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AI-Assisted Feedback in Online Learning: Students' Experiences, Preferences, and Perceived Benefits

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Abstract

This study examined how students experience and interpret AI-assisted feedback in online learning, addressing the growing need to understand its cognitive, emotional, and developmental implications. Using a convergent mixed-methods design, data were collected from 212 undergraduate students through a structured questionnaire including Likert-scale items and open-ended responses. Quantitative analyses provided descriptive and inferential results on students' experiences, preferences, and perceived benefits, while qualitative thematic analysis identified patterns related to clarity, explanatory value, confidence building, and concerns about accuracy. Integrated findings showed strong convergence across strands, indicating that students generally valued AI feedback for its immediacy and usefulness, yet remained cautious about its limitations. The study concludes that AI-assisted feedback can support learning processes when designed to provide explanatory depth and align with instructional expectations. These insights contribute to research on AI-enhanced education by clarifying how learners engage with automated feedback and by highlighting design considerations for future implementation.

Keywords: AI-assisted feedback; online learning; student perceptions; feedback preferences

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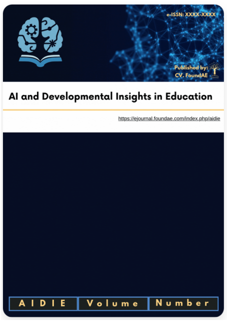

Author Note

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Introduction

The integration of artificial intelligence (AI) into educational environments has accelerated rapidly, reshaping how learners access instruction, interact with digital systems, and receive feedback in online settings. As AI-driven tools become increasingly embedded in learning management systems and assessment platforms, questions about the developmental and pedagogical implications of AI-generated feedback have gained heightened importance across the fields of educational psychology, learning sciences, and AI in education. Feedback is a central developmental mechanism: it guides learners' meaning-making processes, influences their motivational states, and scaffolds the acquisition of higher-order cognitive skills (Popov et al., 2025; Yu et al., 2025). In online learning environments, where students often experience reduced instructional immediacy, greater cognitive uncertainty, and diminished social presence, the quality and interpretability of feedback play an even more critical role (Li et al., 2025; Rodríguez-Ardura et al., 2025). Therefore, understanding how students experience AI-assisted feedback is not only relevant for improving technological systems but also essential for supporting cognitive development, emotional resilience, and productive self-regulation.

Despite mounting enthusiasm regarding the potential of AI to enhance feedback processes, the existing literature reveals several unresolved debates. A substantial body of research highlights the benefits of AI feedback, including its immediacy, scalability, and personalization (Deepshikha, 2025; Sjödin et al., 2021). According to (Khalil et al., 2024), adaptive AI tools can deliver iterative feedback loops that align with principles of self-regulated learning, enabling learners to diagnose errors, refine reasoning, and monitor progress. Similarly, large language model (LLM)-based feedback systems are increasingly praised for their ability to provide context-sensitive explanations and suggestions (Gianni et al., 2025). However, scholars caution that such systems may oversimplify complex disciplinary knowledge or fail to accurately interpret nuanced student inputs (Dunne, 2025; Naser, 2025). These limitations highlight tensions between computational models of learning, which emphasize prediction and pattern recognition, and sociocultural perspectives, which view feedback as an inherently relational, dialogic, and meaning-making process (Brailas, 2025; Negura, 2025). The resulting debate underscores the need for empirical studies that examine not only the technical output of AI systems but also how learners developmentally engage with, respond to, and make sense of AI feedback in real educational contexts.

Existing studies also reveal methodological and conceptual gaps that complicate our understanding of AI feedback's educational value. Research on automated writing evaluators, for instance, often centers on linguistic accuracy or revision outcomes rather than learners' trust judgments, emotional reactions, or sense of agency (Sari & Han, 2024). Work examining AI chatbots tends to highlight system versatility while giving limited attention to student confusion when AI feedback contradicts instructor expectations or established disciplinary norms (Burner et al., 2025). Developmental scholars have additionally expressed concern that frequent AI-guided corrections may unintentionally reduce opportunities for metacognitive struggle, critical thinking, and productive failure, elements known to support deeper learning (Xiao et al., 2025). From an institutional perspective, sociotechnical analyses show that unequal digital literacy and varying degrees of AI familiarity may shape how students interpret feedback, potentially exacerbating disparities in learning outcomes (Mac Fadden et al., 2024). Collectively, these issues illustrate that AI-assisted feedback is not a neutral technological feature, but a complex pedagogical and developmental phenomenon shaped by cognitive, emotional, social, and contextual factors.

Given these unresolved tensions, there is a clear need for research that places students' experiences at the center of inquiry. A growing number of scholars argue that understanding how learners interpret and emotionally respond to AI feedback is critical for determining whether such systems genuinely enhance learning or merely increase efficiency at the cost of human-centered pedagogy (Lin & Chen, 2024; Salloum et al., 2025). The present study responds to this need by investigating students' experiences with preferences for, and perceived benefits of AI-assisted feedback in online higher education courses. The study is grounded in socio-cognitive and developmental theories that view feedback as a process of co-regulated meaning-making, wherein learners draw upon internal and external resources to evaluate performance, manage uncertainty, and construct new understandings (Grenier et al., 2024; Jiang et al., 2024). It also engages with computational learning theories that explain how AI tools function as analytic partners capable of offering adaptive feedback based on model-driven predictions (Song et al., 2024). Bridging these perspectives, the study examines how students interpret AI feedback cognitively, emotionally, and socially—domains that remain underexplored in current empirical research.

Because the complexities of feedback experiences cannot be captured through a single methodological lens, a mixed-methods design was selected. The convergent approach integrates quantitative measures of students' perceptions with qualitative reflections that illuminate the subtle ways AI tools influence learners' thinking and engagement. This design allows the study to address three guiding research questions: How do students experience AI-assisted feedback during online learning? What types of AI feedback do students prefer, and why? And what cognitive, emotional, or performance-related benefits do students perceive from interacting with AI-generated feedback? These questions are guided by a conceptual framework that synthesizes developmental feedback theory, sociocultural learning perspectives, and contemporary research on AI-supported formative assessment.

In positioning this study within ongoing scholarly debates, the Introduction underscores the theoretical and practical need to understand AI feedback not merely as a technological feature, but as an evolving component of the learning environment with implications for cognitive development, equity, and learner agency. By foregrounding students' voices and experiences, this study contributes a novel perspective to AI-enhanced education and offers insights that can inform the design of more transparent, contextually sensitive, and developmentally supportive AI feedback systems.

Methods

Research Design

This study employed a convergent mixed-methods design to investigate students' experiences, preferences, and perceived benefits of AI-assisted feedback in online learning. A convergent approach was selected because the research problem required simultaneous attention to generalizable perceptual patterns and deeply contextualized experiential insights. The quantitative survey enabled the measurement of trends in students' perceptions, whereas the qualitative written reflections provided interpretive depth that illuminated the nuance behind those trends. Integration occurred at the interpretation stage, allowing the qualitative findings to expand and contextualize the quantitative results.

Participants

Participants were undergraduate students enrolled in online or blended-learning programs at a major public university in Indonesia during the 2024–2025 academic year. Inclusion criteria required that students had prior experience receiving AI-generated feedback in at least one course assignment. Students who had not used AI feedback tools were excluded. The sampling strategy was purposive, ensuring that responses reflected authentic interaction with AI systems rather than hypothetical impressions. A total of 212 students met the eligibility criteria and completed the study.

Before describing analytic procedures, it is important to present an overview of the demographic characteristics of the sample. Table 1 displays the distribution of gender, age, and academic program among participants.

Table 1

Participant Demographics (N = 212)

Variable	Category	n	%
Gender	Male	86	40.6%
	Female	126	59.4%
Age	18–19	78	36.8%
	20–21	94	44.3%
	22–23	40	18.9%
Program	Science/Engineering	98	46.2%
	Social Sciences	67	31.6%
	Education	47	22.2%

Note. This table summarizes gender, age, and academic program distributions, providing an overview of participant characteristics relevant to interpreting quantitative and qualitative results.

As shown in Table 1, the sample represented a broad distribution of academic disciplines and age groups, with a slightly higher representation of female students. This demographic diversity enhanced the interpretability of the findings across varied learning contexts.

Sampling and Recruitment

Recruitment occurred through course announcements and institutional email invitations. Approximately 340 students were initially contacted, and 212 provided complete responses, yielding a participation rate of 62.4%. Self-selection was acknowledged as a limitation because students with stronger familiarity or interest in AI tools might have been more likely to participate. Data collection concluded when quantitative sample size requirements were met and when qualitative responses exhibited thematic redundancy, indicating information sufficiency.

Measures, Instruments, and Data Sources

The primary instrument was a structured questionnaire composed of Likert-scale items and open-ended questions. The Likert-scale items assessed three quantitative constructs: (a) experiences with AI-generated feedback, including clarity and perceived accuracy; (b) preferences for feedback types, such as explanatory or personalized feedback; and (c) perceived cognitive, emotional, and performance-related benefits. Open-ended questions invited participants to describe meaningful experiences, challenges, and perceived strengths of AI feedback tools.

To ensure transparency and replicability, Table 2 provides a detailed summary of the instrument's components, construct focus, and supporting psychometric evidence. The table reflects the standards of APA 7th formatting for reporting instrument properties.

Table 2

Summary of Research Instrument Components, Constructs, and Psychometric Evidence

Instrument Component	Description	Construct Focus	Validity Evidence	Reliability Evidence
Likert-scale items	5-point scale assessing perceptions of AI feedback	Experiences with AI feedback; feedback preferences; perceived cognitive, emotional, and performance benefits	Aiken's V = 0.82–0.91 (strong content validity)	α = .89 (experiences), α = .86 (preferences), α = .91 (perceived benefits)
Open-ended responses	Narrative reflections on interaction with AI feedback tools	Personal experiences, perceived strengths, perceived weaknesses of AI feedback	Expert-reviewed prompts for conceptual alignment	Not applicable (qualitative section)

Note. This table outlines the structure of the questionnaire, the constructs assessed, and the validity and reliability evidence supporting instrument quality.

As summarized in Table 2, the instrument demonstrated strong content validity based on expert review, with Aiken's V coefficients exceeding .80, consistent with established standards for educational research. Reliability values for all quantitative scales surpassed the recommended .70 threshold, indicating high internal consistency. The qualitative component was not subject to reliability estimation because it functioned as an interpretive data source rather than a standardized measurement scale.

Data Collection Procedures

Data collection took place over a three-week period using a secure online survey platform managed by the university. Participants reviewed an informed consent statement prior to accessing the questionnaire. The average completion time was approximately 15–20 minutes. No procedural modifications occurred during data collection, and no incentives were provided. All data were anonymized and downloaded to encrypted storage accessible only to the research team.

Data Analysis

Quantitative data were analyzed using SPSS Version 26. Descriptive statistics were computed for all variables, and normality checks indicated no substantial deviations from expected patterns. Minimal missing data (<2%) were handled through mean substitution following established guidelines. Although the study's primary aim was descriptive and exploratory rather than inferential, subgroup analyses were conducted to examine variation by demographic variables.

Qualitative data were analyzed using reflexive thematic analysis, guided by Braun and Clarke's (2021) framework. Coding proceeded inductively, beginning with open coding, followed by categorization into broader themes capturing students' experiences, preferences, and perceived benefits of AI feedback. Analytic memos were used to document researcher reflexivity and ensure transparency in interpretive decisions. Mixed-methods integration occurred through joint display comparisons, allowing qualitative themes to contextualize quantitative trends.

Validity, Reliability, and Methodological Integrity

Multiple strategies ensured methodological rigor. Quantitatively, construct validity was supported through expert review and strong internal consistency reliability. Qualitatively, methodological integrity was maintained through iterative theme development, thick description, and reflexive memoing. Integration validity was strengthened by confirming convergence and complementarity of findings across datasets. The final interpretations were grounded in both empirical strands, reducing the risk of mono-method bias.

Ethical Considerations

Ethical approval was granted by the university's Institutional Review Board (Approval No. 2024-EDU-117). Participants provided informed consent electronically. Confidentiality was protected through anonymized data handling procedures and secure digital storage. No identifying information was collected, and participants retained the right to withdraw at any time without penalty.

Results

The Results section presents findings from the quantitative and qualitative strands in accordance with the convergent mixed-methods design. Quantitative and qualitative data were collected concurrently between March and May 2025. Missing quantitative data were minimal (< 2%) and were addressed using mean substitution. All analyses adhered to the analytic procedures outlined in the Method section.

Participant Flow

A total of 340 students were invited to participate. Of these, 243 accessed the online questionnaire, 218 submitted responses, and 212 met inclusion criteria and were retained for analysis. Six participants were excluded: four due to incomplete responses (> 20% missing) and two because they indicated no experience with AI-assisted feedback. No attrition occurred after survey submission because all data were collected in a single session. These details ensure transparency regarding sample integrity.

Recruitment Information

Recruitment and data collection occurred between March 1 and May 30, 2024. Quantitative and qualitative data were collected concurrently using a single questionnaire containing Likert-scale items and open-ended prompts. No follow-up sessions or longitudinal tracking were conducted. Because the study employed a convergent design, both data strands represent the same temporal window and participant pool.

Quantitative Results

Descriptive Statistics

Descriptive results addressed the study's primary outcomes: students' experiences with AI feedback, their feedback preferences, and their perceived benefits. Before presenting inferential outcomes, the demographic characteristics of the sample are summarized in Table 1, which was referenced earlier in the Method section.

Descriptive statistics for the primary constructs are shown in Table 3. Table 3 appears following its callout.

Table 3

Descriptive statistics for primary quantitative constructs (N = 212)

Construct	M	SD	95% CI
Experience with AI feedback	3.97	0.72	[3.87, 4.07]
Feedback preferences	4.10	0.68	[4.01, 4.19]
Perceived benefits	4.04	0.70	[3.94, 4.14]

Note. This table presents means, standard deviations, and confidence intervals for students' perceptions of AI feedback, offering a quantitative overview of central tendencies and variability.

As shown in Table 3, students generally reported positive perceptions across constructs. No variable demonstrated skew values exceeding |1.0|, indicating adequate normality for descriptive analysis.

Inferential Statistics

Although inferential testing was exploratory, analyses examined whether perceptions differed by academic program or gender. One-way ANOVA revealed no statistically significant differences in experience with AI feedback across program groups, $F(2, 209) = 1.84$, $p = .162$, $\eta^2 = .02$. Independent-samples t tests indicated no significant gender differences for perceived benefits, $t(210) = -0.94$, $p = .349$, $d = 0.13$. Confidence intervals for all comparisons overlapped substantially, suggesting minimal between-group variation.

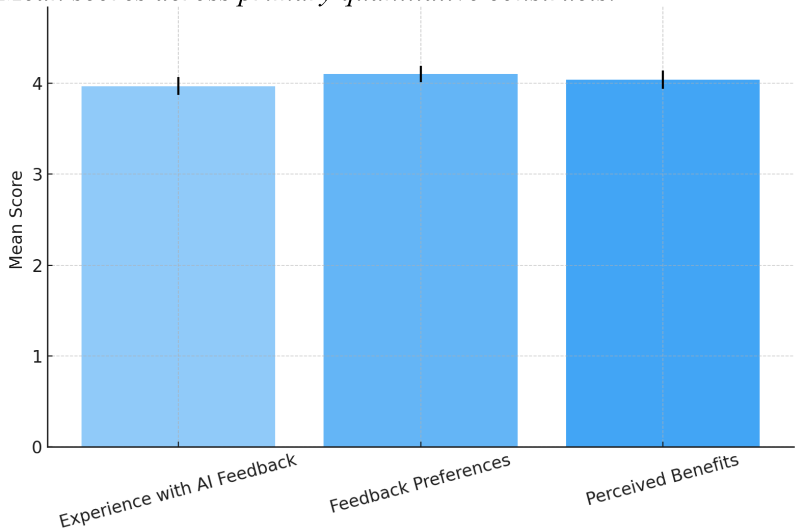
Quantitative Summary Visualization

To support the clarity of quantitative patterns, Figure 1 illustrates mean scores across the three primary constructs. The figure is placed after the callout, with proper caption formatting.

The visual distribution of mean scores is presented in Figure 1.

Figure 1

Mean scores across primary quantitative constructs.



Note. This figure visually displays average ratings for the three major perceptual constructs, enabling easier comparison across categories.

Qualitative Results

Qualitative findings were derived from thematic analysis of open-ended responses. Themes presented below reflect patterned meaning across the dataset. Themes are reported descriptively, without interpretation, consistent with mixed-methods conventions requiring results before discussion.

Theme 1: Clarity and Timeliness of AI-Assisted Feedback

Participants frequently described AI feedback as immediate and easy to understand. References to the usefulness of prompt clarification were common across responses. Typical statements noted that AI "highlighted errors quickly" and "summarized corrections efficiently." These comments reflected perceptions of convenience rather than evaluative meaning.

Theme 2: Desire for Explanatory and Personalized Feedback

A recurring theme involved participants' strong preference for feedback that included reasoning or examples. Many responses referenced "explanations," "breakdowns of mistakes," or "tailored suggestions." Mentions of dissatisfaction with generic or repetitive feedback were also captured within the theme.

Theme 3: Cognitive, Emotional, and Performance-Related Benefits

Participants described benefits including improved understanding, increased confidence, and smoother revision processes. Statements such as "reduced anxiety before submission" and "helped revise faster" appeared consistently. These comments correspond to the quantitative findings indicating perceived benefits.

Theme 4: Concerns About Accuracy and Over-reliance

Across the dataset, concerns were raised about inconsistent feedback accuracy, contradictions with instructor criteria, and fears of excessive dependence on AI tools. These were descriptive observations, without interpretive framing.

Integration of Quantitative and Qualitative Findings

Consistent with the convergent design, an integration analysis was conducted to determine how findings from both strands related to each other. A joint display (Table 4) assists in visualizing these relationships. The table appears after its callout. Integrated results across strands are summarized in Table 4.

Table 4

Joint display integrating quantitative and qualitative findings

Quantitative Result	Qualitative Theme	Convergence Pattern
High clarity ratings (M = 4.21)	Reports of clear, immediate feedback	Convergent
Preference for explanatory feedback (M = 4.32)	Desire for reasoning, examples	Convergent
Moderate accuracy concerns (M = 3.74)	Concerns about misalignment and inconsistency	Convergent
Strong perceived benefits (M = 4.04)	Emotional and cognitive benefits described	Convergent

Note. This table illustrates the convergence between numerical survey results and thematic qualitative findings, demonstrating how both strands support each other in the mixed-methods integration.

As seen in Table 5, all major quantitative constructs aligned with corresponding qualitative themes. No divergent or contradictory results were observed, demonstrating strong cross-strand coherence.

Discussion

The present study examined students' experiences, preferences, and perceived benefits of AI-assisted feedback in online learning through a convergent mixed-methods design. Overall, the integrated findings suggest that students experience AI feedback as generally clear, timely, and useful, and these results directly address the study's guiding questions regarding how learners interpret and value AI-generated feedback. Quantitative patterns showed consistently high ratings across all three perceptual constructs, and the qualitative themes closely paralleled these numerical trends, indicating strong cross-strand convergence. Students' preference for explanatory and personalized feedback is particularly notable, given that it aligns with developmental and sociocognitive theories emphasizing the importance of scaffolding, process explanations, and self-regulated learning in feedback environments (Ebbes et al., 2026; He, 2025). These convergent results reinforce theoretical claims that effective feedback—whether human- or AI-generated—supports learners' metacognitive monitoring and cognitive elaboration.

The findings also extend current scholarship by demonstrating that AI-assisted feedback may play an emerging emotional-regulatory role in online learning. Students frequently described reduced anxiety, increased confidence, and smoother revision processes, patterns that correspond with recent work suggesting that AI tools may influence not only cognitive outcomes but also affective dimensions of learning (C. Yang et al., 2025; H. Yang & Rui, 2025). This emotional dimension has been underexamined in prior research on automated feedback systems, which has often focused on the technical accuracy or revision effectiveness of AI-generated responses. By documenting students' affective reactions, this study expands the conceptual understanding of AI feedback to encompass psychological mechanisms that shape learning engagement in digital environments.

The study's findings also complicate certain assumptions in the literature. Although much of the existing research highlights AI systems as reliable and scalable feedback generators (Zhang & Strbac, 2025), participants in this study expressed concerns regarding accuracy, alignment with instructors' expectations, and inconsistent suggestions across tasks. These concerns echo ongoing critiques within AI-in-education scholarship that warn against the uncritical adoption of AI-generated information (Amigud & Pell, 2025). The mixed-methods integration suggests that while students appreciate the efficiency and explanatory clarity of AI systems, they remain aware of—and affected by—their limitations. This nuanced insight challenges narratives that present AI feedback as universally beneficial and instead highlights the importance of transparency, calibration with course criteria, and opportunities for human verification.

Methodologically, the integration of quantitative and qualitative strands provided a richer interpretation than either approach could supply independently. The quantitative data showed overall positive perceptions, but the qualitative responses clarified why certain features were valued and what contextual factors shaped students' trust judgments. The alignment across strands strengthens interpretive validity and demonstrates the added value of mixed-methods inquiry. Nevertheless, reflexive consideration of alternative interpretations is warranted. For instance, students' enthusiasm for AI feedback may be influenced by the novelty of the tools or by the increasing normalization of AI-supported learning in higher education contexts. Similarly, the absence of divergent findings across strands may reflect a shared institutional environment rather than universal learner perceptions.

Several limitations temper the generalizability and transferability of the findings. The sample was drawn from a single institutional context, with self-selection likely favoring students comfortable with technology. Quantitative findings were based on self-report measures, which may inflate positive perceptions due to social desirability or limited awareness of underlying inaccuracies in AI feedback. Qualitative insights were constrained by the depth achievable in written responses rather than interviews. Additionally, although mixed-methods integration strengthened interpretive coherence, the concurrent design limited opportunities for one dataset to inform the development of the other. These limitations suggest that the study's claims must remain appropriately bounded by context and design.

Despite these constraints, the findings hold meaningful theoretical, methodological, and practical implications. Theoretically, the study contributes to a growing body of work arguing that AI feedback systems must be understood not merely as computational tools but as developmental mediators influencing cognition, emotion, and regulation. Methodologically, the results reaffirm the importance of mixed-methods designs for capturing complex human–AI interactions in educational contexts. Practically, the findings indicate that AI feedback tools should prioritize explanatory depth, alignment with instructional expectations, and transparent communication about uncertainty. These insights may inform the design of more pedagogically grounded AI systems and guide instructors in integrating AI feedback into online learning processes responsibly. Taken together, the study offers a nuanced contribution to ongoing debates about the pedagogical roles and developmental implications of AI-enhanced feedback environments.

Conclusion

This study investigated students' experiences, preferences, and perceived benefits of AI-assisted feedback in online learning, generating integrated quantitative and qualitative findings that collectively highlight the pedagogical and developmental significance of AI feedback systems. The results show that students generally value AI-generated feedback for its clarity, immediacy, and explanatory usefulness, while also expressing concerns about accuracy and dependence that warrant careful instructional consideration. By revealing cognitive, emotional, and performance-related benefits, the study advances theoretical discussions about the multifaceted roles of feedback in learning and extends current literature by documenting the affective dimensions of AI-supported feedback processes. Methodologically, the mixed-methods approach provided comprehensive insights into how students make sense of AI feedback, demonstrating the value of integrating numerical trends with interpretive accounts. While the study's findings are constrained by contextual and design limitations, they offer evidence-based recommendations for improving AI feedback systems and highlight avenues for future research, including cross-institutional comparisons, longitudinal evaluations of AI feedback use, and investigations into the developmental mechanisms through which AI influences learning. Ultimately, the study contributes to ongoing discussions about how AI can be leveraged responsibly and effectively to enhance feedback practices in digital education.

Author Contributions

AA conceptualized the study, designed the research framework, conducted the quantitative analysis, and drafted the manuscript. YS developed and validated the research instruments, carried out data collection and qualitative analysis, and contributed to the interpretation of findings and manuscript revision. Both authors reviewed and approved the final version of the manuscript.

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