DIGITAL TOOLS VS. PERSONALIZED OUTCOMES: INVESTIGATING THE EFFECTIVENESS OF AI-DRIVEN ADAPTIVE QUIZZING IN ADDRESSING AUDITORY VS. VISUAL LEARNER DISPARITIES IN ENGLISH GRAMMAR ASSESSMENT

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Annotation: *This study investigates the efficacy of AI-Driven Adaptive Quizzing (ADAQ) in achieving assessment equity by targeting differences between auditory and visual ESL learners in grammar evaluation. Drawing on Cognitive Load Theory, the research hypothesized that traditional visual-biased testing imposes an undue extraneous load on auditory learners. ADAQ dynamically adjusted the stimulus modality—providing audio prompts for auditory profiles and graphic organizers for visual profiles—to align the assessment format with the dominant learning style. The findings from a quasi-experimental design revealed a statistically significant reduction in the performance gap between the two groups in the ADAQ environment compared to the control group (traditional text-based testing), thereby confirming that personalized digital tools can effectively mitigate assessment bias and enhance the accuracy of linguistic competence measurement.*

Keywords: *Adaptive quizzing, artificial intelligence, learner disparities, auditory learners, visual learners, grammar assessment, personalized learning, digital tools, cognitive load, assessment equity.*

INTRODUCTION

The acquisition of English grammar, particularly in English as a Second Language (ESL) contexts, is foundational to communicative competence [1, p. 15]. However, the assessment of this competence remains a significant pedagogical challenge, complicated by the inherent heterogeneity of the learning environment. Modern educational psychology strongly advocates for the recognition of individual differences, including learning styles, as critical determinants of academic success [2, p. 78]. Specifically, the disparity between auditory learners (who benefit from listening and verbal instruction) and visual learners (who benefit from written text, diagrams, and graphic representations) is highly pronounced during assessment [3, p. 41]. Traditional, paper-based, or visually static digital assessments predominantly rely on textual input and interpretation, thereby creating an inherent bias that inadvertently penalizes auditory learners [4, p. 119].

Literature Review

The Theoretical Deficit: Cognitive Load and Assessment Bias

The theoretical underpinning of this performance gap is best explained by Cognitive Load Theory (CLT), developed by Sweller [5, p. 295]. CLT distinguishes between intrinsic load (the inherent difficulty of the grammar rule), germane load (the effort dedicated to schema construction), and extraneous load (the unnecessary mental effort imposed by poor

instructional design) [6, p. 45]. When an auditory learner encounters a complex grammar question presented only in written form, they must expend cognitive resources on converting the visual input into a more manageable internal acoustic format for processing. This conversion process constitutes a significant extraneous cognitive load, which reduces the working memory capacity available for the actual task of applying the grammatical rule. Consequently, the resulting lower score often reflects assessment bias rather than a lack of competence [7, p. 230]. Addressing this bias necessitates an assessment tool that minimizes extraneous load by aligning the stimulus modality with the learner's preferred processing channel.

Adaptive Technology as a Solution

The integration of Artificial Intelligence (AI) into educational technology, particularly through AI-Driven Adaptive Quizzing (ADAQ), presents a scalable solution to this personalization challenge [8, p. 19]. Unlike static testing, ADAQ utilizes algorithms to dynamically adjust the difficulty, sequencing, and crucially, the modality of assessment items based on the student's real-time interaction and established learning profile [9, p. 101]. Research on adaptive systems confirms their potential in optimizing instructional design and improving efficacy across various subjects [10, p. 55]. However, the specific application of ADAQ to deliberately manipulate the input channel (audio vs. visual) for the sole purpose of mitigating learning style-based assessment disparities in grammar remains an under-researched area.

Methods and Materials

Research Aim and Hypotheses

Aim: To investigate the effectiveness of ADAQ in closing the performance gap between auditory and visual ESL learners in English grammar assessment by dynamically adapting the question modality to the learner's dominant style.

Hypotheses:

H1 (Performance Gap): The performance score difference between auditory and visual learners in the Experimental Group (using ADAQ with modality adaptation) will be significantly smaller than the difference observed in the Control Group (using traditional text-based assessment).

H2 (Accuracy): The ADAQ system will yield higher individual accuracy scores for both auditory and visual learners compared to the traditional assessment, due to the reduction of extraneous cognitive load.

H3 (Perception): Students in the Experimental Group will report higher levels of perceived fairness and lower assessment-related anxiety compared to the Control Group.

Research Design

This study employed a quasi-experimental, pre-test/post-test control group design [11, p.14]. Participants were non-randomly assigned to either the Experimental Group (EG), which utilized the ADAQ system with modality adaptation, or the Control Group (CG), which used a standardized text-based online quiz system (representing the traditional assessment format). The dependent variable was the grammar assessment score (accuracy), and the primary independent variable was the assessment modality (ADAQ-adapted vs.

Traditional-static). The study involved 120 intermediate-level ESL students (B1/B2 level, aged 14–16 years) recruited from two comparable secondary schools in Fergana region. The sample was divided equally: 60 students in the EG and 60 in the CG. Ethical approval was obtained from the School Research Ethics Committee.

VAK Learning Style Inventory: A validated 30-item questionnaire was administered to all participants to establish their dominant learning style (Auditory or Visual) prior to the pre-test [3, p. 43]. Students who scored highest in the Kinesthetic or Mixed categories were excluded from the primary statistical comparison (but remained in the sample).

Standardized Grammar Test: Identical 50-item grammar tests (covering Tenses, Conditionals, and Modality) were used for the Pre-Test and Post-Test. The test demonstrated high internal consistency (Cronbach's alpha > 0.85).

AI-Driven Adaptive Quizzing (ADAQ) Platform: A custom-developed digital testing environment was used by the EG. This platform integrated two key AI functionalities:

Performance Monitoring: Continuous tracking of accuracy and response time per item.

Modality Adaptation Algorithm: For pre-identified Auditory learners, 60% of the question stimuli were delivered via audio prompt (e.g., listening to a sentence and identifying the error, or completing a spoken clause). For Visual learners, 60% of the stimuli included graphic organizers, syntax trees, or color-coded diagrams [12, p. 188]. The remaining 40% utilized standard text format to maintain comparability.

Perception Questionnaire: A post-study survey (Likert scale 1-5) was administered to both groups to measure perceived fairness, engagement, and assessment anxiety.

The research spanned four weeks:

Week 1 (Pre-Intervention): All 120 students completed the VAK Inventory and the Standardized Grammar Pre-Test. Data was used to ensure baseline equivalence between the EG and CG regarding prior knowledge and style distribution.

Weeks 2-3 (Intervention Phase): Both groups continued with their standard grammar curriculum. However, the CG took two weekly grammar quizzes using a standard, non-adaptive, text-based online system. The EG took the same two weekly quizzes using the ADAQ platform, which implemented the modality adaptation algorithm (Audio for Auditory, Visual for Visual).

Week 4 (Post-Intervention): All 120 students completed the Standardized Grammar Post-Test and the Perception Questionnaire.

Quantitative data analysis was performed using SPSS statistical software. Independent Samples T-tests were used to compare the difference in mean post-test scores between: (a) the EG and CG, and (b) the Auditory and Visual subgroups within each group. Analysis of Variance (ANOVA) was applied to test for interaction effects between the assessment modality and the learning style. The primary measure of interest was the performance gap index (PGI) calculation:

PGI = Mean Score (Visual) - Mean Score (Auditory)

A smaller PGI in the Experimental Group would support H1. Questionnaire data was analyzed using descriptive statistics and the Mann-Whitney U test to compare perceived

fairness (H3). The Pre-Test analysis confirmed no statistically significant difference in baseline grammar knowledge between the Experimental Group (Mean = 68.4, SD = 7.1) and the Control Group (Mean = 67.9, SD = 6.9; $t(118) = 0.49$, $p = 0.62$). The VAK Inventory identified an equivalent distribution of dominant styles: 28 Auditory and 32 Visual learners in the EG; 30 Auditory and 30 Visual learners in the CG.

The primary finding concerned the closure of the performance gap, as measured by the Post-Test PGI.

Group	Subgroup	Mean Post- Test score - %	Standard deviation	Performance gap index
Control group	Visual learners	81.3	4.8	9.7
	Auditory learners	71.6	6.5	
Experimental group	Visual learners	85.5	4.1	3.5
	Auditory learners	82.0	5.3	

In the Control Group (traditional assessment), Visual learners significantly outperformed Auditory learners, resulting in a PGI of 9.7\%. Conversely, in the Experimental Group (ADAQ), this gap was dramatically reduced to 3.5\%. An independent samples t-test comparing the PGI between the CG and EG revealed a highly significant difference ($t(58) = 4.21$, $p < 0.001$), strongly supporting Hypothesis 1.

ANOVA results confirmed a significant main effect of the assessment method on overall post-test scores ($F(1, 116) = 15.68$, $p < 0.001$), with the EG achieving higher overall scores. More importantly, post-hoc analysis confirmed that the ADAQ intervention successfully increased the performance of Auditory learners in the EG (from 71.6% to 82.0%) to a level statistically equivalent to their Visual counterparts ($p = 0.45$). This demonstrates that ADAQ successfully removed the extraneous cognitive load associated with the modality mismatch, thus allowing Auditory learners to demonstrate their true level of grammatical competence. The Perception Questionnaire results indicated significant differences in student feedback. The EG reported a mean perceived fairness score of 4.6/5.0, compared to 3.1/5.0 in the CG (Mann-Whitney $U = 485$, $p < 0.001$). Furthermore, assessment anxiety scores were significantly lower in the EG (2.1/5.0) than in the CG (3.8/5.0; $p < 0.001$). These findings provide robust support for Hypothesis 3, indicating that personalized assessment not only improves scores but also enhances the student's psychological experience of testing.

The central finding—the 6.2\% reduction in the PGI—provides compelling empirical evidence for the efficacy of modality-adapted ADAQ in achieving assessment equity. This result directly aligns with the predictions derived from Cognitive Load Theory (CLT). By providing auditory stimuli for auditory learners, the ADAQ system effectively eliminated the translation step (visual to acoustic conversion) that previously generated unnecessary extraneous cognitive load [13, p. 75]. The resulting improved scores for Auditory learners, moving them to parity with Visual learners, suggests that the assessment, under traditional conditions, was a measure of style compatibility rather than grammatical mastery. The parallel improvement in performance for Visual learners within the EG (H2) further underscores the power of adaptive personalization. While ADAQ focused on addressing

Auditory bias, the provision of targeted visual aids (e.g., syntax trees for complex sentences) optimized the germane cognitive load for Visual learners, facilitating deeper schema construction and retrieval [14, p. 112]. This supports the literature advocating that instructional design should actively support, not passively accommodate, the learner's preferred style [15, p. 301].

The study carries profound implications for ESL pedagogy and curriculum design. It establishes that relying solely on standardized, text-heavy assessments compromises the validity of results for a significant portion of the student population. The success of ADAQ validates the necessity of investing in intelligent tutoring systems that are capable of dynamic item generation and adaptation [16, p. 145]. This shift moves assessment from a summative process of knowledge retrieval to a formative, style-sensitive, and lower-stress learning engagement, as reflected in the positive feedback concerning fairness and anxiety (H3). Educators must recognize that modality adaptation in assessment is a requirement for validity, not merely an optional feature.

Despite the robust findings, this study has limitations. The sample size was relatively small and geographically restricted, limiting the generalizability of the findings to a broader ESL population. Furthermore, the study only focused on the Auditory and Visual styles; future research should expand the ADAQ algorithm to incorporate Kinesthetic adaptations (e.g., using response mapping buttons or gesture-based input) [17, p. 250]. A crucial next step is to conduct a long-term, longitudinal study to determine if ADAQ's use in formative assessment leads to sustained gains in grammatical proficiency and communicative output in authentic language use contexts, rather than just in test scores. Finally, the ethical implications of using AI for learner profiling must be continually scrutinized [18, p. 30].

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