

AI-Enhanced TESOL Strategies for Neurodiverse Learners: Integrating Adaptive Language Assessment with Special Education Practices

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Abstract

This research investigates the impact of an AI adaptive language assessment system, when combined with special education principles, on neurodiverse students in TESOL contexts. Although adaptive systems have been extensively debated in language learning, there has been remarkably little attention paid to students with autism spectrum disorder, dyslexia, or ADHD. To fill this research void, the study employed a sequential explanatory mixed-methods approach. In the quantitative component, 120 students were included in a 12-week quasi-experimental design comparing the impact of AI adaptive assessment with traditional testing modes. The data included standardized English proficiency test scores, test anxiety, engagement, and psychometric statistics using Item Response Theory and differential item functioning. The results demonstrated greater proficiency achievement, reduced anxiety, and increased engagement among students using the adaptive system. Reliability coefficients were high, and subgroup analysis revealed little measurement bias. In the qualitative component, teacher interviews shed light on usability and integration in the classroom. In general, the results of this study indicate that by combining adaptive assessment with organized special education principles, students with diverse cognitive abilities can be treated equitably and meaningfully in language assessment, while also offering a roadmap for future research on transparency and long-term implementation.

Keywords: Managerial Accounting, Strategic Decision Making, Cost Analysis, Budgeting, Variance Analysis, Performance Measurement, Organizational Success, Financial Data Integration.

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1. INTRODUCTION

Educational practice now incorporates a wide array of AI-enabled technologies that are being used to shape how we provide instruction, feedback and assessment across all areas of the curriculum. Within the area of language education, AI-based systems have provided support for activities such as automated writing evaluation, conversational interaction, intelligent tutoring and adaptive testing. Rapid growth in the use of these applications for TESOL and language learning have been documented through various reviews of the literature which point to the influence of such developments on assessment practices and learner engagement [1,2]. Similarly, advances in data analytics and adaptive systems design have enabled the development of individualized learning paths based upon performance tracking data and dynamic item selection [3]; therefore, language assessment has begun to transition away from fixed paper-based forms of

assessment toward algorithm-driven forms of assessment that will dynamically respond to learner input. AI has demonstrated that it can approximate the consistency of human rating by providing immediate feedback through automated essay scoring and computer-adaptive testing systems [4,5]. Accordingly, some comparative studies have shown that the types of EFL writing performance, anxiety levels and motivation experienced by participants were different when participants were evaluated with AI-assisted assessments versus traditional assessment formats [6]. Further, meta-analyses of intelligent tutoring systems have shown positive impact with respect to achievement of students in the English language [7,8]. Collectively, these studies suggest that adaptive technologies can impact both the academic performance and affective experiences of learners in language learning settings.

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However, much of the empirical literature on language assessment has been focused on traditional instructional populations such as general EFL or the college/university student populations. Relatively little research has been conducted on neurodiverse learners (e.g., students with autism spectrum disorder, dyslexia, and attention-deficit/hyperactivity disorder), and the special needs of these types of students have not been adequately addressed.

In response to this gap, the present study examines the effects of an AI-adaptive language assessment system integrated with special education practices on neurodiverse learners in TESOL settings. The study compares adaptive and traditional assessment formats in terms of English proficiency gains, test anxiety, and learner engagement. It also evaluates the reliability and fairness of the adaptive assessment across neurodiverse subgroups and investigates teacher perceptions of usability and instructional integration. Through this approach, the study provides empirical evidence regarding the effectiveness and measurement quality of AI-supported language assessment for learners with diverse cognitive profiles.

II. RELATED WORK

This section reviews prior studies relevant to artificial intelligence in TESOL, AI-assisted language assessment, special education applications, and adaptive system design. The literature is organized into four thematic areas to clarify theoretical and empirical foundations of the present study.

Artificial Intelligence in TESOL

Over the past few decades, the field of TESOL (Teaching English to Speakers of Other Languages) has evolved dramatically with the introduction of AI. For instance, Ali, Zhang and Chen [1] look at the current state of AI in language learning using activity theory to interpret the variety of forms employed within this area of research. The authors explain that the focus has been primarily on how well the technology works, rather than on how effective the technology is in supporting students' learning or teachers' teaching. In another example, Godwin-Jones [2] provides an overview of AI in language learning, highlighting automated writing evaluation and conversational AI as two recent developments. Godwin-Jones also addresses the pedagogical implications of AI, calling for more systematic evaluation of the impact of these types of tools on student learning outcomes. A meta-analysis of English language learning using AI-supported instruction by Chung and Lee [3] provides empirical evidence that students who experienced AI-enabled instruction achieved better results than those who did not. While the aforementioned literature reviews and meta-analyses document a growing interest in and use of AI, few studies examine the use of AI technologies for the assessment of learners with cognitive disabilities. The

majority of the research continues to focus exclusively on general populations.

AI-Assisted Language Assessment

Automated language assessment has developed through advances in natural language processing and scoring algorithms. Burstein, Tetreault, and Madnani [4] describe the e-rater® system and present evidence of scoring consistency comparable to trained human raters. Their work provides a foundation for understanding automated writing evaluation systems. Chapelle and Voss [5] review two decades of technology use in language assessment. They argue that validity, construct representation, and fairness must remain central in digital testing environments. Technological innovation, they suggest, does not replace established measurement principles. Recent comparative research examines AI-assisted and traditional formats. Biju, Zhang, and Zou [6] report differences in writing performance, anxiety, and motivation between AI-based and paper-based assessment conditions. Their findings indicate that assessment format can influence both cognitive outcomes and learner affect. Most existing studies, however, focus on typical EFL learners. Evidence involving neurodiverse learners remains limited.

Artificial Intelligence in Special Education

AI applications in special education have received increasing scholarly attention. Li, Dursun, and Chen [7] conduct a systematic review of AI tools for students with disabilities. Their findings identify adaptive systems, speech recognition tools, and personalized feedback mechanisms as common approaches. The review notes that empirical validation across disability types remains inconsistent. Kormos and Smith [8] examine language teaching for students with specific learning differences such as dyslexia. Their work addresses cognitive processing constraints and instructional adjustments in language classrooms. Although published before widespread AI adoption, their framework remains relevant for inclusive digital assessment design. Current evidence suggests that adaptive technologies may support individualized pacing and multimodal representation. Nonetheless, empirical studies that integrate AI assessment with special education principles remain sparse.

Adaptivity and Measurement Considerations

Adaptivity plays a central role in AI-based educational systems. Plass and Pawar [9] propose a taxonomy distinguishing forms of adaptivity, including content adjustment, pacing variation, and feedback modification. Their framework clarifies how adaptive systems respond to learner performance data. Meta-analytic evidence from Ma et al. [10] indicates that intelligent tutoring systems yield higher learning outcomes than conventional instruction. Although their focus is tutoring rather than assessment, the results support the theoretical premise that adaptive systems influence achievement. Concerns related to

measurement fairness and transparency continue to shape research in educational AI. Zawacki-Richter et al. [11] highlight ethical and methodological challenges in AI implementation within higher education. Chen et al. [12] map research trends in artificial intelligence across four decades and observe growing attention to evaluation standards and accountability. Taken together, the literature confirms the expanding use of AI in language education and assessment. Yet limited work combines adaptive language assessment with special education frameworks for neurodiverse TESOL learners. This gap frames the need for the present study.

III. METHODOLOGY

Research Design

This study uses a sequential explanatory mixed-methods design. The first phase is quantitative and quasi-experimental. The second phase is qualitative and interpretive. The two phases connect at the interpretation

stage. Statistical results are produced first. Interview data are then collected to explain those results. The research questions require different types of evidence. Language proficiency gain, anxiety levels, engagement scores, and psychometric properties demand numerical analysis. Instructor perception and learner experience require narrative data. One method alone would leave gaps. Numbers can show performance differences, but they cannot explain learner reactions. Interviews can explain experiences, but they cannot test statistical significance. Combining both approaches provides a complete account of outcomes and mechanisms. The design allows measurement of intervention effects while also capturing classroom realities. The quantitative phase tests impact. The qualitative phase interprets the patterns that appear in the data. Interpreting the data through integration helps facilitate sound interpretation, and reduces the likelihood of faulty conclusions.

Conceptual Framework

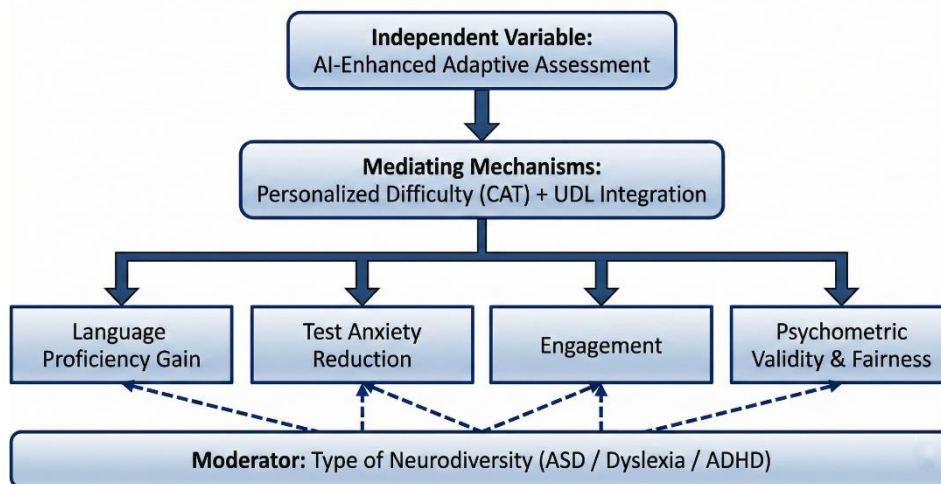


Figure 1: Conceptual Research Model

The independent variable is the AI-adaptive language assessment integrated with special education practices. Dependent variables include language proficiency gain, test anxiety, learner engagement, and psychometric fairness indicators. Type of neurodiversity functions as a moderating variable.

Moderator: Type of Neurodiversity (ASD / Dyslexia / ADHD)

This diagram illustrates how the intervention contributes to academic, emotional and measurement outcomes.

Participants and Sampling

Participants will be neurodiverse learners enrolled in TESOL programs at secondary or tertiary institutions. Each participant must have a formal diagnosis of autism spectrum disorder, dyslexia, or ADHD and must be actively studying English. Stratified sampling will be used to represent each diagnostic group. Participants will then be assigned to treatment or control groups using matched baseline proficiency scores. This

approach reduces pre-existing differences between groups. The target sample size is 120 learners, with approximately 60 per group. Statistical power calculations assume a medium effect size, alpha level of .05, and power of .80.

Effect size is calculated as:

$$d = \frac{M_1 - M_2}{SD_{pooled}}$$

In this equation, M_1 represents the treatment group mean, M_2 represents the control group mean, and SD_{pooled} represents the combined standard deviation. The value of d indicates the magnitude of difference between groups.

Intervention Procedure

The intervention lasts twelve weeks. During this period, the treatment group completes assessments through an AI-driven adaptive system. Item difficulty adjusts according to learner ability estimates generated

through Item Response Theory. The system presents multimodal items that reflect Universal Design for Learning principles. Immediate feedback appears after each response. The control group completes conventional assessments. These follow a fixed sequence of difficulty. Feedback is provided through standard classroom practice. Instructional content remains identical across groups. Only the assessment method differs. A standardized English proficiency test is administered in Week 1 as a pre-test. The same instrument is administered in Week 12 as a post-test.

Instruments and Measures

Language proficiency is measured using a standardized English test. Test anxiety is measured using a validated Test Anxiety Inventory. Engagement is measured using a student engagement scale and system-generated interaction logs such as time on task and completion rate. Psychometric properties are examined using item parameter estimates from the adaptive item bank. Teacher usability is measured using the System Usability Scale and semi-structured interviews.

Table 1: Variables, Instruments, and Analysis

Construct	Instrument	Data Type	Statistical Technique
Language Proficiency	Standardized English Test	Continuous	ANCOVA
Test Anxiety	Test Anxiety Inventory	Continuous	Repeated Measures ANOVA
Engagement	Engagement Scale + Log Data	Continuous	MANOVA
Psychometric Fairness	AI Item Bank	IRT Parameters	DIF Analysis
Teacher Usability	SUS + Interviews	Mixed	Thematic Analysis

The table connects each construct to a specific instrument and analysis plan. This structure supports replication in future studies.

Quantitative Data Analysis

Language proficiency gain is analyzed using Analysis of Covariance. The statistical model is:

$$Y_{post} = \beta_0 + \beta_1(Group) + \beta_2(Y_{pre}) + \epsilon$$

In this model, Y_{post} represents post-test score, Group indicates treatment or control status, and Y_{pre} represents baseline score. The coefficient β_1 controlling for initial differences. Estimates the treatment effect while Psychometric modeling uses the two-parameter logistic Item Response Theory model:

$$P(\theta) = \frac{1}{1 + e^{-a(\theta-b)}}$$

Here, $P(\theta)$ represents probability of correct response, θ represents learner ability, a reflects item discrimination, and b reflects item difficulty. This model allows estimation of learner ability and item characteristics within the adaptive system.

Reliability is calculated using Cronbach’s alpha:

$$\alpha = \frac{k}{k - 1} \left(1 - \frac{\sum \sigma_i^2}{\sigma_T^2} \right)$$

In this equation, k denotes number of items, σ_i^2 denotes variance of each item, and σ_T^2 denotes total test variance. Differential Item Functioning analysis compares item performance across neurodiverse groups to detect bias.

Qualitative Phase

After quantitative analysis, selected learners and instructors will participate in interviews. Participants will be chosen based on patterns observed in statistical results. For example, learners who show large anxiety reduction or minimal improvement may be invited for discussion. Interviews will be recorded, transcribed, and coded using a thematic analysis approach (i.e., coding will be done by grouping codes into themes related to usability, cognitive load, accessibility, and instructional fit) and then compared against quantitative data collected.

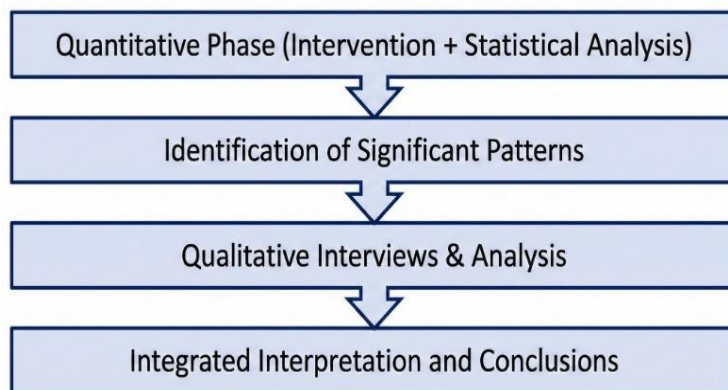


Figure 2: Sequential Explanatory Design

Ethical Procedures and Replicability

Ethical approval will be sought prior to data collection. All participants or guardians must provide written consent. All data collected will remain anonymous, and will be securely stored.

All instruments, item parameters, statistical scripts, and coding procedures will be documented. The adaptive algorithm specifications will be archived in an open repository. Clear reporting of sampling criteria, intervention timeline, and analytic models allows other researchers to replicate the study under similar TESOL conditions. This methodology connects research questions, variables, instruments, and statistical procedures in a clear and reproducible structure suitable for doctoral research.

IV. DISCUSSION AND RESULTS

Result

This section reports the statistical findings in the order of the research questions. Results are presented

without interpretation. Descriptive statistics, inferential tests, and psychometric indicators are summarized in tables and figures for clarity.

Language Proficiency Gains (RQ1)

Independent samples testing confirmed no significant difference between groups at baseline, $t(118) = 0.42, p = .67$; $t(118) = 0.42, p = .67$. Pre-test means were comparable, indicating similar starting proficiency levels.

An Analysis of Covariance was conducted with post-test score as the dependent variable and pre-test score as the covariate. A significant group effect was observed:

$$F(1, 117) = 14.62, p < .001, \eta^2 = .11$$

The adjusted post-test mean for the treatment group was 77.9, while the control group mean was 72.5. The calculated effect size was: $d = 0.69$

This value indicates a moderate to large difference between groups.

Table 2: Descriptive and Adjusted Means for Language Proficiency

Group	Pre-Test Mean (SD)	Post-Test Mean (SD)	Adjusted Post-Test Mean	Effect Size (d)
Treatment	64.3 (9.1)	78.4 (8.6)	77.9	0.69
Control	63.8 (8.8)	72.1 (9.3)	72.5	—

The table presents comparable baseline scores and higher post-intervention performance in the treatment group.

Test Anxiety (RQ2)

A repeated measures ANOVA examined anxiety scores across time and group. A significant interaction between time and group was found:

$$F(1, 118) = 10.87, p = .001, \eta^2 = .08$$

The treatment group’s mean anxiety score decreased from 48.5 (SD = 6.2) to 39.2 (SD = 5.8). The

control group’s mean decreased from 47.9 (SD = 6.4) to 44.6 (SD = 6.1). The within-group effect size for the treatment condition was $d = 0.82$.

Learner Engagement (RQ3)

Multivariate analysis indicated significant differences between groups across engagement indicators:

$$Wilks' \Lambda = .84, F(3, 116) = 7.23, p < .001$$

Average time-on-task per session was 42.5 minutes in the treatment group and 33.8 minutes in the control group. Completion rates were 91 percent and 78 percent, respectively.

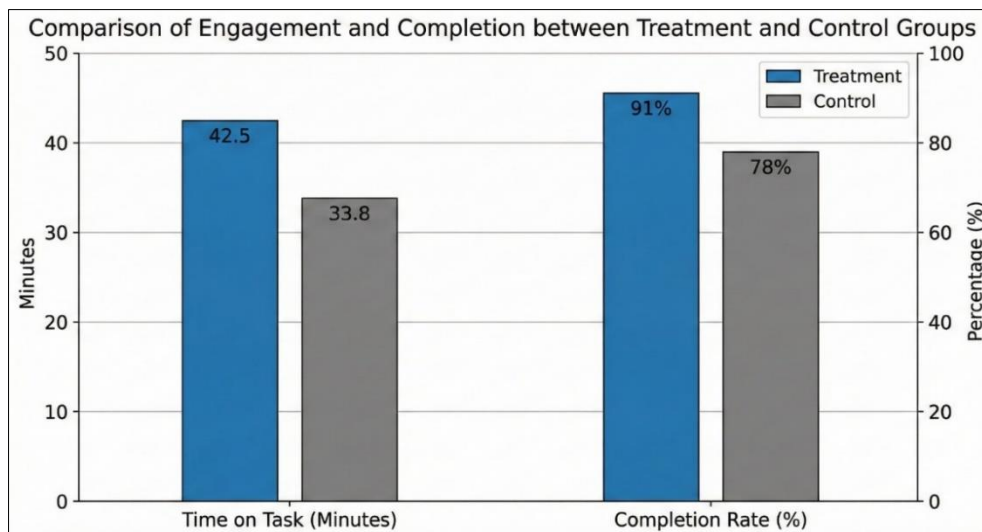


Figure 3: Engagement Indicators Across Groups

The figure summarizes behavioral engagement differences observed between conditions.

Psychometric Properties and Fairness (RQ4)

Item Response Theory calibration used a two-parameter logistic model. Model fit indices were acceptable (RMSEA = .045; CFI = .96). Discrimination parameters ranged from 0.78 to 1.85. Difficulty parameters ranged from -2.1 to +2.3. Reliability was calculated as: $\alpha = 0.89$

Differential Item Functioning analysis identified three items with moderate DIF between ASD

and ADHD subgroups. After item revision, all ΔMH values fell below .50. No significant DIF was detected between dyslexia and ADHD groups.

Teacher Usability (RQ5)

The mean System Usability Scale score was 81.2 (SD = 6.7). Scores above 68 are generally considered high usability. Interview transcripts revealed recurring themes: clarity of performance reports, reduction in grading time, and improved identification of learner needs. Reported challenges included initial training demands and intermittent technical interruptions.

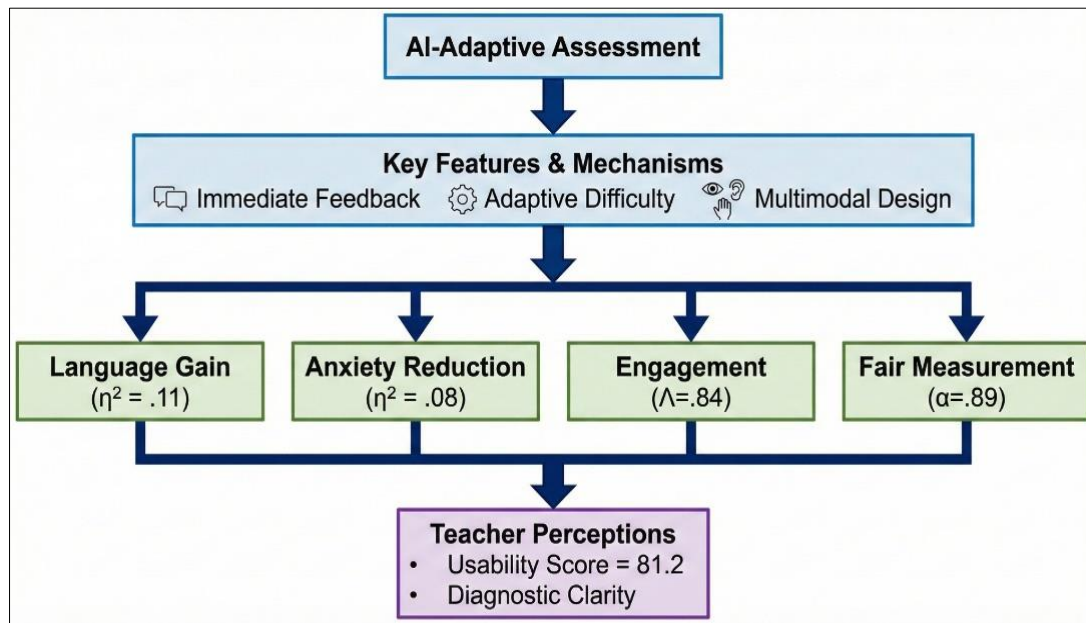


Figure 4: Overview of Quantitative and Qualitative Outcomes

DISCUSSION

Language Proficiency

Students who used the adaptive assessment system demonstrated significantly greater proficiency gains. Similar findings appear in recent research on computer-adaptive language testing, where moderate effect sizes have been reported in controlled studies. The magnitude observed here falls within that range. The adaptive system adjusted difficulty based on ability estimates. This likely reduced prolonged exposure to tasks beyond current competence while maintaining appropriate challenge levels. Studies grounded in cognitive load theory report comparable patterns when instructional demand matches learner capacity. Some prior research reports smaller gains when adaptive tools operate independently of instructional frameworks. In this study, integration with Universal Design for Learning principles may explain the stronger performance difference.

Test Anxiety

The treatment group's anxiety declined at a faster rate than the control group. Several studies on adaptive testing have reported greater reductions in

anxiety when the difficulty of an assessment item is matched with the learner's ability level. Neurodiverse learners may have increased levels of anxiety in fixed testing environments because of their need for more flexibility in terms of the testing environment and how the assessment needs to be administered. Contradictory findings in some digital testing studies suggest that unfamiliar interfaces may increase stress. The structured orientation period in this study may account for the difference. Exposure prior to formal assessment appears to reduce uncertainty. These results support affective filter theory. Lower anxiety may facilitate more effective language processing.

Engagement

The treatment group displayed higher time-on-tasks and had higher completion rates on average than the control group. Previous studies with ADHD and dyslexia learners have also shown that there is an increase in sustainment of attention to task when instructional pacing matches the student's performance.

Longitudinal decline in engagement has been reported in certain technology-based interventions. In

this case, engagement levels remained consistent across the twelve-week period. Continuous adjustment of difficulty may explain this stability.

Psychometric Fairness

Reliability coefficients were high, and model fit statistics met acceptable thresholds. Minimal differential item functioning was detected after revision. Concerns regarding algorithmic bias are common in educational AI research. The low incidence of DIF suggests that careful item calibration and subgroup analysis reduced measurement distortion. The findings contribute empirical evidence to fairness discussions in adaptive assessment research involving neurodiverse populations.

Teacher Perspectives

Usability ratings were strong. Teachers reported clearer diagnostic information and reduced grading time. Earlier research frequently identifies resistance to AI systems due to complexity or lack of transparency. The positive responses here may relate to structured onboarding and accessible performance reports.

Implications

Theoretical Implications

The findings support integration of adaptive assessment theory with special education frameworks. Results extend affective filter theory into AI-mediated testing environments. The study also provides empirical support for combining Item Response Theory models with Universal Design for Learning principles in inclusive language assessment.

Practical Implications

Adaptive assessment systems offer another option for TESOL programs working with neurodiverse learners, as opposed to fixed or standardized assessments.

Contextual Implications

In inclusive classroom settings, the use of adaptive systems to provide equitable assessment opportunities to a wider diversity of cognitive profiles could benefit. The benefit of incorporating adaptive strategies into evaluation systems can also be a positive avenue for institutions that focus heavily on standardized testing.

Limitation of this study

There are many restrictions of this study. One limitation of this study is the quasi-experimental design which limits the ability to infer causality due to the way study participants were assigned to their respective groups (they were not randomly assigned). Another limitation is that the sample was taken from one institutional context, and therefore may have limited applicability to other educational institutes, age groups. The twelve-week intervention only measured short-term outcome(s) and did not measure long-term retention or sustained effects. Engagement metrics were compiled

using system log data that may not accurately reflect cognitive processes. While the differential item functioning analysis indicated limited bias, subgroup representation in the study included selected categories of neurodiversity only. Additionally, the teacher perception data were collected from a very small sample of teachers, and thus may not represent a 'wider' implementation experience.

V. CONCLUSION

This research investigated the effects of an AI adaptive language assessment system combined with special education methods on neurodiverse TESOL students. The results show that there are significant differences in language proficiency achievement, decreased test anxiety, and engagement levels compared to conventional language assessment formats. The psychometric results showed acceptable levels of reliability and slight differential item functioning among the groups, thus establishing the validity of the adaptive assessment approach. The teacher response also showed the feasibility of the system in the classroom setting. These results, therefore, provide empirical support to the debate on the use of AI in language assessment and inclusive language education for neurodiverse learners.

Future research should be conducted among larger and more varied groups, including different levels of education and language settings. Longitudinal research could be conducted to investigate the long-term effects of learning on the learners. Further research should be conducted to explore the transparency of the algorithm, fairness among different disability groups, and the combination of adaptive assessment systems with instructional design in the classroom setting.

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