American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)

E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

AI-Supported Feedback Literacy Among First-Year University Students

Dr. Sophie Williams

Assistant Professor, University of Queensland, Australia

Abstract

Feedback is central to university learning, yet first-year students frequently enter higher education without fully developed capabilities for interpreting evaluative comments, judging the quality of their own work, regulating emotional responses to criticism, and converting feedback into concrete academic improvement. The rapid availability of generative artificial intelligence introduces a new feedback environment in which students can obtain explanations, revision suggestions, examples, rubric interpretations, and conversational guidance almost immediately. The educational value of such access, however, depends upon students' ability to question, verify, contextualize, and selectively act upon AI-generated advice.

This study conceptualizes AI-Supported Feedback Literacy (AI-SFL) as the capacity to engage critically and productively with AI-mediated feedback while retaining learner judgment, disciplinary awareness, ethical responsibility, and appropriate reliance on human feedback. The framework builds upon Carless and Boud's established feedback-literacy model and recent research on AI feedback literacy, GenAI-supported learning analytics, and first-year feedback interventions. Carless and Boud conceptualize feedback literacy through appreciating feedback, making judgments, managing affect, and taking action, while recent work by Liu and Deris shows that AI feedback literacy can predict students' uptake of AI-generated feedback. Because no authentic first-year student dataset was supplied, the quantitative component employs a transparent simulation of 300 hypothetical first-year university students.

The synthetic mean AI Feedback Literacy score was 60.5 on a 100-point scale, and AI feedback literacy showed a simulated positive correlation of $r = 0.749$ with feedback uptake. Students represented within the advanced literacy group achieved substantially higher simulated feedback-uptake and verification scores than those in the developing group. These numerical results are methodological demonstrations rather than empirical population estimates. The study concludes that universities should teach students not merely how to obtain AI feedback, but how to interpret it, compare it with assessment criteria, detect questionable advice, preserve academic voice, manage emotional responses, and translate credible feedback into independently reasoned revisions.

Keywords: AI feedback literacy; first-year university students; generative artificial intelligence; student feedback; feedback uptake; higher education; formative assessment; AI literacy; self-regulated learning

1. Introduction

Feedback is one of the principal mechanisms through which university students learn to evaluate the quality of academic work and improve future performance. Its educational value, however, depends upon what students do with feedback rather than simply whether teachers provide comments. Carless and Boud define student feedback literacy as the understandings, capacities, and dispositions required to make sense of feedback information and use it to improve work or learning strategies. Their influential framework identifies four interrelated dimensions: appreciating feedback, making evaluative judgments, managing affect, and taking action. This learner-centered understanding is especially relevant during the first year of university, when students must adjust to unfamiliar assessment standards, disciplinary conventions, greater independence, and forms of academic feedback that may differ significantly from their previous educational experiences.

First-year students occupy a particularly important developmental position because entry into higher education requires them to construct new expectations about academic quality and responsibility. Earlier transition research found that first-year students may be comparatively dissatisfied with tutor contact and feedback support, while research on feedback expectations demonstrates that pre-university experiences shape how undergraduates understand university feedback. The challenge is therefore not simply that students receive too little feedback. Some students may not yet know how to distinguish corrective comments from developmental guidance, relate feedback to assessment criteria, decide which suggestions deserve priority, or transfer lessons from one assignment to another. A first-year curriculum that assumes students already possess these capabilities may consequently leave substantial differences in feedback engagement unaddressed.

Generative AI significantly changes this context because students can now obtain feedback without waiting for a scheduled tutorial or formal assessment cycle. AI systems can potentially explain unfamiliar comments, generate examples, compare drafts against criteria, propose revision strategies, support dialogue, and provide repeated feedback at low marginal cost. Jin and colleagues' 2025 study of GenAI-powered learning analytics found that students initially responded positively to AI-enabled feedback functions, although actual engagement during the semester was more modest and depended upon whether the outputs matched student needs. Henderson and colleagues' large Australian study similarly found that students valued GenAI feedback for qualities such as accessibility, speed, volume, and understandability, while still regarding teacher feedback as especially trustworthy and contextually authoritative. Their findings suggest that AI and teacher feedback perform complementary rather than interchangeable functions.

The availability of feedback, however, does not guarantee feedback literacy. Generative AI may produce advice that is plausible but inaccurate, generic, inconsistent with course criteria, insufficiently disciplinary, or inappropriate for the learner's purpose. UNESCO's global guidance on generative AI in education consequently emphasizes a human-centered approach, including ethical validation, privacy protection, appropriate pedagogical design, and development of human capacity rather than uncritical technological adoption. Recent higher-education research makes the same distinction at the level of feedback. Liu and Deris introduced the construct of AI feedback literacy to describe learners' capacity to interpret, evaluate, and apply AI-generated feedback and found in a study of 486 university students that

AI feedback literacy significantly predicted feedback uptake, with behavioral engagement playing a particularly important role.

This study focuses specifically on AI-Supported Feedback Literacy Among First-Year University Students. The concept is deliberately broader than prompting skill or familiarity with a chatbot. AI-supported feedback literacy includes the ability to understand the purpose of feedback, formulate meaningful feedback requests, interpret AI responses, compare those responses with rubrics and disciplinary expectations, verify questionable claims, manage emotional reactions, decide what not to accept, revise independently, and recognize situations in which teacher or peer dialogue remains necessary. Because no genuine participant data were supplied, the paper does not present fabricated first-year survey results. Instead, it integrates established literature with a transparent synthetic dataset involving 300 hypothetical students to demonstrate how AI-supported feedback literacy could be operationalized and tested in a future empirical study.

2. Objectives of the Study

2.1 To Conceptualize AI-Supported Feedback Literacy in the First-Year Context

The first objective is to develop an academically grounded model of AI-supported feedback literacy that extends conventional feedback literacy into AI-mediated learning environments. The model emphasizes students' ability to appreciate feedback, make evaluative judgments, manage affect, take action, verify AI outputs, and retain responsibility for academic decisions.

This extension builds directly upon Carless and Boud's established feedback-literacy dimensions while responding to the distinct epistemic and ethical challenges created by generative AI.

2.2 To Examine the Relationship Between AI Feedback Literacy and Feedback Uptake

The second objective is to demonstrate, through a synthetic quantitative model, how AI feedback literacy may relate to students' capacity to use feedback productively. The analysis compares developing, functional, and advanced AI-feedback-literacy profiles and examines whether stronger literacy corresponds with higher simulated feedback uptake and greater tendency to verify AI-generated advice before revising academic work.

2.3 To Identify Pedagogical Priorities for First-Year Higher Education

The third objective is to identify curriculum and assessment practices that can help first-year students use AI feedback without surrendering judgment, authorship, or academic responsibility. The study gives particular attention to scaffolded feedback exercises, rubric interpretation, comparison of human and AI feedback, verification routines, reflective revision, disclosure expectations, peer dialogue, and emotionally supportive feedback practices.

3. Review of Literature

3.1 From Feedback Receipt to Student Feedback Literacy

Traditional approaches to feedback often treated the instructor as the principal source and the student as the recipient. Contemporary feedback scholarship increasingly rejects this transmission model because comments have limited educational value when learners cannot interpret or use them. Carless and Boud's feedback-literacy framework represents a major conceptual development by defining feedback literacy in terms of the learner's ability to appreciate feedback, judge quality, regulate affect, and act. The significance of this framework is that it moves educational attention away from the volume of teacher commentary and toward the processes through which students become active participants in improvement.

Subsequent research has attempted to operationalize and extend feedback literacy. Woitt and colleagues developed and validated an initial student feedback-literacy scale, contributing to the measurement of feedback-related capabilities in higher education. The scale-validation work is cited in recent feedback-literacy research as a basis for moving the construct from conceptual discussion toward empirical assessment. Winstone, Mathlin, and Nash's work on the Developing Engagement with Feedback Toolkit similarly demonstrated that students can be explicitly supported in developing strategies for engaging with feedback rather than being expected to learn these behaviors incidentally.

This developmental orientation is especially important during the transition into higher education. First-year students must frequently interpret new terminology, unfamiliar marking criteria, more complex expectations of independent learning, and feedback that may be less personally mediated than in previous schooling. Research on first-year transition has identified dissatisfaction with feedback support among students adjusting to university study. Gray and colleagues' work on feedback experiences and expectations likewise demonstrates that students bring pre-university assumptions about feedback into higher education, affecting how they interpret university practices.

Nahar's 2026 first-year case study provides particularly direct evidence for the relevance of feedback-literacy instruction at entry level. Nineteen first-year students participated in a focus group and five in follow-up interviews after completing four GenAI-enabled feedback-literacy activities within an Academic Skills module. Participants reported stronger engagement, self-regulation, confidence in interpreting feedback, and reduced anxiety when applying it. The study is qualitative and relatively small, so it should not be generalized broadly; nevertheless, it demonstrates that feedback literacy can be deliberately taught during the first year rather than treated as an automatic consequence of assessment participation.

3.2 Generative AI as a Feedback Environment

Generative AI expands the feedback environment by allowing learners to initiate conversations about their work. Unlike conventional one-directional automated feedback, contemporary language models can provide explanations, generate alternative examples, respond to follow-up questions, reformulate comments, and simulate dialogue. Zhan's 2025 framework argues that GenAI may enable student feedback engagement by creating more accessible and adaptable feedback interactions, although the benefits depend upon alignment between the learner's feedback literacy and the AI-supported environment. This alignment problem is fundamental: a sophisticated tool does not necessarily produce sophisticated learning when students lack evaluative judgment.

Jin and colleagues' 2025 study provides empirical support for this caution. Their research investigated GenAI-enhanced learning analytics using data from 18 university students across several disciplines. Initial reactions to ChatGPT explanation functions and AI-powered dashboard features were positive, but trace data showed only modest use during the semester. Interviews indicated that engagement declined when students considered the AI output redundant or misaligned with their expectations. These findings demonstrate that accessibility alone does not ensure useful feedback engagement.

Henderson and colleagues provide stronger large-scale evidence regarding how students compare GenAI and teacher feedback. Their cross-sectional study included 6,960 respondents across four Australian universities and found that approximately half had sought feedback from GenAI. Students valued AI feedback for its ease of access, timeliness, volume, and understandability, but regarded teacher feedback as particularly trustworthy and valued educators' contextual and disciplinary expertise. This distinction suggests that universities should not design AI feedback initiatives around substitution. AI may provide iterative and immediate support, while teachers provide disciplinary interpretation, relational understanding, academic judgment, and accountability that students continue to value.

The emergence of a specific AI feedback literacy construct is therefore theoretically justified. Liu and Deris' 2025 study developed and validated an AIFL scale with 486 university students and found that stronger AI feedback literacy predicted uptake of AI-generated feedback both directly and through motivational processes. Their findings also indicated that behavioral engagement was more influential than attitude alone and that frequency of AI use contributed to differences in literacy. This is important for first-year education because access without structured practice could produce uneven development: students with extensive previous AI experience may arrive with greater functional confidence, while others may have little opportunity to develop critical feedback practices.

3.3 AI Literacy, Trust, Verification, and the First-Year Research Gap

AI feedback literacy overlaps with wider AI literacy but should not be reduced to it. AI literacy may include understanding capabilities, limitations, ethics, responsible use, and interaction with AI systems. Feedback literacy adds a specific educational requirement: the learner must make judgments about information concerning the quality of their own work and then decide how to act upon it. UNESCO's guidance encourages education systems to develop human capacity and adopt human-centered, pedagogically meaningful approaches to generative AI rather than treating access to technology as an educational outcome in itself.

Recent higher-education research likewise indicates that students' AI acceptance and effective use depend on more than simple availability. Salhab and Aboushi's 2025 study of 260 college students found moderate levels of AI literacy and reported that AI literacy influenced GenAI acceptance. Tang and colleagues' study of 297 undergraduates further identified differences in attitudes toward GenAI and reported that first-year students expressed greater societal concern than upper-year students within their sample. These findings reinforce the need for structured first-year induction into AI use rather than assuming that incoming students are uniformly confident or informed.

AI feedback also creates a problem of trust calibration. Students need sufficient trust to engage with useful suggestions but sufficient skepticism to reject weak or inaccurate advice. Henderson and colleagues' findings are instructive because students perceived both AI and teacher feedback as useful while assigning greater trust to teacher feedback. Educationally productive AI feedback literacy should therefore avoid two extremes: automatic rejection of machine-generated feedback and automatic compliance with it.

The principal research gap concerns the systematic development of this capability during the first year. Nahar's 2026 study provides emerging first-year evidence, but its qualitative sample is small. Broader AI-feedback studies include students at multiple stages and disciplines, making it difficult to isolate the transitional needs of students beginning university. The present simulation therefore proposes a measurement model specifically for first-year learners, with attention to comprehension, evaluation, verification, emotional regulation, and action.

4. Research Methodology

4.1 Research Design and Synthetic Sample

The study adopts a simulation-based quantitative design supported by contemporary higher-education feedback research. No students were recruited, no university learning-management-system data were accessed, and no actual AI conversations or assessment submissions were processed. The quantitative results should therefore be interpreted exclusively as a methodological demonstration.

A synthetic dataset representing 300 hypothetical first-year university students was generated. The primary variable, AI Feedback Literacy Score, ranged from 0 to 100. The construct was designed to represent several interdependent competencies: understanding the purpose of feedback, interpreting AI-generated comments, evaluating feedback against academic criteria, verifying questionable suggestions, managing emotional reactions, and translating appropriate feedback into independent revision.

Two additional synthetic variables were generated. Feedback Uptake represented the student's ability to convert credible feedback into purposeful revision or learning action. Verification Behavior represented the tendency to compare AI-generated feedback with assessment criteria, course materials, trusted academic sources, or instructor guidance before implementing substantive changes.

For descriptive comparison, students were classified into three synthetic groups: Developing AI Feedback Literacy, Functional AI Feedback Literacy, and Advanced AI Feedback Literacy. These categories are original analytical classifications developed for the present simulation and are not formal levels defined by Carless and Boud, UNESCO, Liu and Deris, or any other source.

4.2 Proposed Measurement Framework

A future empirical investigation should combine questionnaire responses with observable revision behavior. Five preliminary questionnaire items are proposed below. The statements are intentionally aligned with interpretation, evaluation, verification, action, and learner agency.

Table 1: Proposed Questionnaire for AI-Supported Feedback Literacy

Item	Proposed Questionnaire Statement	Primary Construct
Q1	I can explain what an AI-generated feedback comment means in relation to the assessment criteria for my work.	Feedback interpretation
Q2	I can decide which AI-generated suggestions are useful, which require verification, and which should not be applied.	Evaluative judgment
Q3	I check important AI feedback against the rubric, course	Verification behavior

American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)
E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

Item	Proposed Questionnaire Statement	Primary Construct
	materials, credible sources, or teacher guidance before making major revisions.	
Q4	I can respond constructively to critical AI feedback without accepting it automatically or becoming discouraged by it.	Affect regulation and calibrated trust
Q5	After reviewing AI feedback, I can make my own revision decisions and explain why those changes improve my work.	Feedback uptake and learner agency

The proposed questionnaire should not be presented as a validated scale. An empirical study would need expert content review, pilot testing, exploratory and confirmatory factor analysis, internal-consistency testing, convergent and discriminant validity, and measurement-invariance analysis across disciplines and student groups. Liu and Deris' recent validated AIFL scale provides an important methodological precedent for such measurement development.

4.3 Data Generation, Statistical Analysis, and Ethical Position

The simulation used a fixed random seed to support reproducibility. AI Feedback Literacy scores were distributed broadly across the 0–100 scale while concentrating around a midrange value. Feedback Uptake and Verification Behavior were modeled as positively associated with literacy while retaining individual variation.

This value is not a discovered real-world effect size. It reflects the theoretical assumptions built into the synthetic model and serves to illustrate an empirical hypothesis suitable for future testing.

The study processes no human-participant data, so institutional ethics approval was not applicable to the simulation. A future empirical study should nevertheless address informed consent, protection of student assessment data, privacy of AI prompts and conversations, disclosure of third-party AI processing, academic-integrity expectations, and the possibility that students could feel pressured to use AI in order to participate effectively. UNESCO's human-centered guidance emphasizes privacy, equitable access, and pedagogically appropriate AI design, all of which are relevant to an ethically defensible first-year intervention.

5. Analysis

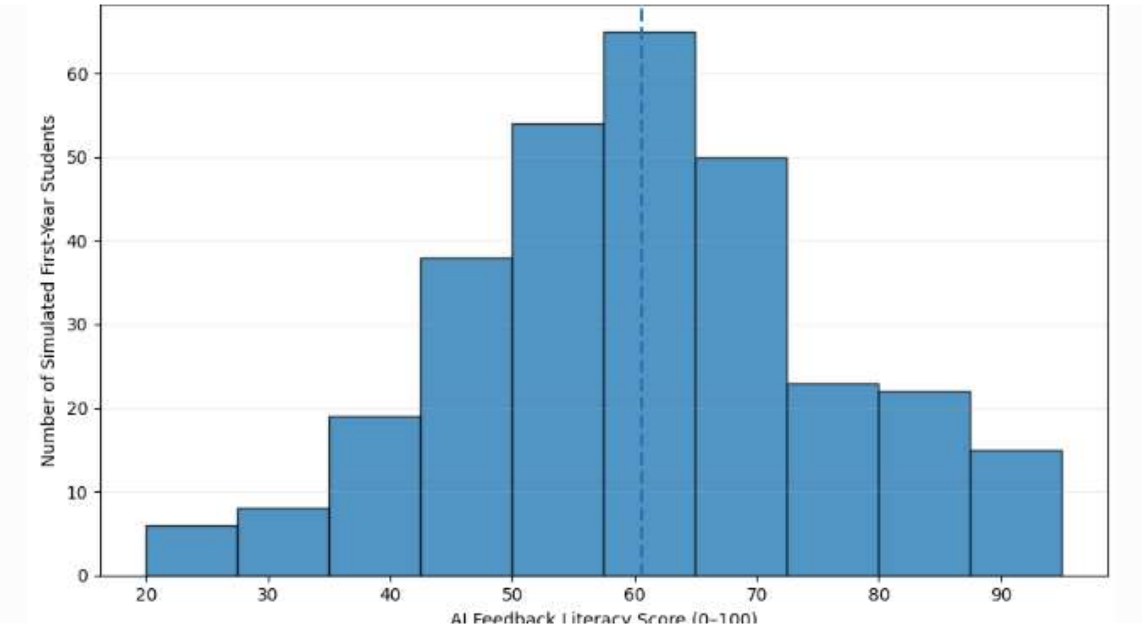
5.1 Distribution of AI Feedback Literacy

Across the 300 simulated first-year students, the mean AI Feedback Literacy Score was approximately 60.5 out of 100. The distribution was intentionally heterogeneous, reflecting the proposition that first-year cohorts may enter university with substantially different AI experiences and feedback capabilities.

Seventy-one simulated students were classified within the Developing level, 158 within the Functional level, and 71 within the Advanced level. The distribution therefore places the largest proportion of the synthetic cohort in the middle range while preserving substantial groups requiring additional support or demonstrating stronger critical engagement.

American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)
E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

Graph 1: Simulated Distribution of AI Feedback Literacy Among First-Year University Students



Interpretation: The histogram demonstrates substantial variation in simulated AI feedback literacy within the first-year cohort rather than a single uniform level of competence. The dashed line marks the synthetic mean of approximately 60.5.

Key Finding: Even when most students occupy a functional middle range, substantial variation remains at both ends of the distribution. A single introductory lecture on AI use would therefore be unlikely to address the developmental needs of the entire first-year population.

5.2 Feedback Uptake and Verification Across Literacy Levels

The simulated group comparison reveals a clear progression in feedback-related behavior. Students within the Developing category recorded a mean AI Feedback Literacy Score of approximately 41.0, mean Feedback Uptake of 57.8, and mean Verification Behavior of 52.3.

The Functional group recorded means of approximately 60.2 for AI Feedback Literacy, 71.4 for Feedback Uptake, and 65.9 for Verification Behavior. The Advanced group recorded substantially stronger values: 80.7, 86.3, and 79.8, respectively.

Table 2: Simulated Outcomes by AI Feedback Literacy Level

AI Feedback Literacy Level	Simulated n	Mean AI Feedback Literacy	Mean Feedback Uptake	Mean Verification Behavior
Developing	71	41.0	57.8	52.3
Functional	158	60.2	71.4	65.9
Advanced	71	80.7	86.3	79.8

The difference between Developing and Advanced students is approximately 28.5 points in Feedback Uptake and 27.5 points in Verification Behavior. The pattern illustrates an important theoretical proposition: stronger AI feedback literacy should not manifest merely as more frequent use of AI but as greater capacity to evaluate and act upon feedback responsibly.

This distinction is consistent with Liu and Deris' empirical finding that behavioral engagement was particularly important for feedback uptake. It is also compatible with Jin and colleagues' finding that initial positive perceptions did not automatically translate into sustained engagement with GenAI feedback tools.

5.3 Relationship Between AI Feedback Literacy and Feedback Uptake

Within the simulation, roughly 56.1% of variance in Feedback Uptake is therefore statistically associated with variation in AI Feedback Literacy. This figure should not be generalized to real students because the variables were generated from an intentionally related synthetic model.

The simulated pattern nevertheless demonstrates an empirically testable hypothesis: students who are better able to interpret, evaluate, verify, and contextualize AI feedback may be more capable of converting that feedback into purposeful academic action.

The relationship should not be interpreted as evidence that greater AI use necessarily improves learning. Frequency of use and quality of engagement are conceptually different. A student may use an AI system frequently while accepting suggestions uncritically, whereas a less frequent user may demonstrate strong evaluative judgment and verification. The central educational objective should therefore be better engagement, not simply increased interaction with AI.

6. Discussion

6.1 First-Year AI Feedback Literacy Should Be Explicitly Taught

The findings support the argument that feedback literacy should be treated as a first-year curriculum outcome rather than an implicit skill students are expected to develop independently. The transition into higher education creates a period in which students are learning not only disciplinary content but also what academic quality means and how feedback should be used. Carless and Boud's model establishes that feedback literacy involves appreciation, judgment, affect, and action, all of which require developmental opportunities. The introduction of GenAI adds a further requirement because students now need to judge both the academic meaning of feedback and the credibility of the system producing it. Nahar's 2026 first-year intervention provides encouraging evidence for explicit teaching. GenAI-supported activities within an Academic Skills module were associated with students' reported improvements in engagement, self-regulation, confidence, and emotional resilience. The educational significance lies less in the use of a particular AI platform than in the structured activity surrounding it. Students were given opportunities to engage with feedback processes rather than being left to seek AI advice independently.

A first-year AI-feedback-literacy curriculum could therefore begin with relatively simple tasks. Students might compare an AI response against a rubric, identify one accurate and one questionable suggestion, rewrite a vague AI comment into a specific revision goal, compare teacher and AI feedback on the same paragraph, or justify why a particular AI recommendation should be rejected. Such exercises make evaluative judgment visible and teach students that good AI use involves critique rather than compliance.

This approach can also reduce inequity. Students enter university with unequal prior exposure to generative AI, and Liu and Deris found that AI-use frequency was related to AI feedback literacy in their university sample. Structured first-year instruction can provide a common minimum foundation rather than allowing previous access or experimentation to determine who is most capable of using AI productively.

6.2 AI and Human Feedback Should Be Designed as Complementary Resources

The second major implication is that universities should avoid framing AI feedback as a replacement for teacher feedback. Henderson and colleagues' large study found that students valued AI feedback for accessibility and timeliness but placed particular trust in educator feedback and valued human contextual and disciplinary expertise. This suggests a complementary architecture in which different sources serve different functions.

AI can be particularly useful before formal submission. Students can ask for clarification of assessment criteria, test whether an argument is understandable, generate questions about weaknesses, compare alternative structures, or obtain iterative comments while drafting. Such use can reduce the tendency for feedback to occur only after an assessment has been completed.

Teacher feedback remains important where interpretation depends on disciplinary standards, course intentions, nuanced judgment, relational understanding, or individualized developmental priorities. Teachers can also challenge AI outputs and model expert evaluation for students. When an instructor explains why an apparently reasonable AI suggestion is inappropriate, students gain feedback literacy and disciplinary literacy simultaneously.

Peer feedback has a complementary role as well. Students develop evaluative judgment partly through assessing the work of others, articulating criteria, and encountering alternative interpretations. GenAI should therefore enrich a feedback ecology containing teacher, peer, self, and technological feedback rather than becoming the dominant source.

The same argument is supported by Jin and colleagues' finding that AI functionality produced uneven value depending upon students' needs and expectations. Effective feedback design should therefore ask which source is best suited to the learning purpose instead of assuming that more automated feedback is automatically better.

6.3 Critical Verification, Learner Agency, and Academic Integrity Must Remain Central

A third implication concerns the relationship between feedback literacy and academic responsibility. AI-generated feedback can easily shift from formative support into substantive rewriting. A student may begin by asking how to improve a paragraph and end by accepting a complete replacement written by the system. If the educational objective is to develop the student's reasoning and communication, technically improved output may conceal reduced learner engagement.

AI-supported feedback literacy should therefore include a boundary between feedback that supports decisions and generation that replaces decisions. Students should remain capable of explaining why they adopted a suggestion, how the revision improves the work, and whether the final expression represents their own reasoning.

Verification is central to this process. An AI response should be treated as provisional academic input rather than authoritative evaluation. Students need routines for comparing advice with rubrics, course materials, credible sources, instructor guidance, and disciplinary expectations. Henderson and colleagues report that students themselves expressed concerns regarding AI reliability and contextual expertise. Such concerns should be developed into structured critical practice rather than merely acknowledged as warnings.

Emotional dimensions also matter. Feedback can produce anxiety, defensiveness, disappointment, or uncertainty, especially during the first year when students are still forming an academic identity. Carless and Boud explicitly include managing affect within feedback literacy, and Nahar's first-year intervention found that students reported reduced anxiety and greater confidence after engaging in scaffolded GenAI-supported activities. AI may offer a low-pressure environment for asking follow-up questions, but institutions should ensure that students do not become isolated from supportive human dialogue.

The strongest educational model therefore combines critical AI use, explicit human oversight, reflective revision, transparent academic-integrity expectations, and opportunities for dialogue. Such a model treats students as developing evaluators rather than consumers of machine recommendations.

7. Conclusion

AI-supported feedback has the potential to expand students' access to formative guidance by making explanation, clarification, dialogue, and iterative revision support available at moments when teacher feedback may not be immediately accessible. The potential is particularly relevant for first-year students who are simultaneously learning disciplinary content, assessment conventions, university standards, and new expectations of independent learning. Yet feedback availability and feedback literacy are not equivalent. Students benefit most when they can understand what feedback means, evaluate whether it is appropriate, regulate their response to criticism, verify uncertain advice, and translate credible feedback into purposeful academic action.

The synthetic analysis developed in this study illustrates this relationship. Across 300 hypothetical first-year students, the mean AI Feedback Literacy Score was 60.5, with substantial dispersion across the cohort. The Advanced literacy group achieved higher simulated Feedback Uptake and Verification Behavior than the Developing group, while AI Feedback Literacy and Feedback Uptake demonstrated a positive synthetic association of r = 0.749. These results are not findings from real university students and should not be interpreted as empirical estimates. Their purpose is to demonstrate a measurable framework through which future research can examine how AI-supported feedback capabilities develop during the first year.

The broader pedagogical conclusion is that universities should move beyond two inadequate responses to generative AI: unrestricted student experimentation and blanket prohibition. Instead, first-year curricula should teach AI feedback literacy deliberately. Students should compare AI feedback with rubrics, interrogate weak suggestions, verify factual or disciplinary claims, examine differences between human and AI feedback, practice reflective revision, disclose AI assistance where required, and preserve responsibility for the intellectual decisions represented in submitted work. Teacher and peer feedback should remain central because recent research indicates that students value AI and human feedback for different reasons and continue to assign particular trust to educator judgment.

Future empirical research should test the proposed framework through longitudinal first-year studies rather than one-time attitude surveys alone. Researchers should examine changes in feedback literacy across semesters, observed revision quality, calibration between perceived and actual competence, disciplinary differences, multilingual learners, first-generation students, AI-access inequalities, emotional responses, and the transfer of feedback learning from one assessment to another. Experimental studies could compare teacher-only, AI-only, and blended feedback designs while maintaining clear academic-integrity boundaries. The principal goal should not be to produce students who are highly dependent on AI feedback, but students who are sufficiently feedback literate to use AI selectively, critically, ethically, and independently.

References

1. Carless, D., & Boud, D. (2018). The development of student feedback literacy: Enabling uptake of feedback. *Assessment & Evaluation in Higher Education, 43*(8), 1315–1325. https://doi.org/10.1080/02602938.2018.1463354.
2. Winstone, N. E., Mathlin, G., & Nash, R. A. (2019). Building feedback literacy: Students' perceptions of the Developing Engagement with Feedback Toolkit. *Frontiers in Education, 4*, 39. https://doi.org/10.3389/feduc.2019.00039.
3. Han, Y., & Xu, Y. (2020). The development of student feedback literacy: The influences of teacher feedback on peer feedback. *Assessment & Evaluation in Higher Education*, *45*(5), 680–696. https://doi.org/10.1080/02602938.2019.1689545.
4. Chong, S. W. (2020). Reconsidering student feedback literacy from an ecological perspective. *Assessment & Evaluation in Higher Education, 46*(1), 92–104. https://doi.org/10.1080/02602938.2020.1730765.
5. Zhang, Z. (2017). Student engagement with computer-generated feedback: A case study. *ELT Journal*, *71*(3), 317–328. https://doi.org/10.1093/elt/ccw089.
6. Bai, L., & Hu, G. (2017). In the face of fallible AWE feedback: How do students respond? *Educational Psychology*, *37*(1), 67–81. https://doi.org/10.1080/01443410.2016.1223275.

7. Roscoe, R. D., Wilson, J., Johnson, A. C., & Mayra, C. R. (2017). Presentation, expectations, and experience: Sources of student perceptions of automated writing evaluation. *Computers in Human Behavior, 70*, 207–221. https://doi.org/10.1016/j.chb.2016.12.076.
8. Zhu, M., Liu, O. L., & Lee, H.-S. (2020). The effect of automated feedback on revision behavior and learning gains in formative assessment of scientific argument writing. *Computers & Education, 143*, 103668. https://doi.org/10.1016/j.compedu.2019.103668.
9. Lee, H.-S., Pallant, A., Pryputniewicz, S., Lord, T., Mulholland, M., & Liu, O. L. (2019). Automated text scoring and real-time adjustable feedback: Supporting revision of scientific arguments involving uncertainty. *Science Education, 103*, 590–622. https://doi.org/10.1002/sce.21504.
10. Xiong, Y., & Wu, Y. F. B. (2019). An automated feedback system to support student learning in writing-to-learn activities. *Proceedings of the 6th ACM Conference on Learning at Scale*, 1–4. https://doi.org/10.1145/3330430.3333657.
11. Lee, Y.-J. (2017). A case study on the long-term effect of automated writing evaluation feedback on writing development. *Journal of the Korea English Education Society, 16*(4), 105–130. https://doi.org/10.18649/jkees.2017.16.4.105.
12. Ducasse, A. M., & Hill, K. (2019). Developing student feedback literacy using educational technology and the reflective feedback conversation. *Practitioner Research in Higher Education, 13*(1), 29–41.
13. Han, Y., & Xu, Y. (2021). Student feedback literacy and engagement with feedback: A case study of Chinese undergraduate students. *Teaching in Higher Education, 26*(2), 181–196. https://doi.org/10.1080/13562517.2019.1648410**.** [Online publication: 2019]
14. Winstone, N. E., Nash, R. A., Parker, M., & Rowntree, J. (2017). Supporting learners' agentic engagement with feedback: A systematic review and a taxonomy of recipience processes. *Educational Psychologist, 52*(1), 17–37.
15. Henderson, M., Ajjawi, R., Boud, D., & Molloy, E. (Eds.). (2019). *The Impact of Feedback in Higher Education: Improving Assessment Outcomes for Learners*. Palgrave Macmillan.
16. Ajjawi, R., & Boud, D. (2017). Researching feedback dialogue: An interactional analysis approach. *Assessment & Evaluation in Higher Education, 42*(2), 252–265.
17. Price, M., Handley, K., Millar, J., & O'Donovan, B. (2010). Feedback: All that effort, but what is the effect? *Assessment & Evaluation in Higher Education, 35*(3), 277–289.
18. Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in Higher Education, 31*(2), 199–218. https://doi.org/10.1080/03075070600572090.
19. Molloy, E., & Boud, D. (2013). Changing conceptions of feedback to improve student learning. In D. Boud & E. Molloy (Eds.), *Feedback in Higher and Professional Education: Understanding It and Doing It Well* (pp. 11–33). Routledge.
20. Sadler, D. R. (1989). Formative assessment and the design of instructional systems. *Instructional Science, 18*(2), 119–144. https://doi.org/10.1007/BF00117714.