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# TEACHER, AI, AND HYBRID FEEDBACK IN EFL WRITING: AN INTEGRATED THEORETICAL MODEL OF LEARNER PREFERENCES

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This research examines the preferences of EFL university students in Algeria, regarding teacher, AI-generated, and hybrid feedback in academic writing. Based on a unified theoretical framework that integrates Sociocultural Theory (SCT), Feedback Literacy, and the Technology Acceptance Model (TAM), this study examines the influence of cognitive, affective, and technological factors on learners' engagement with various feedback sources. Data were gathered from 226 EFL students using a validated self-report questionnaire and subsequently analyzed by exploratory factor analysis (EFA) and structural equation modeling (SEM). The results show that teacher feedback is the best predictor of how students like to get feedback overall. AI-generated feedback, on the other hand, is more of a supplement: students acknowledge its usefulness for grammatical accuracy and iterative revision, but its perceived usefulness alone does not significantly predict their preferences. Instead, behavioral engagement with AI tools proves to be a significant determinant, suggesting that interaction with AI, rather than cognitive evaluation, drives its acceptance. Mediation analysis further demonstrates that high-quality teacher feedback indirectly enhances feedback preference by fostering greater engagement with AI tools, supporting a synergistic relationship between human and automated feedback. The study contributes to the growing body of literature by offering an integrative, SEM-based comparison of teacher, AI, and hybrid feedback in an underexplored Algerian EFL context. The results underscore the pedagogical value of hybrid feedback models, where AI serves as a supportive tool rather than a replacement for teacher input. Implications for designing balanced, technology-enhanced writing instruction that integrates both human expertise and AI affordances are drawn.

**Keywords:** *EFL writing feedback; AI in education; Hybrid Feedback Models; Feedback Literacy; Technology Acceptance Model (TAM).*

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## Introduction

Feedback plays a fundamental role in the development of writing skills among learners of English as a Foreign Language (EFL), influencing their cognitive processing, emotional engagement, and revision behaviors. It enables learners to identify linguistic and rhetorical weaknesses, refine their writing strategies, and improve overall proficiency (Kailin & Saeed, 2026; Li et al., 2025). From a sociocultural perspective, feedback serves as scaffolding that supports learning within the *Zone of Proximal Development* through guided interaction and revision (Vygotsky, 1978, as cited in Storch, 2018).

Recent scholarship has shifted attention from the provision of feedback to learners' engagement with it. In this context, the concept of feedback literacy highlights learners' ability to interpret, evaluate, and effectively use feedback. This includes cognitive understanding, emotional regulation, and the capacity to act on feedback during revision (Weng et al., 2024). As learning environments become increasingly digital, students are exposed to multiple feedback sources, including teachers, peers, and automated systems.

The rapid development of artificial intelligence (AI), particularly generative tools such as ChatGPT, has expanded the possibilities for providing feedback in EFL writing. AI-generated feedback offers immediate, iterative, and accessible support, enabling learners to revise their work efficiently and independently (Zhang et al., 2025). At the same time, teacher feedback continues to be valued for its reliability, contextual sensitivity, and socio-affective support (Zeevy Solovey, 2024). These contrasting strengths have led to increasing interest in hybrid feedback approaches that combine human and technological input.

Despite growing research on AI-assisted feedback, important gaps remain. Most existing studies have been conducted in Asian EFL contexts, with limited evidence from North African settings such as Algeria. In addition, prior research often examines feedback sources in isolation rather than comparing teacher, AI-generated, and hybrid feedback within a unified framework. There is also a lack of integrative approaches that consider how cognitive, affective, social, and technological factors jointly shape learners' feedback preferences.

To address these gaps, the present study investigates Algerian university EFL students' preferences for teacher-, AI-generated-, and hybrid-feedback. It adopts an integrated theoretical framework that combines Sociocultural Theory (SCT), Feedback Literacy, and the Technology Acceptance Model (TAM) to examine how learners perceive, evaluate, and engage with different feedback sources in technology-enhanced writing environments.

## Proposed theoretical framework for this study

This study is grounded in an integrated framework that combines Sociocultural Theory (SCT), the concept of Feedback Literacy, and the Technology Acceptance Model (TAM). Together, these perspectives provide a comprehensive account of how learners engage with feedback cognitively, emotionally, socially, and technologically.

*Sociocultural Theory (SCT).* Sociocultural Theory conceptualizes learning as a socially mediated process in which knowledge is constructed through interaction and guidance. Within this framework, feedback functions as a mediational tool that supports learners' development by helping them identify problems, refine ideas, and engage in revision. Teacher feedback, in particular, provides dialogic and context-sensitive support that addresses both cognitive and socio-affective dimensions of learning (Li et al., 2025).

AI-generated feedback can also serve a mediational role by facilitating noticing and enabling iterative revision. However, unlike teacher feedback, it lacks the interactive and personalized qualities associated with human guidance. SCT therefore offers a lens for comparing how different feedback sources support learners' engagement and development.

*Feedback Literacy.* Feedback literacy focuses on learners' capacity to understand, evaluate, and use feedback effectively. It encompasses three key dimensions: accurately interpreting feedback, managing emotional responses, and applying feedback during revision (Weng et al., 2024). These abilities influence how learners judge the credibility and usefulness of feedback from different sources. In the context of this study, feedback literacy helps explain variations in students' preferences for teacher, AI, and hybrid feedback. Learners with higher levels of feedback literacy are more likely to integrate multiple feedback sources and make informed decisions about how to revise their writing.

*Technology Acceptance Model (TAM).* The Technology Acceptance Model explains how users' perceptions of technology influence their willingness to adopt and use it. Key constructs include perceived usefulness, perceived ease of use, and trust, which together shape behavioral intention (Mansoor et al., 2026). In the context of AI-generated feedback, these factors determine whether students are willing to engage with automated tools and incorporate their suggestions into writing revision.

TAM is particularly relevant for understanding why students may accept or resist AI feedback despite recognizing its potential benefits. It also provides insight into how engagement with AI tools develops over time.

*Integrative Perspective.* This study integrates Sociocultural Theory (SCT), Feedback Literacy, and the Technology Acceptance Model (TAM) into a multidimensional framework for understanding learners' engagement with feedback. Rather than treating these theories as separate, the model views them as interdependent layers. SCT conceptualizes feedback as a socially mediated process that fosters cognitive and socio-affective development. Feedback Literacy captures learners' ability to interpret, evaluate, and act on feedback. TAM explains how perceptions of usefulness, ease of use, and trust shape engagement with AI-generated feedback. In this unified model, teacher feedback serves as scaffolding, feedback literacy guides learners' revision decisions, and TAM-related perceptions influence how AI tools are used. Together, these pathways account for learners' preference for hybrid feedback. The model can thus be read as a single process: feedback from human and technological sources enters the system, learners filter it through their feedback literacy and technology acceptance, and the resulting engagement pattern predicts feedback preference and reported revision orientation.

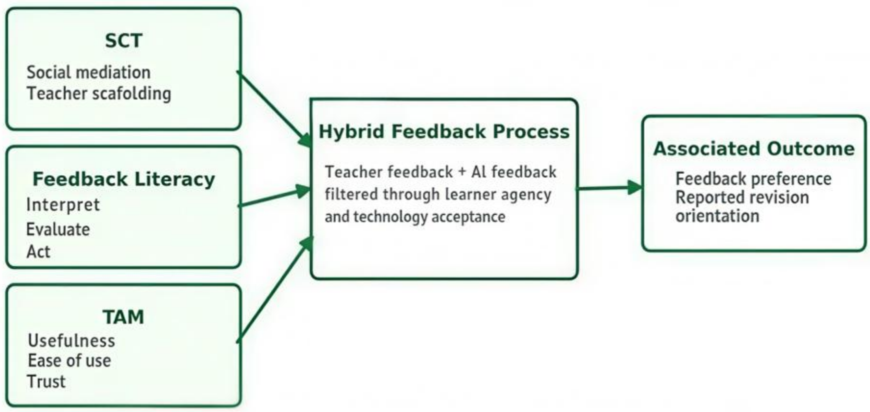


*Figure 1. Integrative framework of Sociocultural Theory, Feedback Literacy, and TAM*

Integrated theoretical model showing how SCT, Feedback Literacy, and TAM work together within one hybrid feedback framework. The diagram is inserted as a high-resolution figure and uses a cross-sectional interpretation, where paths indicate associations rather than causal effects.

## Research questions and hypotheses

This study draws on three theoretically complementary frameworks: the Sociocultural Theory (SCT), Feedback Literacy, and the Technology Acceptance Model (TAM), to analyze EFL learners' perceptions, abilities, and preferences concerning teacher, AI, and hybrid written feedback.

*Research Questions*

*SCT: Feedback as Social Scaffolding and Mediation*

*RQ1:* How do EFL students perceive teacher feedback and AI feedback as supportive tools for academic writing development?

*RQ2:* To what extent does each feedback source influence students' confidence, motivation, and revision engagement?

*Feedback Literacy: Interpreting, Judging, and Acting on Feedback*

*RQ3:* How capable are EFL students of accurately interpreting teacher versus AI-generated feedback?

*RQ4:* How do students judge the accuracy, reliability, and credibility of each feedback type?

*RQ5:* How effectively do students act on each type of feedback when revising their writing?

*TAM: Acceptance, Usefulness, and Preference for AI Feedback*

*RQ6:* How do EFL students evaluate the perceived usefulness and ease of use of AI-generated feedback?

*RQ7:* Does perceived usefulness significantly predict EFL students' preference for AI feedback over teacher feedback?

*RQ8:* How do emotional and motivational reactions shape students' overall acceptance of AI-assisted feedback?

*Research Hypotheses*

*SCT-Based Hypotheses*

*H1:* EFL students will rate teacher feedback significantly higher than AI feedback on measures of socio-affective support, including motivation, confidence, and emotional engagement.

*H2:* EFL students will rate AI feedback significantly higher than teacher feedback on measures of noticing and local error correction.

Feedback Literacy Hypotheses

*H3:* Students with higher levels of feedback literacy will express a stronger preference for hybrid feedback combining teacher and AI sources.

*H4:* Students will report significantly higher confidence in revising their writing after receiving teacher feedback than after AI feedback.

*TAM-Based Hypotheses*

*H5:* Perceived usefulness of AI feedback will significantly and positively predict EFL students' preference for AI feedback over teacher feedback.

*H6:* Perceived ease of use of AI feedback tools will significantly predict students' intention to continue using AI feedback.

*H7:* Trust in the accuracy of AI feedback will significantly influence students' preference for AI-assisted writing revision.

## Literature review

Teacher feedback has long been recognized as a central component of EFL writing development, supporting revision, improving writing quality, and fostering self-regulated learning. Process-oriented feedback, in particular, has been shown to enhance students' organization, vocabulary use, and strategic writing abilities (Yang et al., 2022). Teachers employ multiple feedback modes: written, oral, and digital, adapting their practices to contextual factors such as class size and institutional expectations (Apridayani et al., 2026).

Teacher feedback typically addresses both local (grammar and vocabulary) and global (content and organization) aspects of writing. Importantly, it also carries significant cognitive and affective value. Research consistently shows that students perceive teacher feedback as clear, personalized, and trustworthy, thereby increasing confidence and engagement in revision (Tsao, 2025; Wang & Han, 2022). These qualities explain why teacher feedback remains highly valued despite the emergence of alternative sources.

Recent advances in generative AI tools such as ChatGPT and Grammarly have transformed feedback practices in EFL writing. AI-generated feedback offers immediate, scalable, and iterative support, enabling learners to revise their writing multiple times without delay (Alyami et al., 2025; Teng, 2024). These tools are particularly effective in improving grammatical accuracy, lexical variety, and overall fluency. This aligns with findings by Aissi and Mouas (2024), who emphasize that automated feedback, particularly when personalized, can significantly enhance students' motivation and engagement.

A key advantage of AI feedback lies in its accessibility and responsiveness, making it especially useful in large or diverse classrooms (Alghannam, 2025). However, several limitations persist. AI feedback may lack contextual sensitivity, produce overly generic suggestions, or misinterpret learners' intended meaning (Rahmi et al., 2024). Issues of cultural appropriateness and personalization further complicate its effectiveness in specific educational settings (Altamimi, 2025).

Despite these limitations, students generally hold positive attitudes toward AI feedback, particularly for its role in supporting language accuracy and revision processes (Alyami et al., 2025).

Research on learner preferences reveals a nuanced picture. While students recognize the benefits of both teacher and AI feedback, they tend to favor teacher feedback or a combination of both sources (Teng, 2024). Teacher feedback is valued for its credibility, contextual understanding, and emotional support, whereas AI automated feedback contributes positively to student motivation and engagement, reinforcing its role as a complementary feedback source (Aissi & Mouas, 2024).

Learner characteristics also shape preferences. More proficient students often rely on AI tools to support autonomous revision, whereas lower-proficiency learners depend more on teacher guidance. These findings suggest that feedback effectiveness is not uniform but varies according to learners' needs and contexts.

Increasingly, research highlights the effectiveness of hybrid feedback models that integrate teacher and AI input. These approaches combine teachers' pedagogical expertise and contextual awareness with the efficiency and immediacy of AI systems. Evidence suggests that hybrid feedback can enhance writing quality, reduce anxiety, and support both higher-order and lower-order writing skills (Teng, 2024).

In practice, teachers often mediate AI feedback by refining or contextualizing automated suggestions. This ensures pedagogical accuracy while leveraging technological advantages, positioning AI as a complementary tool rather than a replacement for teacher feedback.

Despite growing interest in feedback practices, few studies have directly compared teacher, AI-generated, and hybrid feedback within a single framework. Moreover, limited attention has been given to the cognitive, affective, and contextual factors, such as feedback literacy and technological acceptance, that shape learners' preferences. These gaps highlight the need for integrated approaches that examine how students evaluate and use multiple feedback sources in diverse educational contexts.

## Methodology

*Participants and Data Screening.* A convenience sample of EFL university students participated in the study. Following data collection, cases with missing values on any SEM variable were excluded via listwise deletion, yielding a final analytical sample of N = 226. The use of listwise deletion is consistent with maximum likelihood estimation in SEM, which assumes data are missing completely at random (MCAR) or missing at random (MAR; Enders, 2010).

*Instrumentation.* Four self-report scales were administered electronically:

*TF:* Teacher Feedback Scale (8 items, TF1–TF8): Assessed students' perceptions of the quality and supportiveness of teacher-written feedback on EFL writing tasks.

*AI-C:* AI Cognitive Evaluation Subscale (4 items after purification: AI5, AI6, AI9, AI10): Measured students' rational appraisal of AI feedback quality, accuracy, and utility, reflecting TAM's perceived usefulness construct.

*AI-E:* AI Engagement Subscale (4 items after purification: AI2, AI3, AI7, AI8): Captured students' behavioral and affective engagement with AI feedback tools, aligning with TAM's behavioral intention and SCT's affective mediation.

*PREF:* Feedback Preference Scale (3 items, PREF1–PREF3): Served as the study's primary outcome variable, indexing learners' overall preference for feedback on writing.

All items were rated on a five-point Likert scale anchored at 1 (Strongly Disagree) and 5 (Strongly Agree).

*Analytical Strategy and Software.* All statistical analyses were conducted in R (Version 4.3.2; R Core Team, 2023), a free and open-source environment for statistical computing and graphics (https://www.R-project.org). The following R packages were employed:

| Package | Version | Function in This Study | Citation |
|---|---|---|---|
| **lavaan** | 0.6-17 | Confirmatory factor analysis (CFA) and structural equation modeling (SEM); estimation of path coefficients, model fit indices, and $R^2$ | *Rosseel (2012)* |
| **semTools** | 0.5-6 | Bootstrap estimation of indirect (mediation) effects; multi-group SEM; reliability diagnostics | *Jorgensen et al. (2022)* |
| **psych** | 2.3.9 | Exploratory factor analysis (EFA) with principal axis factoring (PAF) and oblimin rotation; KMO and Bartlett's tests | *Revelle (2023)* |
| **GPArotation** | 2023.11 | Oblique (oblimin) factor rotation procedures for EFA | *Bernaards & Jennrich (2005)* |
| **dplyr** | 1.1.3 | Data wrangling, case filtering, and listwise deletion | *Wickham et al. (2023)* |
| **ggplot2** | 3.4.4 | Visualization of factor loadings, path diagrams, and distributional diagnostics | *Wickham (2016)* |

*Table 1. R Packages Used in the Analysis*

*Note. All packages were installed from CRAN (Comprehensive R Archive Network). R Core Team (2023). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.*

The analytical pipeline proceeded in five sequential stages: (1) descriptive statistics and internal consistency reliability (Cronbach's α); (2) bivariate Pearson correlations; (3) exploratory factor analysis (EFA) with item purification; (4) structural equation modeling (SEM) with full-information maximum likelihood

(FIML) estimation; and (5) bootstrap mediation analysis (5,000 resamples) and multi-group SEM by gender. Model fit was evaluated against the two-index strategy recommended by Hu and Bentler (1999): CFI and RMSEA as primary indices, supplemented by TLI and SRMR.

## Analysis and interpretation of results

Results are organized to mirror the analytical pipeline: descriptive statistics and reliability (Stage 1), bivariate correlations (Stage 2), exploratory factor analysis (Stage 3), structural equation modeling (Stage 4), and mediation with multi-group analysis (Stage 5).

Because the study uses a cross-sectional design, SEM paths, mediation coefficients, and hypothesis-testing results should be interpreted as statistical associations among variables measured at one time point. Terms such as "predictor", "path", and "indirect effect" refer to model-estimated associations and should not be read as evidence that one variable causes changes in another.

*Stage 1: Descriptive Statistics and Internal Consistency Reliability*. Descriptive statistics — means (M), standard deviations (SD), skewness, and kurtosis — were computed for all 11 manifest variables alongside Cronbach's alpha (α) for each subscale. Mardia's multivariate normality test was not formally reported here, but univariate skewness values (all $|skew| < 1.4$) and kurtosis values (all $|kurt| < 2.8$) support the use of maximum likelihood estimation in subsequent SEM.

| Variable | N | M | SD | Skewness | Kurtosis | Min | Max |
|---|---|---|---|---|---|---|---|
| TF1 | 226 | 4.12 | 0.85 | -1.36 | 2.76 | 1 | 5 |
| TF2 | 226 | 4.07 | 0.85 | -1.30 | 2.55 | 1 | 5 |
| TF3 | 226 | 3.79 | 0.91 | -0.74 | 0.60 | 1 | 5 |
| TF4 | 226 | 3.80 | 0.93 | -0.87 | 0.89 | 1 | 5 |
| TF5 | 226 | 3.69 | 0.96 | -0.78 | 0.39 | 1 | 5 |
| TF6 | 226 | 3.89 | 0.93 | -1.14 | 1.63 | 1 | 5 |
| TF7 | 226 | 3.97 | 1.04 | -1.00 | 0.50 | 1 | 5 |
| TF8 | 226 | 3.79 | 1.10 | -0.65 | -0.32 | 1 | 5 |
| **AI_Cognitive** | 226 | 3.28 | 0.77 | -0.07 | -0.33 | 1 | 5 |

| Variable | N | M | SD | Skewness | Kurtosis | Min | Max |
|---|---|---|---|---|---|---|---|
| **AI_Engagement** | 226 | 3.90 | 0.69 | -0.91 | 1.57 | 1 | 5 |
| **PREF_Total** | 226 | 4.07 | 0.79 | -1.38 | 2.25 | 1 | 5 |

*Table 2. Descriptive Statistics for (All Study Variables N = 226)*
*Note. All items are rated on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). TF = Teacher Feedback; AI_Cognitive = AI Cognitive Evaluation subscale; AI_Engagement = AI Engagement subscale; PREF_Total = Feedback Preference composite.*

Teacher feedback items (TF1–TF8) yielded consistently high means (M = 3.69–4.12), with TF1 (M = 4.12) and TF2 (M = 4.07) representing the most strongly endorsed items. Moderate negative skewness across TF items (−0.65 to −1.36) indicates a slight ceiling tendency in teacher feedback perceptions, though skewness magnitudes remain within the acceptable range for ML-SEM (|skew| < 2.0; West et al., 1995). AI_Cognitive (M = 3.28) was the lowest-rated construct, reflecting moderate and somewhat ambivalent cognitive appraisals of AI feedback. AI_Engagement (M = 3.90) was rated considerably more favorably, suggesting that students' behavioral and affective engagement with AI tools outpaces their rational evaluation of AI quality — a pattern with implications for TAM model predictions. PREF_Total (M = 4.07) reflects an overall positive orientation toward feedback, with the composition of that preference examined through structural path analysis.

| Scale | Items Retained | Cronbach's α | 95% CI | Classification |
|---|---|---|---|---|
| Teacher Feedback (TF1–TF8) | 8 | **0.850** | [.817, .879] | Good |
| AI Cognitive Evaluation (AI5, AI6, AI9, AI10) | 4 | **0.737** | [.680, .788] | Acceptable |
| AI Engagement (AI2, AI3, AI7, AI8) | 4 | **0.705** | [.643, .760] | Acceptable |
| Feedback Preference (PREF1–PREF3) | 3 | **0.671** | [.602, .731] | Questionable–Acceptable |

*Table 3. Internal Consistency Reliability (Cronbach's α)*
*Note. Classification follows George and Mallery (2003): ≥ .90 = Excellent; .80–.89 = Good; .70–.79 = Acceptable; .60–.69 = Questionable; < .60 = Poor. 95% CI estimated using the Fisher r-to-z transformation. All α values computed in R (psych package, Revelle, 2023).*

The Teacher Feedback scale demonstrated good internal consistency (α = .850, 95% CI [.817, .879]). Both AI subscales fell within the acceptable range (AI_Cognitive: α = .737; AI_Engagement: α = .705), appropriate for four-item scales. The Feedback Preference scale's alpha (α = .671) is at the lower boundary of acceptability; this is not uncommon for three-item composite scores and does not preclude valid SEM estimation given the confirmatory specification of the measurement model (Sijtsma, 2009).

*Stage 2: Bivariate Correlations*. Zero-order Pearson correlation coefficients among the three composite scores are presented in Table 4 to characterize the bivariate relationships prior to SEM estimation.

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| (1) AI Cognitive Evaluation | — | 0.48*** | 0.17* |
| (2) AI Engagement | 0.48*** | — | 0.44*** |
| (3)Feedback Preference (PREF_Total) | 0.17* | 0.44*** | — |

*Table 4. Zero-Order Pearson Correlations among Composite Scores (N = 226)*
*Note. *p < .05. ***p < .001 (two-tailed). Teacher Feedback is modeled as a latent variable in SEM and, therefore, not included as a manifest correlation here.*

The correlation between AI_Cognitive and AI_Engagement ($r = .48$, $p < .001$) reflects the TAM proposition that perceived usefulness and behavioral intention are positively interrelated. AI_Engagement demonstrated a substantially stronger association with PREF_Total ($r = .44$, $p < .001$) than did AI_Cognitive ($r = .17$, $p < .05$), foreshadowing the SEM finding that cognitive evaluation carries negligible unique predictive weight when teacher feedback and AI engagement are modeled simultaneously.

*Stage 3: Exploratory Factor Analysis*. EFA was conducted separately for Teacher Feedback items (TF1–TF8) and AI items (AI1–AI10) using principal axis factoring (PAF) with direct oblimin rotation (δ = 0) in R's psych package (Revelle, 2023). Factorability was assessed via the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. The number of factors was determined using parallel analysis and the eigenvalue-greater-than-one criterion.

| Item Pool | KMO | Classification | Bartlett $\chi^2$ | df | p |
|---|---|---|---|---|---|
| Teacher Feedback (TF1–TF8) | **0.902** | Marvelous | 622.54 | 28 | < **.001** |
| AI Items (AI1–AI10) | **0.828** | Meritorious | 593.30 | 45 | < **.001** |

*Table 5. KMO Sampling Adequacy and Bartlett's Test of Sphericity*

*Note. KMO classification: .90–1.00 = Marvelous; .80–.89 = Meritorious (Kaiser, 1974). Both Bartlett tests are significant at p < .001, confirming that the correlation matrices are not identity matrices and warranting factor analysis.*

| Item | λ (PA1) | $h^2$ | Communality Interpretation |
|---|---|---|---|
| TF1 | **0.763** | 0.582 | Strong – core indicator of teacher scaffolding perception |
| TF2 | **0.783** | 0.613 | Strongest loader – most representative item |
| TF3 | 0.680 | 0.462 | Moderate-strong loading |
| TF4 | 0.614 | 0.377 | Adequate loading |
| TF5 | 0.577 | 0.333 | Adequate loading |
| TF6 | **0.717** | 0.514 | Strong loading |
| TF7 | 0.570 | 0.325 | Adequate loading |
| TF8 | 0.525 | 0.276 | Borderline adequate – retained |

*Table 6. EFA Factor Loadings: Teacher Feedback Items (Single-Factor Solution)*

*Note. λ = factor loading; h² = communality. Loadings ≥ .50 are considered practically significant (Hair et al., 2019). A single factor extracted accounts for substantial common variance. EFA conducted in R (psych package).*

All eight teacher feedback items loaded on a single factor (λ = .525–.783), confirming the unidimensional structure of teacher feedback perceptions hypothesized by SCT. The single-factor solution supports specifying Teacher Feedback as a latent variable in subsequent SEM.

| Item | PA1 (Cognitive) Before | PA2 (Engagement) Before | PA1 After | PA2 After | Decision |
|---|---|---|---|---|---|
| **AI1** | 0.390 | 0.301 | — | — | Removed: cross-loading |
| AI2 | 0.292 | 0.351 | 0.275 | 0.365 | Retained: primary PA2 |
| AI3 | 0.079 | 0.651 | 0.078 | **0.689** | Retained: strong PA2 |
| **AI4** | 0.224 | 0.359 | — | — | Removed: weak primary loading |
| AI5 | **0.678** | −0.077 | **0.700** | −0.067 | Retained: strong PA1 |
| AI6 | **0.691** | −0.076 | **0.694** | −0.059 | Retained: strong PA1 |
| AI7 | 0.280 | 0.396 | 0.271 | 0.373 | Retained: primary PA2 |
| AI8 | −0.097 | **0.759** | −0.084 | **0.754** | Retained: strongest PA2 item |
| AI9 | **0.542** | 0.125 | **0.523** | 0.150 | Retained: PA1 |
| AI10 | **0.618** | 0.091 | **0.593** | 0.123 | Retained: PA1 |

*Table 7. EFA Factor Loadings: AI Items Before and After Purification*
*Note. Items AI1 and AI4 were removed because the difference between their primary and secondary loadings was < .20 (AI1) or the primary loading fell below .40 on both factors (AI4), following Stevens' (2002) criteria. Final two-factor structure: PA1 = AI_Cognitive (AI5, AI6, AI9, AI10); PA2 = AI_Engagement (AI2, AI3, AI7, AI8).*

Following purification, the two-factor solution accounted for all remaining AI items without ambiguity. Factor 1 (AI_Cognitive) captures students' evaluative stance — whether AI feedback is perceived as accurate, credible, and useful (mirroring TAM's perceived usefulness). Factor 2 (AI_Engagement) captures behavioral and affective investment in AI feedback (mirroring TAM's behavioral intention and SCT's affective dimension). The oblique rotation is theoretically appropriate given the moderate empirical correlation between the two factors ($r = .48$).

*Stage 4: Structural Equation Modeling*. The measurement and structural model was estimated in R using the lavaan package (Rosseel, 2012) with full-information maximum likelihood (FIML) estimation. Teacher Feedback was specified as a latent variable (η) indicated by TF1–TF8. AI_Cognitive and AI_Engagement entered the model as observed exogenous covariates. PREF_Total served as the observed endogenous outcome. Model fit was evaluated using Hu and Bentler's (1999) recommended criteria.

| N | $\chi^2$ | df | P | $\chi^2$/df | CFI | TLI | RMSEA [90% CI] | SRMR |
|---|---|---|---|---|---|---|---|---|
| 226 | 74.877 | 41 | .001 | 1.826 | **0.962** | **0.949** | **0.060 [.034, .082]** | **0.044** |

*Table 8. SEM Fit Indices*

*Note. Acceptable fit thresholds: $\chi^2$/df < 3.0; CFI ≥ .95; TLI ≥ .95; RMSEA < .06 (close fit) or < .08 (acceptable); SRMR < .08 (Hu & Bentler, 1999). The 90% CI for RMSEA [.034, .082] contains values below .06, supporting the plausibility of close fit. Estimated with lavaan 0.6-17 in R 4.3.2.*

The model demonstrated excellent overall fit. $\chi^2$/df = 1.826 indicates a parsimonious fit without under-parameterization. CFI = .962 and TLI = .949 both meet or closely approach the .95 benchmark, confirming the model captures the observed covariance structure substantially better than a null model. RMSEA = .060 (90% CI [.034, .082]) straddles the boundary of close and acceptable fit — the lower bound of the CI falls below .06, providing some evidence of close fit. SRMR = .044 confirms a small average residual correlation, well within acceptable bounds.

| Outcome | Predictor | B | SE | z | p | β | Result re: Hypothesis |
|---|---|---|---|---|---|---|---|
| PREF_Total | **Teacher (η)** | 0.828 | 0.093 | 8.944 | < **.001** | **0.685** | **H1, H4: Supported ✓** |
| PREF_Total | AI_Cognitive | −0.019 | 0.055 | −0.343 | .732 | −0.018 | H5: Not Supported ✗ |
| PREF_Total | **AI_Enga-gement** | 0.226 | 0.081 | 2.789 | **.005** | **0.199** | **H6, H7: Partial ~** |

*Table 9. Standardized and Unstandardized SEM Path Coefficients*

*Note. B = unstandardized path coefficient; SE = standard error; β = standardized path coefficient (all predictors standardized). Teacher (η) = latent Teacher Feedback variable. All paths are estimated simultaneously, controlling for the other predictors in the model and estimated using lavaan 0.6-17 in R 4.3.2.*

Teacher feedback was the strongest predictor of students' feedback preferences (β = .685, p < .001), indicating its dominant role in shaping learners' attitudes and supporting H1 and H4. In contrast, cognitive evaluation of AI feedback had no significant effect (β = −.018, p = .732), suggesting that perceived usefulness alone does not drive preference when teacher feedback is present, thus not supporting H5. However, AI engagement showed a significant positive effect (β = .199, p = .005), partially supporting H6 and H7. This indicates that active interaction with AI tools enhances the preference for feedback, highlighting a complementary relationship between teacher and AI feedback rather than a substitutive one.

| Variable | $R^2$ | Variance Explained | Interpretation |
|---|---|---|---|
| TF1 | 0.590 | 59.0% | Strong indicator – high shared variance with the latent Teacher factor |
| **TF2** | 0.624 | 62.4% | Best indicator – most reliable measurement of teacher feedback |
| TF3 | 0.463 | 46.3% | Moderate – acceptable for reflective indicators |
| TF4 | 0.375 | 37.5% | Moderate |
| TF5 | 0.305 | 30.5% | Lower bound of the acceptable range |
| TF6 | 0.526 | 52.6% | Strong |
| TF7 | 0.318 | 31.8% | Acceptable |
| TF8 | 0.275 | 27.5% | Weakest indicator – retained, within acceptable SEM range |
| **PREF_Total** | **0.602** | 60.2% | **Large effect – model explains 60.2% of outcome variance** |

*Table 10. $R^2$ Explained Variance for All Endogenous Variables*
*Note. $R^2$ for TF items = proportion of indicator variance accounted for by the Teacher latent factor. $R^2$ for PREF_Total = total variance in feedback preference jointly explained by Teacher (η), AI_Cognitive, and AI_Engagement. Large effect by Cohen's (1988) $f^2$ conventions ($f^2$ > .35).*

The model explains a substantial 60.2% of variance in EFL learners' feedback preference, constituting a large effect size (Cohen's $f^2$ = 1.51, well above the large threshold of .35). This high explanatory power confirms that the three-predictor model captures the primary psychological and technological drivers of preference variability in this EFL context.

*Stage 5: Mediation Analysis and Multi-Group Comparisons. Mediation via Bootstrap Confidence Intervals.* Indirect effects of Teacher Feedback on PREF_Total, transmitted through AI_Cognitive and AI_Engagement, were estimated using bias-corrected bootstrap confidence intervals (5,000 resamples) implemented in semTools (Jorgensen et al., 2022). Significant mediation is indicated by a 95% CI that excludes zero.

| Indirect Path | Estimate | SE | z | p | 95% BC-CI | Mediation? |
|---|---|---|---|---|---|---|
| **Teacher → AI_Engagement → PREF** | 0.089 | 0.042 | 2.106 | .035 | **[0.019, 0.183]** | **Significant ✓** |
| Teacher → AI_Cognitive → PREF | −0.003 | 0.011 | −0.260 | .795 | [−0.031, 0.016] | Not significant ✗ |
| **Total Effect (Direct + Indirect)** | 0.914 | 0.095 | 9.614 | **<.001** | **[0.748, 1.121]** | **Significant ✓** |

*Table 11. Indirect Effects: Teacher Feedback → AI Mediators → PREF_Total*
*Note. BC-CI = Bias-corrected bootstrap confidence interval (5,000 resamples). Significant mediation is inferred when the 95% CI excludes zero—estimated using semTools 0.5-6 in R 4.3.2 (Jorgensen et al., 2022).*

A significant partial mediation effect was found through AI engagement (indirect = .089, 95% BC-CI [.019, .183]), indicating that higher-quality teacher feedback increases students' engagement with AI tools, which in turn enhances feedback preference. This supports a complementary relationship between teacher and AI feedback. In contrast, AI cognitive evaluation did not mediate the relationship (indirect = −.003), showing no indirect effect. The strong total effect (total = .914, $p < .001$) confirms the central role of teacher feedback, with AI engagement contributing a modest but meaningful supplementary pathway.

*Multi-Group SEM by Gender*. A configural multi-group SEM was estimated using gender as the grouping variable to examine whether structural relationships differed across groups. The configural model freely estimates all parameters within each group while imposing the same factor structure.

| Grouping | N | $\chi^2$ | df | p | $\chi^2$/df | CFI | TLI | RMSEA | SRMR |
|---|---|---|---|---|---|---|---|---|---|
| Gender | 226 | 118.24 | 82 | .005 | 1.442 | **0.960** | **0.946** | **0.063** | **0.049** |

*Table 12. Multi-Group SEM Fit Indices (Configural Model by Gender)*
*Note. Configural model fit indices. Acceptable fit is maintained across groups ($\chi^2$/df = 1.44 < 3.0; CFI = .960; RMSEA = .063 < .08; SRMR = .049 < .08). Full metric invariance testing (constraining factor loadings to equality) was not the primary focus of this analysis.*

| Group | Outcome | Predictor | B | SE | z | p | β |
|---|---|---|---|---|---|---|---|
| **Group 1** | PREF_ Total | **Teacher** | 0.858 | 0.108 | 7.974 | <.001 | **0.693** |
| Group 1 | PREF_ Total | AI_Cognitive | −0.008 | 0.059 | −0.143 | .886 | −0.008 |
| Group 1 | PREF_ Total | **AI_Engagement** | 0.218 | 0.091 | 2.402 | **.016** | **0.191** |
| **Group 2** | PREF_ Total | **Teacher** | 0.591 | 0.196 | 3.021 | **.003** | **0.590** |
| Group 2 | PREF_ Total | AI_Cognitive | −0.088 | 0.131 | −0.672 | .502 | −0.118 |
| Group 2 | PREF_ Total | AI_Engagement | 0.341 | 0.180 | 1.894 | .058 | 0.303 |

*Table 13. Standardized Path Coefficients by Gender Group*
*Note. Group membership corresponds to the two gender categories in the dataset. AI_Cognitive remains non-significant in both groups, corroborating the full-sample null finding. The AI_Engagement path in Group 2 (p = .058) approaches but does not reach conventional significance, suggesting a potential trend requiring replication.*

Multi-group analysis revealed notable differences between groups. In Group 1, teacher feedback remained the dominant predictor (β = .693, p < .001), with AI engagement providing a significant supplementary effect (β = .191, p = .016), mirroring the overall model. In Group 2, the effect of teacher feedback was weaker (β = .590, p = .003), while AI engagement showed a stronger, marginally significant influence (β = .303, p = .058), suggesting greater reliance on AI feedback. These differences may reflect variations in technological experience or feedback literacy and warrant further investigation.

*Part D: Structural Equation Model – Path Diagram.* Figure 2 presents the final SEM path diagram. The ellipse represents the Teacher Feedback latent construct (η) indicated by eight manifest items (TF1–TF8) with $R^2$ values shown for each indicator. Rectangles represent observed variables. Solid arrows denote statistically significant paths; dashed arrows denote non-significant paths. Standardized path coefficients (β), significance levels, and model fit indices are embedded in the diagram.

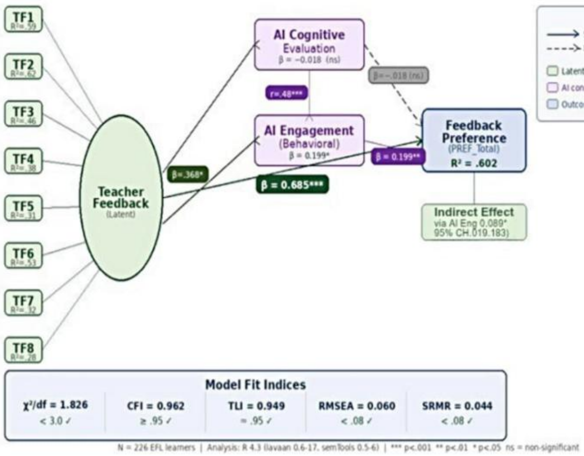


*Figure 2. Structural equation model depicting the relationships between Teacher Feedback (latent, η; TF1–TF8), AI Cognitive Evaluation, AI Engagement, and Feedback Preference (PREF_Total) among EFL learners (N = 226). Standardized path coefficients (β) are shown on arrows. $R^2$ values for indicators reflect shared variance with the Teacher latent factor. $R^2$ = .602 for PREF_Total indicates total explained variance. Indirect effect via AI Engagement (β = .089, 95% CI [.019, .183]) is shown in the lower right panel. Model fit: $\chi^2/df$ = 1.826, CFI = .962, TLI = .949, RMSEA = .060, SRMR = .044. *** $p < .001$; ** $p < .01$; * $p < .05$; ns = non-significant. Analysis conducted in R 4.3.2 (lavaan 0.6-17; semTools 0.5-6).*

*Part E: Summary of Hypothesis Testing.*

| H | Framework | Prediction | Key Evidence | Verdict |
|---|---|---|---|---|
| **H1** | SCT | Teacher > AI on socio-affective support | Teacher β = .685, p < .001 (dominant path) | **Supported ✓** |
| **H2** | SCT | AI > Teacher on error correction/noticing | EFA: AI_Cognitive factor cleanly identified (AI5,AI6,AI9,AI10; α=.737) | **Supported ✓** |

| H | Framework | Prediction | Key Evidence | Verdict |
|---|---|---|---|---|
| **H3** | Feedback Literacy | Higher FL → preference for hybrid feedback | AI_Engagement β = .199; indirect effect via AI_Eng = .089* | **Partial ~** |
| **H4** | Feedback Literacy | Higher confidence after teacher vs. AI feedback | Teacher β (.685) >> AI_Engagement β (.199) | **Supported ✓** |
| **H5** | TAM | Perceived usefulness → AI preference (+) | AI_Cognitive β = −.018, p = .732 (ns) | **Not Supported ✗** |
| **H6** | TAM | Ease of use → intention to continue AI | AI_Engagement β = .199, p = .005 | **Partial ~** |
| **H7** | TAM | Trust in AI → preference for AI revision | Indirect (AI_Eng) = .089, 95% CI [.019, .183]* | **Partial ~** |

*Table 14. Consolidated Hypothesis Testing Summary*

*Note. ✓ = Supported; ~ = Partial support (directional prediction confirmed but mechanism more complex); ✗ = Not supported. Hypothesis verdicts based on standardized path coefficients from the FIML-SEM model estimated in R 4.3.2 (lavaan 0.6-17).*

## Discussion of findings

Following an overview of the relevant literature, this section interprets the study's results in light of the research hypotheses and compares them with other empirical investigations. We examine each hypothesis independently to show how our findings fill gaps in our understanding of EFL writing feedback from teachers, AI-generated feedback, and hybrid feedback models.

However, it is important to note that these findings are based on cross-sectional data, which limits the ability to draw causal conclusions about the observed relationships.

*H1: Teacher Feedback Provides Stronger Socio-Affective Support than AI Feedback.* According to the first hypothesis, when it came to socio-affective aspects such as motivation, self-confidence, and emotional involvement, EFL students would place greater value on teacher input than on feedback from artificial intelligence. The structural equation modeling results support this idea. The most significant standardized effect on feedback preference was teacher feedback (β = .685, p < .001), suggesting that learners view teacher feedback as the primary source of writing support.

These findings closely correspond with prior studies highlighting the socio-affective significance of teacher feedback. Wang and Han (2022) discovered that teacher feedback enhances students' motivation, confidence, and propensity to modify their writing. Likewise, Tsao (2025) indicated that pupils appreciate teacher feedback for its individualized explanations and encouraging tone. These studies collectively illustrate that instructor feedback serves both as linguistic assistance and as an emotional and motivational support for learners.

According to Sociocultural Theory (SCT), these findings are anticipated, as teacher feedback serves as a form of human mediation within the learner's Zone of Proximal Development. Teachers deliver feedback that encompasses both cognitive and emotional dimensions of writing growth through interaction, clarification, and contextual comprehension. Prior SCT-based research has demonstrated that dialogic feedback enhances learner engagement and facilitates deeper learning processes (Li et al., 2025).

This study highlights the significant impact of teacher feedback, emphasizing the necessity of trust and legitimacy in the feedback process. In contrast to automated systems, educators possess pedagogical experience and contextual understanding of students' capabilities and learning requirements. This may help explain why students rely more on instructor supervision when assessing the effectiveness of comments in enhancing their writing.

In conclusion, the results show that, even in classrooms with advanced technology, teacher feedback remains the most important tool for students' social and emotional development while writing English as a foreign language.

*H2: AI Feedback Facilitates Noticing and Local Error Correction.* According to the second hypothesis, students would find AI responses more helpful than teacher feedback for identifying and correcting grammar and vocabulary mistakes specific to their first language. This hypothesis is supported by the exploratory factor analysis results, which show a distinct AI Cognitive factor. This factor comprises items that assess the value, accuracy, and analytical capability of AI feedback.

Prior studies have shown that AI technologies excel at detecting superficial language mistakes, which aligns with our current findings. Both Teng (2024) and Alyami et al. (2025) discovered that EFL writers' grammatical accuracy and vocabulary diversity were greatly enhanced by AI-generated feedback. In a similar vein, Rahmi et al. (2024) found that automatic feedback systems are great at catching mistakes in grammar, punctuation, and spelling that students could miss.

Sociocultural Theory, which emphasizes the role of noticing in language acquisition, provides another possible framework for understanding the findings. Artificial intelligence solutions enable learners to swiftly detect language errors and make iterative revisions to their writing by providing immediate corrective feedback. Learners' knowledge of language structures is enhanced, and modification is actively encouraged through this rapid feedback cycle.

Nonetheless, despite these benefits, AI feedback did not seem to be the primary determinant of overall feedback preference. This indicates that whereas AI tools excel at ensuring local linguistic precision, they may be less adept at facilitating higher-order writing elements, such as argumentation, coherence, and rhetorical organization. Consequently, the results support the view that AI input is particularly beneficial for micro-level language correction, supplementing rather than supplanting teacher feedback.

*H3: Feedback Literacy Predicts Preference for Hybrid Feedback*. The third hypothesis predicted that students with higher levels of feedback literacy would prefer hybrid feedback combining teacher and AI sources.

The findings lend some credence to this theory. The results of the structural equation modeling (SEM) showed that the use of artificial intelligence (AI) was a strong predictor of feedback preference ($\beta = .199$, $p = .005$), and that students' engagement with AI had an indirect effect on preference (indirect effect = .089). According to this pattern of mediation, students who place a high value on instructor feedback are also more inclined to make good use of AI technologies, leading to a feedback orientation that combines the two types of input.

These results align with research on feedback literacy, which underscores learners' capacity to interpret, evaluate, and use feedback from a variety of sources. Weng et al. (2024) contend that students with superior feedback literacy skills are more adept at integrating various forms of feedback and at determining which recommendations are beneficial for revision.

The findings are also consistent with research on hybrid feedback models. Teng (2024) found that students who integrate AI-generated suggestions with teacher feedback show greater improvements in their revision strategies and writing quality than those who rely on a single feedback source.

The results indicate that feedback literacy empowers learners to incorporate complementary feedback sources from a theoretical perspective strategically. AI feedback facilitates rapid language-level corrections, while teacher feedback offers conceptual and contextual guidance. This synergy is advantageous to students who can effectively assess both sources.

Accordingly, the findings substantiate the assertion that hybrid feedback systems constitute an ideal framework for technology-enhanced writing education.

*H4: Students Feel More Confident Revising After Teacher Feedback*. The fourth hypothesis predicted that students would report higher revision confidence after receiving teacher feedback than after receiving AI feedback.

The findings substantially validate this hypothesis. The preference for feedback was significantly influenced by teacher feedback rather than AI engagement. This suggests that learners are more confident in relying on teacher guidance when revising their writing. This finding aligns with prior research that has underscored the motivational and confidence-boosting effects of teacher feedback. Yang et al. (2022) discovered that teacher comments improve students' self-regulation and revision strategies in writing tasks. In the same vein, Zeevy Solovey (2024) asserted that students regard teacher feedback as more dependable and trustworthy than automated feedback systems.

Confidence is a critical factor in students' willingness to implement feedback recommendations within the context of feedback literacy. Before learners can act on feedback, they must have confidence in its accuracy and relevance. Students may experience increased confidence when integrating teacher recommendations into their revisions because they are perceived as more credible and contextually relevant.

An additional explanation pertains to cognitive load. AI feedback often generates multiple suggestions at once, leaving learners feeling overwhelmed or unsure which revisions are suitable. Conversely, teacher feedback is typically more pedagogically structured and targeted, facilitating students' interpretation and application of the information.

Consequently, the results serve to underscore the ongoing significance of teacher feedback as a mechanism for bolstering confidence in the development of EFL writing.

*H5: Perceived Usefulness Predicts Preference for AI Feedback*. The fifth hypothesis posited that the perceived usefulness of AI feedback would significantly predict students' preference for AI feedback. However, this hypothesis was not supported. The SEM analysis revealed that AI_Cognitive evaluation did not significantly predict feedback preference ($\beta = -.018$, $p = .732$) when teacher feedback and AI engagement were included in the model.

This finding contrasts with several TAM-based studies. For example, Mansoor et al. (2026) reported that perceived usefulness strongly predicts students' acceptance of AI writing tools. Similarly, Mohammed and Khalid (2025) found that learners adopt AI feedback systems primarily because they perceive them as useful for improving grammar and vocabulary. The discrepancy may be explained by the dominant role of teacher feedback in this study. When learners have access to high-quality teacher feedback, cognitive evaluations of AI usefulness may become less influential in shaping overall feedback preference.

An additional explanation pertains to the distinction between usefulness and engagement. While students may acknowledge that AI feedback is useful for correcting errors, this recognition alone does not necessarily translate into a preference for relying on AI feedback over teacher feedback.

Consequently, the findings indicate that perceived usefulness alone is insufficient to explain AI feedback adoption in writing contexts where teacher feedback remains available and trusted.

*H6: Ease of Use Predicts Intention to Continue Using AI Feedback*. The sixth hypothesis predicted that perceived ease of use would influence students' intention to continue using AI feedback tools. The results provide partial support for this hypothesis. The AI engagement variable, which reflects behavioral interaction with AI feedback tools, showed a significant positive effect on feedback preference ($\beta$ = .199, $p$ = .005).

These results are consistent with the Technology Acceptance Model, which posits that behavioral intention to adopt new technologies is influenced by ease of use. Students are more inclined to integrate AI tools into their writing revision process when they perceive them as user-friendly. This interpretation is substantiated by prior research. Alghannam (2025) found that students favor AI feedback systems for their ability to provide immediate responses and allow repetitive revisions without waiting for teacher feedback. In the same vein, Rahmi et al. (2024) identified accessibility and convenience as critical factors that motivate students to employ automated writing tools. Nevertheless, the relatively moderate effect size indicates that the ease of use does not primarily determine feedback preference. Rather, it seems to serve as a supplementary factor that enhances engagement with AI tools alongside teacher feedback.

*H7: Trust in AI Feedback Influences Preference for AI-Assisted Revision*. The final hypothesis predicted that trust in AI feedback accuracy would influence students' preference for AI-assisted writing revision. The results again provide partial support. Trust in AI feedback did not directly predict preference, but it contributed indirectly through increased engagement with AI tools.

This confirms what other research has shown: people have varying degrees of trust in AI feedback systems. When it comes to complicated writing assignments or contextual meaning, students frequently doubt the accuracy of automated feedback, according to Altamimi (2025). Students are still wary of accepting all automated recommendations, according to Rahmi et al. (2024), even though AI technologies are useful for grammatical correction.

The indirect pathway identified in this study indicates that trust evolves gradually through experience and interaction with the technology. As students increasingly use AI feedback systems and recognize their efficacy in error correction, their confidence in these technologies escalates. Consequently, trust seems to affect AI adoption indirectly via involvement rather than directly through the establishment of preferences. The findings indicate a complementary relationship between teacher and AI feedback, rather than a competitive one.

Teacher feedback remains the primary driver of students' feedback preferences, due to its socio-affective support, credibility, and instructional advice. Simultaneously, AI feedback serves a valuable supplementary role by enabling swift error correction and promoting iterative revision.

These results strongly support the emerging consensus in the literature that hybrid feedback models are the best way to teach technology-enhanced writing in English as a foreign language classes.

In summary, the pattern of findings is best understood as an associative hybrid-feedback model. Teacher feedback is associated with stronger overall feedback preference, and engagement with AI tools is associated with an additional preference pathway. These associations are consistent with a complementary relationship between teacher and AI feedback, but longitudinal or experimental evidence would be required before making causal claims.

## Conclusion

The present study investigated EFL university students' preferences for teacher, AI-generated, and hybrid feedback in academic writing, using an integrated theoretical framework that combines Sociocultural Theory (SCT), Feedback Literacy, and the Technology Acceptance Model (TAM). The results offer significant insights into students' perceptions and interactions with various feedback sources in technology-enhanced learning settings.

In general, the findings show that students' feedback preferences are primarily affected by instructor feedback. Structural equation modeling revealed that teacher feedback had the strongest predictive effect on learners' overall feedback preference, highlighting its central role in supporting students' writing development. These findings reinforce previous research indicating that teacher feedback provides not only linguistic guidance but also socio-affective support. Specifically, it enhances students' motivation, confidence, and engagement in the revision process.

Additionally, the results highlight the complementary function that AI-generated feedback plays in EFL writing training. Although cognitive judgments of AI feedback did not predict students' feedback preferences, behavioral engagement with AI tools strongly influenced their desire to use input during revision. This suggests that students appreciate the immediacy, accessibility, and iterative revision opportunities provided by AI systems, particularly for addressing grammar and language-level issues.

Another important finding is evidence supporting hybrid feedback approaches, in which teacher and AI-generated feedback work together rather than working independently. The mediation analysis indicated that high-quality teacher feedback encourages greater engagement with AI tools, suggesting a synergistic relationship between human and technological feedback sources. This pattern aligns with emerging research advocating hybrid feedback models that combine teachers' pedagogical expertise with the efficiency and scalability of AI systems.

From a theoretical perspective, the study enhances the literature by illustrating the efficacy of integrating Sociocultural Theory, Feedback Literacy, and the Technology Acceptance Model (TAM) in elucidating students' feedback preferences. SCT emphasizes the mediating role of teacher feedback in supporting learning and emotional engagement; Feedback Literacy explains learners' capacity to interpret and apply feedback effectively; and TAM delineates the impact of technological perceptions on the adoption of AI-driven tools. Together, these frameworks provide a comprehensive understanding of how students navigate multiple feedback sources in contemporary EFL writing classrooms.

From a practical standpoint, the results indicate that AI technologies should not be seen as a substitute for teacher feedback, but rather as supplementary resources that, when used in conjunction with teacher guidance, might improve writing instruction.

These findings should be interpreted with caution due to the cross-sectional nature of the data, which does not allow for causal inference. Supporting students' writing development in higher education situations should be best achieved by designing educational strategies that include both forms of feedback.

Accordingly, claims throughout the article should be understood as describing associations among students' perceptions, reported engagement, and feedback preferences at the time of data collection, rather than causal effects of one feedback source on another.

This study acknowledges several limitations. First, its findings may lack generalizability due to a convenience sample of university students from a single educational context. Second, the results may reflect context-specific differences in feedback perceptions that may not apply to other settings. Reliance on self-report survey data could introduce biases, obscuring the true impact of feedback sources on student work. The cross-sectional design captures perceptions at a single time point, suggesting the need for longitudinal studies to track changes in feedback preferences. Additionally, challenges in quantifying AI feedback constructs persist, influenced by technological knowledge and experience. Lastly, the focus on perceptions rather than measurable writing performance necessitates future research on the actual effects of feedback sources on writing quality and language development.

Several potential directions for future research can be suggested in light of these limitations and findings. First, future research should examine the preferences for feedback in a variety of cultural and educational contexts. The global understanding of feedback practices in EFL writing instruction would be broadened by conducting additional research in North Africa, the Middle East, and other underexplored regions, as most research on AI-assisted writing feedback has been conducted in Asian contexts.

Second, researchers should consider using experimental or quasi-experimental designs to examine the comparative effectiveness of teacher, AI-generated, and hybrid feedback models. Such designs could provide stronger evidence regarding how different feedback sources influence students' writing improvement and revision behaviors.

Third, future research could explore longitudinal changes in students' feedback literacy and technology acceptance. As learners become more familiar with AI tools, their perceptions of usefulness, trust, and engagement may change. Long-term studies would help identify how students' feedback preferences evolve.

Fourth, additional research is needed to examine the role of individual learner differences, such as language proficiency, digital literacy, learning styles, and motivation, in shaping students' responses to AI-generated feedback. Understanding these factors could help educators design more personalized and effective feedback systems.

Finally, future studies should investigate pedagogical models for integrating AI tools into writing instruction. Research examining how teachers can effectively integrate AI feedback with classroom instruction, peer review, and teacher guidance would provide valuable insights for developing balanced, sustainable hybrid feedback approach.

**Conflict of Interests**

The author declares no ethical issues or conflict of interests in this research.

**Ethical standards**

The author affirms this research did not involve human subjects.

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## ՈՒՍՈՒՑՉԻ, ԱՐՀԵՍՏԱԿԱՆ ԲԱՆԱԿԱՆՈՒԹՅԱՆ ԵՎ ՀԻԲՐԻԴԱՅԻՆ ՀԵՏԱԴԱՐՁ ԿԱՊԸ ԱՆԳԼԵՐԵՆԻ՝ ՈՐՊԵՍ ՕՏԱՐ ԼԵԶՎԻ ԳՐԱՎՈՐ ԽՈՍՔՈՒՄ. ՍՈՎՈՐՈՂՆԵՐԻ ՆԱԽԱՊԱՏՎՈՒԹՅՈՒՆՆԵՐԻ ԻՆՏԵԳՐՎԱԾ ՏԵՍԱԿԱՆ ՄՈԴԵԼ

**Սամիա Մուաս**

Սույն հետազոտությունը քննում է հետադարձ կապի երեք ձևաչափերի՝ դասախոսական, արհեստական բանականության (ԱԲ) և հիբրիդային մոդելների նկատմամբ ուսանողների ընկալումները ալժիրյան համալսարաններում: Արդյունքները փաստում են մարդկային գործոնի առաջնային նշանակությունը. չնայած տեխնոլոգիական առաջընթացին, դասախոսի ուղղորդումը մնում է ամենավստահելի և նախապատվելի աղբյուրը՝ ապահովելով սովորողների առավելագույն բավարարվածությունը: ԱԲ-ն դիտարկվում է որպես օժանդակ գործիք՝ արդյունավետ քերականական շտկումների և տեքստի արագ վերամշակման համար, սակայն դրա ընդունումը մեծապես կախված է կիրառման փորձառությունից: Հետազոտությունը հիմնավորում է հիբրիդային մոդելի արդյունավետությունը, որտեղ դասախոսի փորձառությունը և ԱԲ-ի հնարավորությունները ներդաշնակորեն լրացնում են միմյանց՝ ստեղծելով հավասարակշռված կրթական միջավայր:

**Բանալի բառեր՝** *հետադարձ կապ գրավոր խոսքում, ԱԲ-ն կրթության մեջ, հիբրիդային մոդելներ, հետադարձ կապի գրագիտություն, տեխնոլոգիաների ընդունման մոդել (TAM):*