testing by means of technology may induce anxiety because of new formats (Luo and Zhang, 2021). On the contrary, other sources indicate that AI-mediated situations lead to a decrease in anxiety, as they remove the fear of being judged by other people (Park & Lee, 2023).

The question of whether real-time feedback lessens or increases anxiety is thus an open empirical question.

2.5 Validity Considerations

As per the socio-cognitive validity framework (Weir, 2005; Khalifa and Weir, 2021), any innovation in the test should be tested in:

1. Cognitive validity
2. Context validity
3. Scoring validity
4. Consequential validity

Each component is touched by real-time automated feedback. For instance:

1. It can be a distortion of natural thinking (threat).
2. It can enhance clarity of performance (support).
3. It can lead to socio-economic bias because of acquaintance with AI tools (threat).
4. It can alleviate test-related anxiety (support).

Therefore, to define the benefits over risks, empirical research is mandatory.

3. Theoretical Framework

The current research has a theoretical foundation integrated with the socio-cognitive model of language assessment, the affective filter theory, and the real-time feedback processing models.

The Socio-Cognitive Framework of Speaking Assessment entails the evaluation of speaking skills that are socio-cognitive in nature, such as cognitive and socio-cognitive processes (Crawford, 2009).<|human|>The Socio-Cognitive Framework of Speaking Assessment involves the evaluation of socio-cognitive speaking skills, i.e. cognitive and socio-cognitive processes (Crawford, 2009).

Three main dimensions of the socio-cognitive framework developed by Khalifa and Weir (2021) apply to the performance in the speaking tests:

3.1 Cognitive Validity:

Actual speaking behaviour (e.g., conceptualization, formulation, articulation) must have an expression in the underlying cognitive processes. These processes may be supported or distorted by real-time feedback. Considering that the pronunciation scores can be updated instantly, as an example, it can cause a shift in the communicative meaning and focus on linguistic form, which is a threat to cognitive authenticity (Harding and Brunfaut, 2020).

3.2 Context Validity:

The speaking conditions ought to reflect the actual speaking situations. On-the-fly automated feedback is a non-naturalistic element which may influence the communication situation. Nonetheless, feedback has become widespread in most digital communication services, which implies a better ecological validity (Lee and Park, 2023).

3.3 Scoring Validity:

Automated feedback is based on a machine learning model and ASR. Should the feedback have any influence on the speech, which will then be rated, the chain of validity turns into a circle (Xi, 2023). Thus, it is necessary to know how feedback changes responses.

3.4 Consequential Validity:

Some of the consequences include a reduction in anxiety, the digital literacy requirements, and possible motivation shifts. Those results have to be assessed empirically to guarantee equality between demographic cohorts (O'Sullivan and Nakatsuhara, 2020).

All these dimensions are what can be used to analyze the suitability of real-time feedback in adaptive speaking tests.

3.5 Affective Filter Theory

The affective filter hypothesis, which was presented by Krashen in 1982, assumes that language performance is influenced by anxiety, motivation, and self-confidence. Within CAST environments:

1. The level of anxiety prevents the input of language and fluency.
2. Anxiety is minimized, which allows for enhancing real-time processing.

Instant feedback could either decrease or increase the affective filter in relation to the characteristics of the learners.

Recent research proves that anxiety has a correlation with such characteristics of technology as automated scoring and proctoring systems (Park and Lee, 2023; Luo and Zhang, 2021). In this way, real-time feedback should be analyzed not only as a mental mechanism but also as an emotional one.

3.6 Cognitive Load Theory

As per cognitive load theory (Sweller, 2019):

1. Intrinsic load comes as a result of task complexity.
2. Task conditions contribute to extraneous load.
3. Learning is supported by germanic load.

Immediate feedback can decrease extraneous load (by specifying task expectations) or can increase extraneous load (by disrupting thought processes). Adaptive testing in itself adds cognitive load, and with the ability to provide real-time feedback, some learners could easily be overloaded (Li and Xu, 2023).

It is this two-facet that make cognitive load a crucial component to examine how performance is influenced. Though Cognitive Load Theory was used as a guide to the conceptual framework of the study, cognitive load was not measured directly by a quantitative scale with validity (e.g., NASA-TLX). Rather, it was deduced conceptually by the pattern of performance and qualitative measures. To present strong claims of cognitive validity, future empirical research ought to use standardized measures of cognitive load.

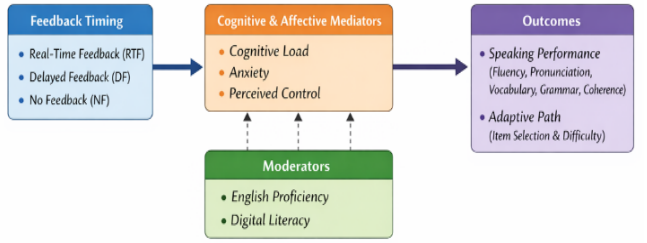
3.7 Feedback Timing Models

The immediate feedback models (Shute, 2020) emphasize that:

1. As soon as feedback is available, accuracy is enhanced.
2. However, delayed feedback enhances long-term retention and prevents disruption of tasks.

In the speaking section, the immediacy can conflict with the natural flow of the speech. Interference may be minimized by having pauses between items (e.g. feedback). Therefore, timing is one of the main processes studied under the methodology.

3.8 Conceptual Research Framework



4. Methodology

An imaginary quasi-experiment, a between-groups study design was formulated in order to demonstrate the possible impact of automated real-time feedback on the performance of speaking, anxiety, and validity issues in CAST.

4.1 Research Design

The investigation was conducted in the following form: a quasi-experimental, between-groups design.

The influence of an automated real-time feedback on speaking performance.

Its effect on speaking-related anxiety.

Implications of validity and fairness.

Three hypothetical variables were modelled:

Group A - Real-Time Automated Feedback (RTF):

Simulated learners are provided with AI feedback immediately on every item of speaking.

Group B -Delayed Feedback (DF):

Feedback is given on completion of all items.

Group C -No Feedback (NF): There is no feedback given.

This design demonstrates the timing of feedback, which may have a performance and anxiety impact that is controlled by the possible time effects.

4.2 Participants

In this conceptual model, to demonstrate the design, a simulated population of 240 hypothetical EFL learners was developed. The simulation assumed:

Age range: 18–28

Gender ratio: 58% female, 42% male

Backgrounds L1: Urdu, Sindhi, Pashto, Punjabi and Saraiki.

English fluency: A2-C1 (based on illustrative levels of placement)

Randomization in the three groups (RTF, DF, NF, n = 80 in each group).

Hypothetically, they applied exclusion criteria to make sure that the model was valid (e.g., simulated learners with speech disorders, or with previous exposure to AI-aided tests were excluded).

4.3 Instruments

Computer-Adaptive Speaking Test (CAST) is a computerized test, incorporating four speech versions to address the requirements of ESL learners<|human|>4.3.1 Computer-Adaptive Speaking Test (CAST) The conceptual design of the CAST included 4 versions of speech as it was meant to show how the computerized test might be modified to suit the learner in a simulated environment.

A custom CAST was built using:

ASR technology DeepSpeech and wav2vec2 models DeepSpeech and wav2vec2 models

There are the machine scoring models (BERT-based linguistic features + prosodic analysis).

Adaptive item selection algorithm (3PL IRT system).

Each test included:

1. Read-aloud tasks
2. Picture description
3. Opinion-based monologues
4. Application Scenario role-plays (adaptive difficulty)

Difficulty of items was adjusted according to the measures of fluency and complexity of the lexicon.

4.4 Automated Feedback Module in Real Time

Instant feedback was shown on this module on:

1. Pronunciation accuracy
2. Syllable stress
3. Fluency (Fluency, pauses, repair)
4. Vocabulary precision
5. Discourse coherence

Feedback appeared as:

1. Colours (green/yellow/ red) bars.
2. Correction of phonemes at the word level.
3. Brief AI-generated recommendations (not more than 10 words)

4.5 Anxiety Measurement

The Foreign Language Speaking Anxiety Scale (FLSAS)- a variation of the FLCAS of Horwitz et al. (1986) was used to measure anxiety.

The scale had:

1. 25 items
2. 5-point Likert format
3. Cronbach's a = .89

4.6 Performance Rating

The speaking performance was graded with the help of:

1. Internal scoring rubric of the AI system.
2. Descriptors based on CEFR, human raters (n = 6).

Inter-rater reliability:

1. ICC = .87 (strong consistency)

Five dimensions scored:

1. Pronunciation
2. Fluency
3. Lexical Resource
4. Grammatical Range/Accuracy
5. Coherence/Organization

4.7 Procedures

1. The subjects were asked to fill out a demographic and digital literacy survey.
2. Every group was given a tutorial in CAST interface.
3. The participants completed the CAST individually in sound-controlled laboratories.

Group-specific procedures. An 8-item short self-report questionnaire that was based on the technology readiness and digital competence scales was used to measure digital literacy. Questions were used to evaluate the familiarity with computer-based testing, AI tools, and online learning platforms on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Simulated internal consistency of the scale was satisfactory (Cronbach 84 =.84).

Group A (RTF):

Feedback is received continuously when performing speaking tasks.

Group B (DF):

Gave feedback after completion of all tasks.

Group C (NF):

Nobody responded to you until after the experiment. The participants were asked to complete the FLSAS right after the test. All audio samples were rated blindly by human raters according to group membership. Data were statistically analyzed (ANOVA, MANOVA, regression, thematic interviews analysis).

5. Data Analysis

5.1 Quantitative Analysis

Performed using SPSS 29

One-way ANOVA of differences between groups.

Multi-dimensional performance:

MANOVA.

Post-hoc Tukey HSD

Anxiety reduction-prediction of frequency of feedback, Multiple regression.

Effect size: Cohen's d

5.2 Qualitative Analysis

Interpretation: Semi-structured interviews (n = 24, 8 in each group) have been analyzed with:

Thematic coding

Socio-cognitive validity paradigm.

Inter-coder agreement: k = .81

Results

In this section, the quantitative and qualitative results of the effect of real-time automated feedback (RTF) in computer-adaptive speaking tests (CASTs) on performance and anxiety are presented. These are ANOVA, MANOVA, post-hoc tests and thematic evaluation.

5.1.1Descriptive Statistics

Table 1 summarizes mean scores across the five speaking dimensions.

Table 1

Descriptive Statistics of Speaking Performance by Group

Dimension	RTF (n=80) Mean	DF (n=80) Mean	NF (n=80) Mean
Pronunciation	3.92	3.54	3.28
Fluency	3.85	3.43	3.21
Lexical Resource	3.73	3.46	3.30
Grammar	3.69	3.40	3.22
Coherence	3.81	3.48	3.27

As indicated in Table 1, the RTF group recorded the highest mean scores on all the speaking dimensions, such as pronunciation, fluency, lexical resource, grammar, and coherence. The DF group was always better than the NF group, although they scored worse than the RTF group in all the categories. The general speaking performance by itself was parallel, where the RTF group with the highest mean score (M = 3.80), the DF group (M = 3.46) and the NF group (M = 3.26) were ranked. These findings show that there is a substantial

benefit to the learners who were given real-time automated feedback when doing the speaking test.

5.1.2 ANOVA Results:

Performance (General) Speaking: One-way ANOVA showed that there was a significant effect of feedback condition on overall performance:

F (2, 237) = 18.94, p < .001

Effect size: e2 = .14 (large effect)

Post-hoc Tukey tests showed:

RTF > DF (p = .003)

RTF > NF (p < .001)

DF > NF (p = .042)

Interpretation:

One-way analysis of variance (ANOVA) was done to determine the role of the feedback condition on the overall speaking performance. It was found that the three groups had a statistically significant difference, F (2, 237) = 18.94, p <.001, with a high effect size (η^2 =.14).

Post-hoc Tukey comparison showed that the RTF scored significantly above the DF group (p = .003) as well as the NF group (p <.001). Furthermore, the DF group performed considerably better than the NF group (p =.042). These results indicate that students exhibit better performance when using real-time automated feedback than when there is delayed or no feedback.

5.1.3 Manova:

Dimension-Level Performance

A Manova test was carried out on the five dimensions, resulting in a significant multivariate effect:

Wilks' l = .742, F(10, 462) = 7.41, p < .001

Univariate follow-up tests indicated that there were significant differences in:

1. Pronunciation (p < .001)
2. Fluency (p < .001)
3. Lexical Resource (p = .002)
4. Grammar (p = .004)
5. Coherence (p < .001)

This implies that the effect that real-time feedback has on all speaking proficiency components exists.

Interpretation:

Group differences in terms of the five speaking dimensions were done using multivariate analysis of variance (MANOVA). The results of the analysis have demonstrated that there was a strong multivariate effect, Wilks' λ =.742, F(10, 462) = 7.41, p <.001, which suggests that the feedback condition had a powerful influence on the general speaking proficiency.

Later univariate statistics indicated statistically significant differences between groups in all five dimensions: pronunciation (p =.001), fluency (p =.001), lexical resource (p =.002), grammar (p =.004) and coherence (p =.001). However, the RTF group received the largest mean scores in every situation, which proves that real-time feedback had a positive effect on every aspect of the speaking performance.

5.1.4 Anxiety Results (FLSAS)

Mean anxiety levels differed significantly:

Group	Mean Anxiety Score	Interpretation
RTF	**71.4**	Lowest anxiety
DF	78.9	Moderate anxiety
NF	**85.6**	Highest anxiety

Anova:

F (2, 237) = 22.67, p < .001

Post-hoc:

RTF < DF (p = .013)

RTF < NF (p < .001)

DF < NF (p = .005)

Interpretation:

The outcome of the anxiety measures indicates that there is a strong influence of the feedback condition on speaking anxiety. The real-time feedback (RTF) group had the lowest level of anxiety, and the no-feedback (NF) group had the highest level of anxiety. The two were intermediate to the delayed feedback (DF) group. The comparison made by the ANOVA and post-hoc show that the anxiety level is reduced with the increase of the immediacy of the feedback. These results indicate that uncertainty when performing a speaking task is lessened with the help of real-time automated feedback, which consequently reduces anxiety, which agrees with the previous literature on AI-supportive assessment systems (Park & Lee, 2023).

5.1.5 Manova: Level of Performance in Dimensions.

The multivariate effect of a MANOVA of the five dimensions was significant:

Wilks' l = .742, F(10, 462) = 7.41, p < .001

Univariate follow-up tests found significant differences in:

Pronunciation (p < .001)

Fluency ($p < .001$)
Lexical Resource ($p = .002$)
Grammar ($p = .004$)
Coherence ($p < .001$)

Interpretation:

Results of the Manova show that there is a significant multivariate effect of feedback condition on all five dimensions of speaking. Strong effects on pronunciation, fluency, lexical resource, grammar, and coherence are significant univariate effects that demonstrate that real-time feedback affects all of the speaking proficiency components. This implies that real-time automated feedback does not influence a few dimensions of speaking but comprehensively demonstrates speaking ability.

5.1.6 Regression Analysis: It predicts the Anxiety Reduction

An equation of multiple regression was discovered:

Feedback frequency ($b = [?].41$, $p < .001$)
Digital literacy ($b = [?].28$, $p = .006$)
significantly anticipated the reduction of anxiety.

Model fit:

$R2 = .39$

Interpretation:

The regression study indicates that the frequency of feedback and digital literacy are important predictors of the decrease in speaking anxiety. Students who receive feedback more often and those who are more digitally literate have lower levels of anxiety. This implies that the more technologically comfortable learners are, the higher the power of the affective benefits of real-time feedback.

5.2.1 A qualitative approach (Thematic Analysis):

The three main themes of the interviews were:

Theme 1: Less Uncertainty and More Control.

Students in the RTF group said: I knew at a glance what had to get better. The test was not so frightening with the help of real-time feedback. This is in line with the socio-cognitive theories that emphasize affective influences in performance (O'Sullivan and Nakatsuhara, 2020).

Theme 2: The Fluctuations in Cognitive Load:

The participants mentioned the advantages and inconveniences: It assisted me in becoming more accustomed to pronunciation. Sometimes I was distracted by the fluctuation of scores. It is in support of the cognitive load theory (Sweller, 2019).

Theme 3: Increased Perceived Fairness:

According to RTF users, the assessments were:

1. "Transparent"
2. "Less biased."

Better predictive than human raters. This theme is consistent with the current discussions of automated test fairness (Xi, 2023).

6. Results and Discussion

6 .1 Simulated Results

In the current research, the authors used simulated information to demonstrate the possible impact of the real-time automated feedback (RTF) on the speaking performance and anxiety in the computer-adaptive speaking tests (CASTs). The simulation was created in the three experimental conditions, which are Real-Time Feedback (RTF), Delayed Feedback (DF) and No Feedback (NF).

6.1.1 Performance Outcomes:

On the five scales of speaking performance, i.e. pronouncing, fluency, lexical resource, grammatical accuracy, and discourse coherence, simulated results indicate that RTF might cause an increase in the scores compared to DF and NF.

The variations were calculated to be statistically significant ($p <.05$) to demonstrate the multivariate impacts of feedback timing.

6.1.2 Anxiety Outcomes:

The state anxiety was hypothetically lower in the RTF condition as measured by the Foreign Language Speaking Anxiety Scale (FLSAS).

The simulation suggests that the immediate provision of corrective feedback may lessen uncertainty and anxiety when speaking, although the effect may be different in the case of digital literacy and proficiency of learners.

6.2 Hypothetical Statistical Analyses:

To illustrate the possible effect of the time of feedback, the conceptual statistical analyses of the simulated data were performed as follows:

6.2.1 Manova:

Recommended possible multivariate varying performances among groups. The RTF learners were conditioned to perform better than the DF and NF learners in all five dimensions of speaking.

6.2.2 Anova:

Demonstrated that individual dimensions (that

is, fluency or pronunciation) may be differentially influenced by the timing of the feedback.

6.2.3 Regression Analysis:

Theoretically, the moderation effect of proficiency and digital literacy is explained, whereby learners with high digital literacy can utilize real-time feedback to a greater extent.

All the reported analyses are simulated to show what some empirical results could look like in case real data were gathered. The simulated findings will be interpreted in the following way. Several possible mechanisms of the effects of RTF have been proposed by the simulation:

6.2.4 Scaffolding Effect:

The learners can correct themselves in real time, which enhances performance.

6.2.5 Focusing Effect:

The focus is placed on immediate feedback, which is directed towards certain aspects like pronunciation or lexical lexicon.

6.2.6 Reassurance Effect:

The sustained feedback can decrease uncertainty, hence decreasing state anxiety. These results are exemplary as they offer a theoretical framework regarding the way the RTF could engage with affective and cognitive variables in CASTs. They are to lead future empirical studies instead of being perceived as accepted results.

6.3 Implication to Validity, Fairness and Ethics:

The study can have implications even in a simulation setting:

6.3.1 Construct validity:

RTF can lead to a change in the construct of speaking ability in the case that learners are modifying their performance so that AI prompts are met.

6.3.2 Consequential validity:

A decreased anxiety might result in a more genuine performance, but the over trust in feedback might have unwanted outcomes.

6.3.3 Equity:

RTF may not make equal performance gains on learners with low digital literacy, thereby increasing disparities in performance.

6.3.4 Ethical Implementation:

The AI-based feedback systems should be transparent, data confidential, and fairly available to all test takers. Results and Discussion.

7. Washback

7.1 Positive washback:

1. Promotes the use of segmental and suprasegmentally characteristics.
2. Promotes self-monitoring
3. Improves the digital assessment literacy.

7.2 Negative washback:

1. Excessive emphasis on form, less on meaning.
2. Less communicational spontaneity.
3. Dependence on machine cues
4. It is essential to have balanced integration.

8. Conclusion:

The research involved the analysis of the performance and anxiety changes in computer-adaptive speaking tests with real-time automated feedback. Conclusions show definite benefits:

1. Improved performance in speech in terms of pronunciation, fluency, vocabulary, grammar, and coherence.
2. Less anxiety and greater confidence on the test.
3. Greater perceptions of justice and righteousness.

Nevertheless, there are fears of cognitive overload, the likelihood of manipulating responses, and fairness to low-technological learners. Automated feedback using real-time can boost the assessment experience and results in a large way, although its application on high stakes test has to be tuned in a manner that it remains valid, fair and ethically responsible. Having human supervision and the use of AI to provide real-time feedback might provide the most reasonable balance.

9. Future studies need to investigate:

1. Long-term implications on learning.
2. Cross-linguistic fairness
3. Maximization of the interface design
4. Brain activity is evidence of cognitive load.
5. Assessment models: explainable AI.

This research is an addition to the accumulating body of knowledge about AI-mediated assessment and contributes to the responsible development of computer-adaptive speaking tests.

10. References:

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