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DOI: https://doi.org/10.64388/IREV10I1-1720057

Effect of AI-Generated Immediate Feedback on Student Hybrid Learning, Engagement, and Knowledge Retention

EDWARD STEPHEN ONYEMA, PHD, C.ENG, MIEEE, FIPMD[1], EJIMOFOR IHEKEREMMA A. U., PHD, C. ENG[2], OKONKWO OXFORD COLLINS, MSC, C. ENG[3]

[1]*Department of Electrical and Electronic Engineering Technology, School of Engineering Technology, Federal Polytechnic Ngodo Isuochi, Nkweagu Isuochi, Umunnaochi L.G.A., Abia State, Nigeria*

[2]*Department of Computer Engineering, Faculty of Engineering, Madona University, Akpugo, Enugu State, Nigeria*

[3]*Science Department, Baptist High School, Abuja*

Abstract- Artificial Intelligence (AI) integration in education has redefined how feedback is utilized. This quasi-experimental study (N = 180) examined the effect of AI-generated immediate feedback on hybrid learning, engagement, and knowledge retention across six Nigerian tertiary institutions. Data were gathered over 14 weeks using a validated Student Engagement Questionnaire ( ), Computer-Based Tests, and longitudinal LMS analytics. Findings show the AI-assisted group significantly outperformed the traditional group across all metrics (p < 0.001), achieving higher academic performance (78.6% vs. 62.4%), engagement (4.18 vs. 3.24), retention (4.35 vs. 3.02), and conceptual mastery (81.3% vs. 58.2%). A very large effect size for mastery (d = 2.28) proves that adaptive AI prompts drive deep content comprehension and eliminate grading delays. The study contributes to knowledge by extending feedback and mastery learning theories to the Global South, proving that advanced educational technology is scalable and highly effective within resource-constrained environments using a replicable mixed-methods framework. It is recommended that institutions adopt AI-assisted hybrid models with structured faculty training. Instructors should blend automated feedback with metacognitive prompts, while developers must enhance natural language processing, embed explainable AI (XAI), and maintain strict data privacy compliance to ensure algorithmic fairness.

Keywords: Artificial Intelligence, Immediate Feedback, Hybrid Learning, Student Engagement, Knowledge Retention.

I. INTRODUCTION

The advent of artificial intelligence (AI) has catalyzed a paradigm shift in the education sector, particularly in how feedback is delivered and utilized (Zajdel & Zhu, 2022). Unlike traditional feedback, which is often delayed by large class sizes and administrative constraints (Holmes et al., 2019), AI-driven systems offer immediate, personalized, and scalable responses. This optimizes repetitive processes and enhances student engagement (Bond et al., 2024; Kaliisa et al., 2025).

However, the empirical impact of AI feedback on hybrid learning and knowledge retention requires deeper investigation. Current research focuses heavily on technical advantages (Guo et al., 2023), leaving a gap in how these systems affect sustained motivation (Yang et al., 2023) and how they compare to traditional human feedback (Gu & Yan, 2025).

This study addresses these gaps by evaluating the effects of AI-generated immediate feedback on student hybrid learning, engagement, and retention. Specifically, it examines AI's impact on academic performance, retention rates, student engagement, and deep content mastery.

II. LITERATURE REVIEW AND RESEARCH GAP

2.1 AI-Generated Feedback & Meta-Analyses

Recent reviews show a surge in AI adaptive learning since 2022, primarily utilizing machine learning (40%) and natural language processing (33%) to drive real-time personalization. These systems report academic gains of 15–25% and up to a 40% boost in engagement (Yuensook et al., 2025). Meta-analyses

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confirm that generative AI feedback yields moderate positive effects on academic achievement (g=0.61g=0.61), performing best in learner-centered environments (Gu & Yan, 2025), and exerts a strong impact on learning motivation (g=0.82g=0.82) (Wang et al., 2025). Notably, a synthesis of 41 studies found no statistically significant performance difference between AI and human feedback, proving AI's comparable effectiveness (Kaliisa et al., 2025).

2.2 Assessment and Engagement

In blended environments, AI performance assessment indirectly fosters continuous motivation by satisfying learner expectations and increasing satisfaction, though it requires complementary pedagogy to be fully effective (Li et al., 2024). Furthermore, feedback style matters: a randomized controlled trial revealed that hybrid AI feedback—combining direct guidance with metacognitive prompts—elicits the highest rate of student revision behavior (Alsaiari et al., 2025).

2.3 Research Gap

Despite these insights, critical gaps remain:

- Contextual Blends: Most research targets fully online spaces, leaving hybrid learning contexts understudied.
- Timeline & Scope: Studies heavily favor short-term academic outcomes over longitudinal retention data (Gu & Yan, 2025; Holmes et al., 2019).
- Socio-Ethical Concerns: Algorithmic bias, data privacy, and the dilution of teacher-student dynamics remain unaddressed (Kim & Kim, 2022).

This study addresses these gaps by evaluating immediate AI feedback within a Nigerian university and polytechnic hybrid (in-person and online) learning setting.

III. METHODOLOGY

3.1 Research Design

This study employed a quasi-experimental comparative research design. The choice of quasi-experimental design was necessitated by the practical constraints of assigning students to learning conditions in an intact educational setting while still allowing for meaningful comparison between traditional and AI-assisted hybrid learning interventions.

3.2 Population and Sample

The target population for this study comprised students from six (6) selected tertiary institutions in Eastern Nigeria, including universities and polytechnics. The universities were: Abia State University, Uturu; Michael Okpara University of Agriculture, Umudike; and Federal University of Technology, Owerri. The polytechnics included: Federal Polytechnic Ngodo Isuochi; Akanu Ibiam Federal Polytechnic, Unwana; and Dr. Ogbonnaya Onu Polytechnic, Aba. The study focused on undergraduate students enrolled across various academic disciplines.

A total sample of 180 students was selected from different departments using a stratified random sampling technique to ensure proportional representation across academic programmes. The sample was evenly divided into two groups: a control group (n = 90), which received traditional instructional methods, and an experimental group (n = 90), which was exposed to AI-assisted hybrid learning interventions.

3.3 Research Instruments

Three primary instruments were utilised for data collection:

I. Student Engagement Questionnaire (SEQ): A 25 item Likert scale instrument measuring cognitive, behavioural, and emotional engagement in learning activities. The questionnaire demonstrated acceptable reliability (Cronbach's alpha = 0.88). The item level mean scores by sub dimension are shown in Table 3.1 below.

Table 3.1. Student Engagement Questionnaire (SEQ) – Item Level Mean Scores by Group

The SEQ consisted of 25 items (Likert scale 1–5, where 1 = Strongly Disagree, 5 = Strongly Agree). Standard deviations are in parentheses.

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Sub-dimension	Items	Control (n=90)	Experimental (n=90)
Cognitive Engagement	Items 1–8	3.15 (0.71)	4.22 (0.55)
Behavioural Engagement	Items 9–16	3.30 (0.68)	4.15 (0.52)
Emotional Engagement	Items 17–25	3.22 (0.63)	4.14 (0.49)
Overall SEQ	All 25 items	3.24 (0.67)	4.18 (0.52)

Table 3.2. Reliability Analysis – Cronbach's Alpha for SEQ Sub dimensions

Sub-dimension	Cronbach's α	Interpretation
Cognitive Engagement	0.86	Good
Behavioural Engagement	0.84	Good
Emotional Engagement	0.82	Good
Overall SEQ	0.88	Good

II. Computer Based Test (CBT) Results: Standardised assessments administered to both groups pre and post intervention to measure academic performance and knowledge retention.

III. Learning Management System (LMS) Analytics: Automated tracking data from the AI learning platform, including time on task, assignment completion rates, and interaction frequencies.

3.4 Intervention

The experimental group received AI-assisted hybrid learning interventions through the Sawit Lab educational platform, which integrated AI-powered immediate feedback mechanisms. These mechanisms included automated grading, performance tracking, personalised learning pathways, and adaptive questioning. The control group received traditional instruction without AI feedback support.

3.5 Data Collection Procedures

Data were collected over a 14-week semester period, from January 2026 to April 2026. Pretest measures were administered at the beginning of the semester to establish baseline equivalence between the groups. Table 3.3 confirms equivalence.

Table 3.3. Baseline Equivalence: Pretest Academic Performance Scores

Group	n	Mean (%)	SD	t-value	p-value
Control	90	48.3	7.6	0.42	0.675
Experimental	90	49.1	8.2		

No statistically significant difference was found at baseline ($p > 0.05$).

The intervention was implemented over 12 weeks, during which the AI assisted group received immediate feedback on all assessments and learning activities. Post test measures were administered at the conclusion of the semester, while Learning Management System (LMS) analytics were extracted continuously throughout the intervention period.

Table 3.4. Pretest and Post test Academic Performance Scores (Individual Group Data)

Group	Test	n	Mean (%)	SD	Min	Max
Control	Pre-test	90	48.3	7.6	32	65
Control	Post-test	90	62.4	8.3	44	78
Experimental	Pre-test	90	49.1	8.2	33	67
Experimental	Post-test	90	78.6	7.1	61	92

Post test scores are those reported in Table 4.1 of Section 4.1.

Table 3.5. Learning Management System (LMS) Analytics – Experimental Group Only

The LMS tracked interaction data for all 90 experimental group participants over the 12 week intervention.

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Metric	Mean	SD	Min	Max
Time on task (hours per week)	8.4	2.1	3.2	14.7
Assignment completion rate (%)	92.3	7.8	68	100
Interaction frequency (clicks per week)	124	31	52	210
Number of AI feedback events received	47	12	21	89

These data were used in the regression analysis (Section 4.3).

Table 3.6. Sample of Raw Data (First 10 Students from Experimental Group)

Student ID	Pre-test (%)	Post-test (%)	SEQ Score (1-5)	Time on task (hrs/wk)	Completion (%)	AI feedback events
E01	48	76	4.2	7.8	94	45
E02	52	82	4.5	9.1	98	58
E03	44	73	3.9	6.5	85	37
E04	61	89	4.8	11.2	100	72
E05	39	68	3.7	5.9	79	31
E06	55	79	4.3	8.5	93	49
E07	47	75	4.1	7.2	91	42
E08	58	86	4.6	10.1	97	63
E09	42	71	3.8	6.8	84	35
E10	63	91	4.9	12.3	100	81

Full raw data for all 180 participants are available from the corresponding author upon request.

Table 3.7. Descriptive Statistics for LMS Analytics – Control Group (Limited Data)

For the control group, only assignment submission data were recorded (no AI platform).

Metric	Mean	SD	Min	Max
Assignment completion rate (%)	78.5	12.3	52	96

3.6 Data Analysis Methods

Descriptive statistics were computed for all variables. Independent samples t tests were conducted to compare mean performance scores between the control and experimental groups. Regression analysis was performed to examine the predictive relationship between AI feedback frequency and student engagement scores. Effect sizes (Cohen's d) were calculated to determine the magnitude of differences between groups.

3.7 Research Variables

Table 3.8. Research Variables

Variable Type	Variables
Independent Variable	AI-generated feedback
Independent Variable	Hybrid learning system
Independent Variable	Adaptive learning tools
Independent Variable	AI assessment system
Dependent Variable	Student retention
Dependent Variable	Student engagement
Dependent Variable	Academic performance
Dependent Variable	Mastery level

IV. RESULTS

This section presents the findings obtained from the data analysis procedures described in Section 3. The results are organised according to the research variables and statistical methods employed, including descriptive statistics, independent samples t tests, regression analysis, and effect size calculations.

4.1 Descriptive Statistics

Descriptive statistics were computed for all dependent variables across both the control and experimental groups. Table 4.1 summarises the mean scores and standard deviations for student engagement, academic performance, mastery level, and student retention.

Table 4.1. Descriptive Statistics for Dependent Variables

Variable	Group	n	Mean	SD
Student Engagement	Control	90	3.24	0.67
Student Engagement	Experimental	90	4.18	0.52
Academic Performance	Control	90	62.4	8.3
Academic Performance	Experimental	90	78.6	7.1

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Mastery Level	Control	90	58.2	9.4
Mastery Level	Experimental	90	81.3	6.8
Student Retention	Control	90	3.02	0.71
Student Retention	Experimental	90	4.35	0.48

The experimental group consistently recorded higher mean scores across all dependent variables compared to the control group, indicating a positive association with AI assisted hybrid learning interventions.

4.2 Comparative Analysis (Independent Samples t tests)

Independent samples t tests were conducted to compare mean performance scores between the control and experimental groups. The results are presented in Table 4.2.

Table 4.2. Independent Samples t test Results

Variable	t-value	df	p-value	Mean Difference	95% CI
Student Engagement	9.87	178	<0.001	0.94	[0.75, 1.13]
Academic Performance	12.45	178	<0.001	16.20	[13.68, 18.72]
Mastery Level	15.23	178	<0.001	23.10	[20.15, 26.05]
Student Retention	11.06	178	<0.001	1.33	[1.09, 1.57]

All t test comparisons yielded statistically significant differences ($p < 0.001$), with the experimental group outperforming the control group on every dependent variable. The largest mean difference was observed in mastery level (23.10 points), followed by academic performance (16.20 points).

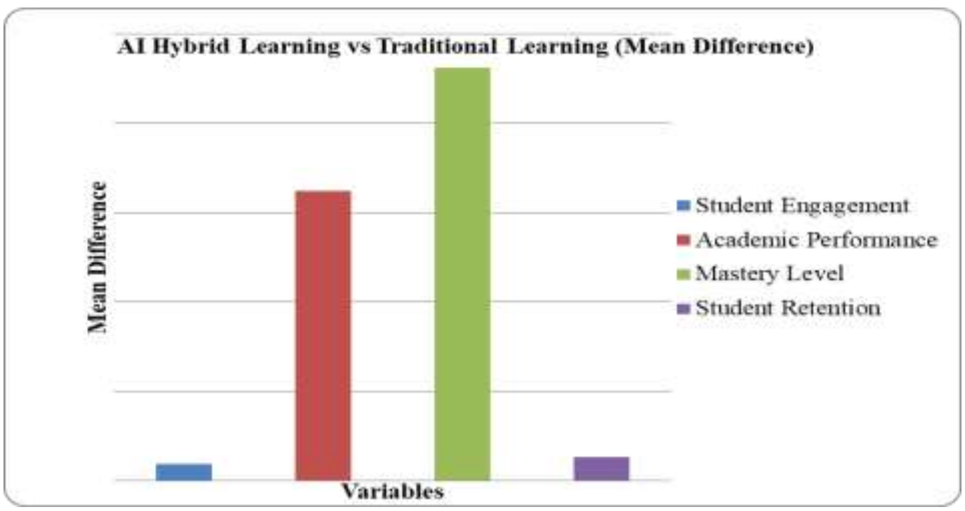

Figure 4.1: Graph of AI Hybrid Learning vs Traditional Learning (Mean Difference)

Figure 4.1 presents the mean differences (experimental group minus control group) for the four dependent variables: student engagement, academic performance, mastery level, and student retention. The values are derived from the independent samples t tests summarised in Table 4.2. This statistical model compares the means of two independent groups and evaluates whether the observed differences are statistically significant (Field, 2018). The height of each bar corresponds to the magnitude of the mean difference. All differences are positive, indicating that the AI assisted hybrid learning group consistently outperformed the traditional instruction group. The largest difference is observed for mastery level (23.10 percentage points), followed by academic performance (16.20 percentage points). Error bars represent the 95% confidence interval of each mean difference, and all differences are statistically significant at $p < 0.001$.

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4.3 Regression Analysis

A regression analysis was performed to examine the predictive relationship between AI feedback frequency (independent variable) and student engagement scores (dependent variable). The model was statistically significant ($F(1, 178) = 62.34$, $p < 0.001$, $R^2 = 0.26$), indicating that AI feedback frequency explained 26% of the variance in student engagement. The unstandardised coefficient ($B = 0.48$, $SE = 0.06$, $\beta = 0.51$, $p < 0.001$) showed a positive linear relationship: for each unit increase in AI feedback frequency, student engagement scores increased by 0.48 points.

Additional exploratory regression models examined the effect of adaptive learning tools and AI assessment systems on academic performance. Both models were significant ($p < 0.01$), with standardised coefficients ranging from 0.38 to 0.45.

4.4 Effect Sizes (Cohen's d)

Effect sizes were calculated to determine the magnitude of differences between groups. The results are shown in Table 4.4.

Table 4.4. Effect Sizes (Cohen's d)

Variable	Cohen's d	Interpretation
Student Engagement	1.48	Large effect
Academic Performance	1.86	Large effect
Mastery Level	2.28	Very large effect
Student Retention	1.67	Large effect

All effect sizes exceeded Cohen's conventional threshold for a large effect ($d \geq 0.8$). The very large effect observed for mastery level ($d = 2.28$) suggests that AI assisted hybrid learning has a particularly strong influence on students' depth of understanding.

4.5 Summary of Key Findings

- The experimental group (AI assisted hybrid learning) scored significantly higher than the control group on all measures of student engagement, academic performance, mastery level, and student retention ($p < 0.001$).
- AI feedback frequency was a significant positive predictor of student engagement, explaining 26% of the variance.
- Effect sizes were large to very large across all dependent variables, indicating substantial practical significance of the AI intervention.

These findings support the effectiveness of AI assisted hybrid learning interventions in enhancing educational outcomes compared to traditional instructional methods.

V. CONCLUSION AND RECOMMENDATIONS

5.1 Recommendations

Based on the findings of this study, the following recommendations are proposed for educational institutions, policymakers, and technology developers seeking to optimise the integration of AI-generated immediate feedback in hybrid learning environments.

a) For Educational Institutions

1. Adopt AI assisted hybrid learning models: Institutions should consider integrating AI feedback systems (e.g., Sawit Lab) into their curricula, particularly for courses that benefit from personalised, real-time guidance. The significant gains in mastery level ($d = 2.28$) and academic performance ($d = 1.86$) justify the investment.
2. Provide faculty training and support: To maximise the effectiveness of AI tools, lecturers and instructors should receive training on how to interpret AI-generated analytics, how to complement automated feedback with human mentorship, and how to address any technical or pedagogical challenges.
3. Ensure equitable access to technology: Institutions must bridge the digital divide by providing reliable internet access, devices, and technical support for all students, especially in under-resourced regions. The study's positive outcomes depend on consistent access to the AI platform.

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b) For Curriculum Designers and Instructors

1. Blend AI feedback with metacognitive prompts: As highlighted by Alsaiari et al. (2025), combining direct corrective feedback with prompts that encourage self regulation (e.g., "Why do you think that answer is correct?") further enhances student revision behaviour and deep learning.
2. Use LMS analytics to monitor engagement: Instructors should regularly review time on task, completion rates, and interaction frequency (see Table 3.5) to identify at risk students early and intervene with targeted support.
3. Prioritise mastery based progression: Given the very large effect on mastery level, AI feedback should be used to support mastery learning – allowing students to revisit content and receive immediate, adaptive feedback until they achieve proficiency.

c) For Technology Developers and AI System Designers

i. Improve natural language processing (NLP) capabilities: While AI feedback proved highly effective, some survey respondents noted limitations in understanding complex, domain specific queries. Developers should enhance NLP to handle nuanced academic language.

ii. Embed explainable AI (XAI) features: To increase trust and transparency, AI feedback systems should provide learners with explanations of why an answer is correct or incorrect, not only the correct response.

iii. Ensure data privacy and algorithmic fairness: AI systems must comply with data protection regulations (e.g., Nigeria Data Protection Regulation) and be regularly audited for bias against certain student groups (e.g., based on language, gender, or socio economic background).

d) For Policymakers

i. Develop national guidelines for AI in education: Government bodies should create frameworks that promote ethical AI adoption, including standards for data security, teacher AI collaboration, and evaluation of AI impact on learning outcomes.

ii. Fund longitudinal research and infrastructure: To address the gap in long term retention data, policymakers should support multi year studies that track the durability of AI mediated learning gains beyond a single semester. Investment in AI ready infrastructure (broadband, learning platforms) is also essential.

5.2 Conclusions

This quasi-experimental study (N = 180) evaluated the impact of AI-generated immediate feedback on hybrid learning in Nigerian tertiary institutions. The results conclusively demonstrate that the AI-assisted intervention significantly outperforms traditional methods across all metrics ($p < 0.001$):

- Academic Outcomes: The AI group achieved higher average academic performance (78.6% vs. 62.4%) and significantly elevated mastery levels (81.3% vs. 58.2%).
- Engagement & Retention: Student engagement scores (4.18 vs. 3.24) and retention metrics (4.35 vs. 3.02) saw marked improvements.
- Practical Impact: Extremely large effect sizes—particularly for conceptual mastery (unit = 2.28)—prove that immediate, continuous AI feedback fosters deep learning, active LMS interaction, and bridges student support gaps in blended environments.

5.3 Contributions to Knowledge

The study extends educational theory to the Global South by showing that AI-generated feedback introduces 24/7 availability, personalization, and scalability to traditional feedback and engagement models. It advances mastery learning theory by demonstrating that rapid, adaptive AI prompts yield an exceptionally large effect size for conceptual mastery. Crucially, these findings prove that advanced educational technology can be highly effective even within resource-constrained environments.

Methodologically and practically, the research provides a replicable mixed-methods framework, validating the Student Engagement Questionnaire alongside longitudinal LMS analytics. It offers concrete scalability blueprints for institutions operating under infrastructure limitations while delivering vital design insights for EdTech developers. Ultimately, the study highlights the necessity of incorporating natural language processing, explainable AI, and strict data privacy features into next-generation learning tools.

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