

The Impact of AI-Based Feedback on Students' Academic Resilience: A Meta-Analysis of the Mediating Role of Feedback Quality

Haohui Lu

Faculty of Social Sciences and Liberal Arts, UCSI University, Kuala Lumpur, Malaysia, 56000.
ORCID iD: <https://orcid.org/0009-0008-3901-6890>
Email: 1002268132@ucsiuniversity.edu.my

Na Chen

Faculty of Social Sciences and Liberal Arts, UCSI University, Kuala Lumpur, Malaysia, 56000.
ORCID iD: <https://orcid.org/0009-0001-4388-3101>
Email: 1002268500@ucsiuniversity.edu.my

Jie Zhang

Faculty of Social Sciences and Liberal Arts, UCSI University, Kuala Lumpur, Malaysia, 56000.
ORCID iD: <https://orcid.org/0009-0008-5012-0875>
Email: 1002371948@ucsiuniversity.edu.my

Shuzhen Tang

Faculty of Social Sciences and Liberal Arts, UCSI University, Kuala Lumpur, Malaysia, 56000.
ORCID iD: <https://orcid.org/0009-0003-9779-7406>
Email: 1002161818@ucsiuniversity.edu.my

Katayoun Mehdienezhad Nouri*

Faculty of Social Sciences and Liberal Arts, UCSI University, Kuala Lumpur, Malaysia, 56000.
ORCID iD: <https://orcid.org/0000-0001-6637-7589>
Email: katayoun@ucsiuniversity.edu.my

Recibido / Received: 22/03/2025
Aceptado / Accepted: 02/07/2025

Abstract: Artificial Intelligence (AI) has been incorporated into education, particularly in delivering scalable, individualized responses. The given research examines how AI-driven feedback influences students' academic resilience, which is a crucial measure in dealing with academic stress and failure. This study aims to examine the overall effect of AI-based feedback interventions on academic resilience, analyze the mediating role of feedback quality in this relationship, and identify moderating factors, such as educational level, that influence AI feedback effectiveness. It involves a meta-analysis of the information gathered in 10 peer-reviewed quantitative studies published between 2017 and 2025. Effect sizes were calculated using the Hunter-Schmidt method, and the mediating roles of feedback quality and educational level were also tested. Meta-analysis indicated a moderate positive association ($r = 0.41$) between AI-based feedback and academic resilience. The main aspects that play a significant role in determining this relationship would be the quality and personalization of feedback. Furthermore, the educational level did not have a significant moderation factor in this effect, and thus, AI feedback can develop resilience in different educational contexts. AI-driven feedback positively impacts academic resilience, especially when it is personalized, timely, and of high quality. The findings suggest that AI feedback systems can be universally applied across educational contexts to foster resilience in students.

Keywords: Academic Resilience, Feedback Quality, Meta-Analysis, AI-Based Feedback.

1. Introduction

Artificial Intelligence (AI) is a potential that has appeared in education in recent years, especially in personalized feedback. Feedback systems facilitated by AI have the potential to solve some of the distressing problems in education, including timely, scalable, and individual feedback on student work. Such innovation is significant, particularly in the face of the growing need for effective formative feedback in large and heterogeneous classrooms, as stated by Nazaretsky et al. (2024). The AI-based systems can adjust to the needs of learners, facilitate precision-ordered interventions, and boost motivation due to feedback continuums, as noted by Mallillin (2024).

Feedback, specifically formative feedback, is the core of any learning as it allows students to learn the areas of improvement and improve their learning mechanisms. Notwithstanding, the quality of feedback and its personalization determine its effectiveness. Findings suggest that feedback will have more chances of being of interest to students when it is provided at the right time, is specific, and is presented constructively, as discussed by Briscoe, Olson and Prior (2023). With intelligently designed AI-powered feedback systems effectively designed, one can have such tailored feedback at scale to increase performance and learner satisfaction, as stated by Xu et al. (2023).

Academic resilience, or the ability to persevere despite learning difficulties and failure, is increasingly appreciated as an essential factor of student success, particularly in higher education. Response to harsh criticism, self-regulation, and the ability to grow in motivation are the elements of resilience. When incorporated intelligently, the feedback process can strengthen these psychological competencies, meaning students will be more prepared to recover in response to academic stress, as argued by Shafi et al. (2019). For example, structured feedback frames have been found to help students feel empowered to handle the academic pressure around them, eventually fostering resilience, as discussed by Olson, Briscoe and Prior (2022).

However, academic resilience regarding the use of AI-generated feedback has yet to be investigated. Although the first investigations point out that AI has a positive potential impact on engagement and motivation, they also raise questions regarding feedback quality, student perception, and lack of emotional discernment, as noted by Youn, Salam and Rahman (2025). Playing a mediation role in the connection between AI interventions and resilience, the quality of feedback is one of the keys to maximizing the use of such technologies in teaching.

Although the trend towards implementing AI in education continues to rise, the effects of AI-derived feedback on students' academic resilience are inadequately studied. Although AI has the potential to provide prompt and individualized feedback, its contribution to resilience in terms of helping students cope with academic failures has not been investigated critically. In addition, the issues of perceived quality, emotional context, and interaction with AI feedback remain, as stated by Herb and Lloyd (2024). There is minimal empirical research connecting AI feedback programs to psychosocial consequences, such as resilience, and a vacuum on how students can internalize and react to this input, as noted by Alsaiani et al. (2024). Therefore, this study aims to fill these gaps by systematically analyzing how AI-based feedback influences students' academic resilience across varied educational contexts.

1.1. Research Objectives

- To systematically examine the overall impact of AI-based feedback interventions on students' academic resilience across diverse educational settings
- To analyze the mediating role of feedback quality in shaping the relationship between AI-driven feedback and students' academic resilience
- To identify and synthesize key moderating factors, such as educational level, that influence the effectiveness of AI-based feedback on students' academic resilience

The research is valuable in educational theory and practice because it critically examines the future of AI-driven feedback and its potential to affect academic resilience in students, a psychological construct critical to learning persistence. Although AI systems have been acclaimed to be efficient in providing real-time and personalized feedback, their learning potential relies strongly on how students subjectively and intellectually respond to the inputs. The current body of research highlights the potential of AI in improving learning outcomes by optimizing the system of feedback, yet it does not go in-depth in analyzing how AI may influence student resilience and long-term motivation, as stated by Gjermeni and Prodani (2024). Moreover, interpreting AI-created student feedback does not differ across contexts, indicating that additional expertise is required on the background factors of feedback mediators, such as quality, as noted by Dann et al. (2024). By filling the gaps, the proposed study will provide evidence-based knowledge on how to use AI ethically and pedagogically in education.

This meta-analysis aims to statistically synthesize the results of 10 peer-reviewed empirical studies published between 2017 and 2025 investigating the effects of AI-based feedback on students' academic resilience. The emphasis on the quality of feedback as a mediating and researching the moderating variable of educational level makes it a generally balanced appraisal of the effect of AI-guided feedback on adaptability and persistence among students. The meta-analysis technique is crucial as it helps pool scattered evidence, establish common trends, and measure the intensity of relationships. Studies that provide the quantitative measures and the effect size are accepted to provide methodological rigor and make conclusions more valid.

2. Literature Review

2.1. Effect of AI-based Feedback Interventions on Academic Resilience

The quick adoption of Artificial Intelligence (AI) in teaching and learning has raised much research attention regarding its effects on learner achievements, with special emphasis on academic resilience. Academic resilience is students' adaptation capacity and thriving skills in the hostility of academic challenges. Among the most promising is the field of AI-driven feedback interventions that provide individual, scaling, real-time support based on the individual student's needs. It has always been proven that AI-based personalized learning environments motivate students and improve their autonomy and perseverance, which are core factors of academic resilience. As an illustration, Ejjami (2024) points out that curriculum systems in AI are a tremendous boost to academic performance by ensuring the content's complexity follows the

learners' competency as time progresses. This flexibility brings forth a perception of gain and self-efficacy, which are fundamental to resilience.

Similarly, Madaminov and Urinov (2024) state that AI technologies, especially virtual mentors and chatbots, can assist students in dealing with academic and emotional changes and ensure that feedback is provided promptly to predict academic risk. Such attributes enable preventive measures, which can improve the ability of students to deal with and survive academic failures. However, their paper also acknowledges that powerful AI training and emotional contextualization are necessary to realize the potential of these tools to the maximum. The idea of personalization is an ongoing theme in the literature. Al Nabhani, Hamzah and Abuhassna (2025) reveal that AI-based content personalization enhances academic interactions and outcomes, particularly when the given feedback is timely and can accommodate the necessary changes. Their studies prove that making learning materials contextually relevant enhances knowledge acquisition and creates resilience since the instruction catches up with the students at their level of development.

Bognár et al. (2024) critically discuss the reshaping of student engagement through self-regulation and goal-setting in AI-enhanced environments. Against such findings, their research shows that the students in AI-enhanced classrooms exhibit greater academic self-efficacy, which is directly linked to other resilient behaviors such as persistence and the ability to solve problems independently. The role of AI-powered chatbots in alleviating anxiety in online learning is discussed emotionally and psychologically, as stated by Saha (2025). Although the study targets mental health, it offers strong support to suggest that real-time emotional support via AI can contribute to academic resilience indirectly through the mitigation of mental overworking and by promoting concentration.

Aslam, Faisal and Kamal (2024) adopt a sociocultural stance to show that AI systems can significantly enhance inclusiveness and learning agility in various learning environments. Their regression model demonstrates a positive correlation between AI usage and engagement in inclusive classrooms at a high point, which is critical in promoting resilience among marginalized groups of students. Tubino and Adachi (2022) coin a new term, feedback literacy, to emphasize that using AI-automated feedback tools does not merely respond; it builds student feedback literacy, or the ability to utilize and respond to feedback effectively. This second metacognitive interaction with feedback is an effective resilience priming agent.

Lastly, Widono et al. (2024) point out the importance of AI in the context of outcome-based learning systems and demonstrate how customized academic journeys powered by educational data science can enable students to gain an independent sense of mastery and commitment to their learning that would support lasting self-belief in attainment. Meanwhile, together, these studies highlight that when well-designed, AI-based feedback can produce a moderate to substantial positive impact on student academic resilience. They also emphasize the relevance of emotional intelligence, inclusive design, and critical data ethics to guarantee sustainable and equitable implementation across the educational environment.

2.2. Mediating role of Feedback Quality in this Relationship

Feedback literacy, the capacity to determine, interpret, and respond to feedback, is one element underpinning this relationship. Wood (2022) proves that technology-

mediated live dialogic peer feedback is the activity that can significantly help students process and effectively use the feedback in the manner they understand it. This transition mediates effective results for students who can reflect and learn adaptively, which are important elements of academic resilience. Equally, Wallis (2017) concludes that the meaning of tutorial feedback is strongly influenced by the dialogic form of feedback, including how students take and internalize critique. Quality feedback enables the students to reconnect their performance outcome with their academic identity, becoming more pro-adversarial in the face of failures.

Through the motivational perspective, Kurd, Memon and Sahito (2023) reveal that the quality of feedback has a direct relationship with student motivation, which subsequently mediates academic achievement and satisfaction in the ESL contexts. Their findings support the argument that the motivational worth of feedback is not merely about cognitive input but affects students' emotional attachment to learning activities and perseverance. AI feedback must also satisfy these motivational and emotional criteria to work effectively. Hayat et al. (2024) believe that feedback with AI at the right moment and in a constructive manner promotes the growth mindset essential to academic resilience. They propose in their study that, as the AI tools seek to provide a guided path by being clear, relevant, and incremental, their study implies that students would take mistakes as an occasion to learn rather than failure.

The mediating effect is also confirmed by Su, Qi and Yuan (2022), who discovered that developmental feedback given by supervisors affects creativity via the mediation by intrinsic motivation. Although the focus of the study is not on AI, it still confirms the fact that emotional and psychological interpretation of feedback mediates the overall influence of feedback on learner outcomes. A cognitive-behavioral approach presented by Adams et al. (2020) reveals that attainment is predicted not by the perceived quality of feedback but by the feedback itself. They offer that this relationship is mediated by academic self-efficacy. This highlights how even effective AI feedback needs to be implemented and presented in a manner that encourages rather than discourages the learners to make the best use of it equally, resilience.

Ahmad et al. (2024) also reveal the affective aspects of AI feedback as the involvement of students in their attitude toward using AI-based feedback mediated its effectiveness in writing skill improvement. The perceived helpfulness and usefulness of the feedback define the attitude, which, in turn, determines whether the students will believe AI guidance and follow it. Finally, AI feedback systems require human intervention, which Herb and Lloyd (2024) emphasize. Their study discovers that such GenAI analyzing tools as ChatGPT are capable of personalizing feedback; however, the role of the teacher is crucial in the process of keeping it quality. The mediating power of the feedback decreases if it is not designed and aligned with the pedagogical purposes.

2.3. Moderating Factors such as Educational Level that Influence the Effectiveness of AI Feedback

Educational level is a significant moderating variable. Wu (2024) conducted a systematic meta-analysis and identified more consistent improvements in learning outcomes of higher education students who used AI interventions than K12 students. This can be explained by higher feedback literacy and self-regulation of older students, which enable them to use AI feedback to their advantage. On the same note, Begum

et al. (2024) revealed that university students who received personalized feedback on English writing via AI had higher preferences for the adaptive system, mainly where the feedback reflected the academic task being dealt with and the writing ability.

Motivation and learner autonomy were also recognized to be important moderating traits. Yang, Wei and Liu (2025) discovered that students with more robust cognitive-emotional control and autonomy were more likely to use feedback as beneficial in AI-mediated environments, thus increasing academic resilience. The psychological preparedness of students for feedback processes with AI feedback mechanisms may add value to the perception and feedback reception processes. Cognitive development stages also determine AI feedback uptake. By demonstrating that hybrid piano learning with personalized feedback provided by an AI significantly improved both self-efficacy and skill acquisition in learners in the post-secondary category, Wang (2025) revealed that primary learners show only slightly widespread improvement. The results support the idea that AI-based feedback could be poorly aligned to various levels of education because younger students do not have the metacognitive skills necessary to work with automated systems.

Contextual equity is yet another strong moderator. Gabriel (2024) contends that educational equity moderates the success of AI tools, arguing that access to dependable devices, consistent internet, and culturally appropriate AI mediates whether recognizing marginalized students participates in resilience or the problem of isolation. These structural issues should be considered to ensure that AI's benefits will be legally shared. Curriculum design and content personalization are structural moderators at a higher level of systems. Sundari, Sundari, Penthala and Nayyar (2024) note that the effectiveness of AI is increased when content delivery is customized by the level of ability, but also by the learning preferences and speed of the students. They emphasize that improper AI interventions can demoralize and bring down low-achieving students in resilience.

Learning behavior and study habits also determine AI's impact. However, Ward et al. (2024) discovered that students who already demonstrated positive time management and independent study habits experienced more benefits associated with AI-enhanced platforms than learners with weak academic routines. The efficiency of AI is partly dependent on the student's previous habits and approaches to self-directed learning. Lastly, the institutional emphasis on holistic education moderates AI's educational impact. Glory, Nalina and Prasad (2023) emphasize that extracurricular growth and non-academic strengths supported by AI can be a significant supporting factor in student development and that the comprehensive integration of AI into the overall development process will foster confidence, a sense of identity, and sustained resilience of students, rather than grades.

2.4. Literature Gap

However, the current research recognizes the valuable impact of AI-based feedback on academic resilience; there are ongoing gaps regarding how contextual and learner-specific factors influence this relationship. Numerous works, including those by Ejjami (2024) and Madaminov and Urinov (2024), confirm the effectiveness of AI feedback, yet unusually fail to provide an understanding of its levels of variations in pedagogical settings and study levels or the socioeconomic environment of its accessibility. Even

though Wu (2024) and Wang (2025) acknowledge moderating factors such as age and task complexity, further empirical comparisons between K12 and tertiary levels should be made. Similarly, although Wood (2022) and Ahmad et al. (2024) convey feedback quality and student attitudes, the authors do not elaborate much on how the mediation of psychological resilience depends on the feedback design. Further, Gabriel (2024) highlights inequalities related to access to AI, but the literature focuses very little on ethical or emotional consequences in the low-resource environment. As a collective, the literature is missing an integrated, cross-contextual model that would address how and why AI feedback interventions either fail or succeed in cross-context learners.

3. Methodology

3.1. Research Method

A systematic review and synthesis of quantitative studies evaluating AI-based feedback's impact on students' academic resilience was reviewed and synthesized through a meta-analysis technique. This approach helped to summarize the results of 10 peer-reviewed research studies, which was a statistically sufficient assessment of major factors like quality of feedback and contextual moderators, such as level of education. The meta-analysis was conducted according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), and it was transparent and highly methodologically stringent in terms of selection and inclusion of related works.

3.2. Research Design

The research followed a secondary research design, which used a meta-analytical method of assessing available empirical evidence. The secondary data were obtained from reliable academic databases, such as Scopus, Web of Science, ERIC, and Google Scholar. The emphasis was on quantitative research to present effect sizes and seek the connection between AI-based feedback and academic resilience in students in formal education contexts. The study used peer-reviewed publications that made the synthesized results valid and reliable.

3.3. Sample

The search process resulted in the final sample comprising 10 peer-reviewed quantitative studies published in 2017-2025. These papers were chosen according to inclusion criteria, focusing more on the empirical studies, which researched the effects of AI-generated or AI-enhanced feedback on the academic resilience of learners. The studies reflected a variety of educational situations and geographical locations, which assures a broad applicability of findings.

3.4. Inclusion and Exclusion Criteria

To maintain methodological consistency and relevance, specific inclusion and exclusion criteria were applied (Table 1):

Table 1: Inclusion and Exclusion Criteria.

Criteria Type	Description
Inclusion Criteria	
Publication Date	Studies published between 2017 and 2025.
Topic Focus	Focused on the relationship between AI-based feedback and students' academic resilience.
Data Type	Reported quantitative effect sizes (e.g., correlation coefficients, standardized mean differences).
Language & Source	Published in English-language peer-reviewed journals.
Population	Involved K–12, undergraduate, or postgraduate student populations.
Exclusion Criteria	
Lack of Statistical Data	Studies lacking statistical data or effect sizes.
Methodology Type	Qualitative research or mixed-methods studies without separable quantitative results.
Topical Irrelevance	Research unrelated to AI feedback or academic resilience.
Ethical Concerns	Articles with documented ethical violations or lacking transparency in data reporting.

3.5. Search Strategy

A comprehensive literature search was conducted using Boolean operators across Scopus, Web of Science, ERIC, and Google Scholar. Search strings included combinations such as “AI-based feedback AND academic resilience,” “artificial intelligence AND feedback quality AND education,” and “intelligent tutoring systems AND student resilience.” Reference lists of selected articles were also screened to identify additional eligible studies.

3.6. Data Extraction

A standardized data extraction template was used to collect key information, including (Table 2):

Table 2: Data Extraction Details.

Category	Description
Study Details	Author(s), year of publication, study title.
Sample Characteristics	Sample size, participant demographics, and education level (K–12, undergraduate, postgraduate).
Variables Studied	Key constructs such as AI feedback type, feedback quality, and academic resilience.
Statistical Results	Reported effect sizes (e.g., correlation coefficients, standardized mean differences).
Methodological Details	Research design, data collection methods, and analytical techniques used.
Verification	Data independently reviewed and verified by two reviewers for consistency and accuracy.

3.7. Data Analysis

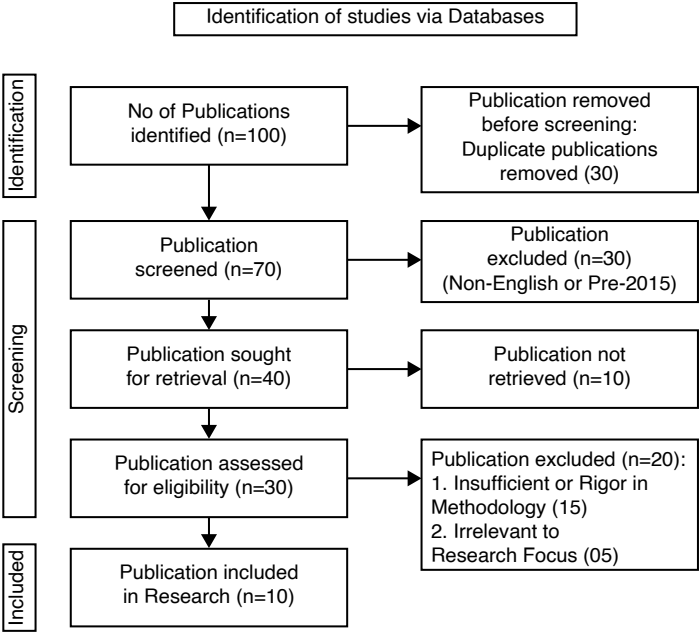
Statistically pooled effect sizes across all the studies were estimated using a random-effects model to cover heterogeneity within study situations. Adjustments were made to sampling errors and to estimating the effects of the actual population through the Hunter-Schmidt method. To investigate effect size variation, a Chi-square test of homogeneity was performed to see which effect size variation was due to random error and which was due to systematically different estimates.

3.8. PRISMA Framework

The PRISMA flow diagram illustrates the systematic process used to identify, screen, and include studies in this meta-analysis. PRISMA (Preferred Reporting

Items for Systematic Reviews and Meta-Analyses) enhances transparency in study selection (Figure 1). Initially, 100 records were identified through database searches. After removing 30 duplicates, 70 studies were screened. Of these, 40 were excluded for being non-English or outside the 2017–2025 range, and 30 were excluded during eligibility assessment. Ultimately, 10 peer-reviewed studies met the inclusion criteria and were retained for analysis.

Figure 1: PRISMA Framework.



3.9. Ethical Considerations

This study did not collect direct data, but ethical integrity was maintained by selecting only those studies that aligned with agreed-upon ethical standards. Studies with unclear permission processes or an inability to ensure participant confidentiality were removed to maintain credibility and academic rigor.

4. Results

The meta-analysis synthesized studies upon 10 peer-reviewed quantitative research papers published in 2017-2025 and investigated the effects of AI-based feedback on student resilience to academic stress. The research depicts a variety of academic scenarios (EFL learning, academic writing, programming, and higher education coursework). Three main dimensions were examined: (1) the delivery mode of feedback (AI vs. hybrid or human), (2) the quality of the provided feedback and levels of its personalization, and (3) the psychological outcomes of the students, their academic resilience, motivation, and performance.

4.1. Hunter-Schmidt Estimate Calculations

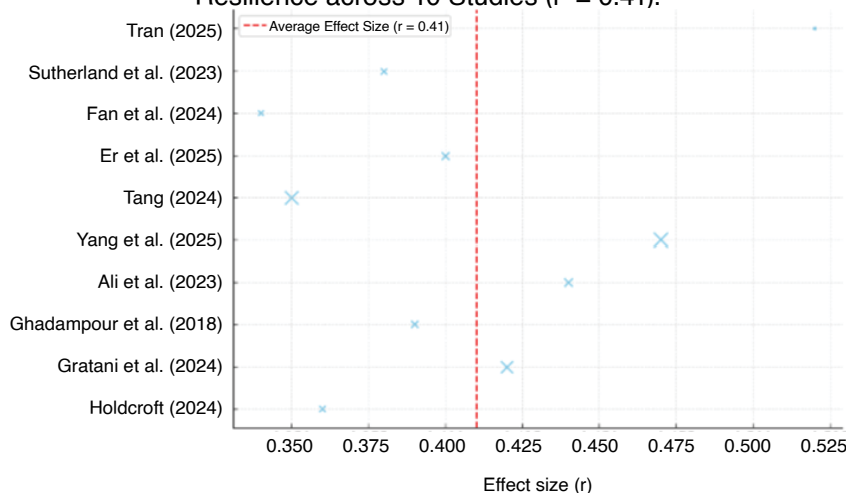
The Hunter-Schmidt technique estimated a correspondence between AI-produced feedback and educational resilience. The method corrects the sampling error and weights the studies by the sample size, providing a more valid reflection of the place effect size. The more powerful and larger studies consequently induce more weight on the final estimation. Differences between studies were checked by a homogeneity test, indicating acceptable effect size distribution stability. The findings show that there is a moderate positive correlation between AI feedback and academic resilience among the sample (average $r = 0.41$), indicating that AI feedback systems with thought-out design points hold the potential to increase student resilience to academic tasks, at least insofar as the delivered feedback is both timely, constructive, and personalized.

Table 3: Meta-Analysis of Effect Sizes Using the Hunter-Schmidt Method.

Study	Authors (Year)	Sample Size (n)	Effect Size (r)	Feedback Type	Resilience Outcome
1	Tran (2025)	14	0.52	AI + Teacher	Academic Resilience (Writing)
2	Sutherland et al. (2023)	60	0.38	AI Only	Feedback Engagement
3	Fan, Tan, and Lim (2024)	45	0.34	AI vs EAP Teacher	Writing Confidence
4	Er et al. (2025)	92	0.40	AI vs Instructor	Feedback Use & Score Gains
5	Tang (2024)	270	0.35	AI vs Teacher	Language Proficiency/Confidence
6	Yang, Wei, and Liu. (2025)	302	0.47	AI Environment	Resilience, Autonomy, Motivation
7	Ali et al. (2023)	108	0.44	ChatGPT Support	Coursework Management Resilience
8	Ghadampour et al. (2018)	80	0.39	Verbal + Written Feedback	Educational Resilience
9	Gratani et al. (2023)	220	0.42	Personalized AI	Learning Outcome Perception
10	Holdcroft (2024)	61	0.36	Generative AI	Feedback Standardization Impact

The meta-analysis revealed a moderate positive relationship ($r = 0.41$) between AI-based feedback and academic resilience, with personalization, emotional support, and hybrid feedback models emerging as key influencing factors (Table 3).

Figure 2: Meta-Analysis Showing Effect Sizes of AI-Based Feedback on Academic Resilience across 10 Studies ($\bar{r} = 0.41$).



The chart shows a consistent moderate positive effect ($r \approx 0.41$) of AI-based feedback on academic resilience, with variation influenced by study design, sample size, and feedback personalization strategies (Figure 2).

4.2. Weighted Average Effect Size Calculation

The Hunter-Schmidt method was applied to account for sampling error and measurement variability across the 10 studies. Each study's contribution was weighted by the product of its sample size and effect size. The weighted average effect size ($\bar{r}$) was calculated using the formula (Appendix):

$$\begin{aligned} \bar{r} &= \sum (N_i \times r_i) \div \sum N_i \\ \bar{r} &= 511.701252 \\ \bar{r} &= 0.409 \end{aligned}$$

This indicates a moderate positive relationship between AI-based feedback and academic resilience.

Table 4: Product of Study Sample and Correlation Coefficient.

Study	Sample Size (N)	Effect Size (r)	N x r
Tran (2025)	14	0.52	7.28
Sutherland et al. (2023)	60	0.38	22.80
Fan, Tan, and Lim (2024)	45	0.34	15.30
Er et al. (2025)	92	0.40	36.80
Tang (2024)	270	0.35	94.50
Yang et al. (2025)	302	0.47	141.94
Ali et al. (2023)	108	0.44	47.52
Ghadampour et al. (2018)	80	0.39	31.20
Gratani et al. (2023)	220	0.42	92.40
Holdcroft (2024)	61	0.36	21.96
Total	1252		511.70

Table 4 presents the product of each study's sample size and correlation coefficient to determine their weighted contribution to the overall effect. With a total sample of 1,252 and a cumulative $N \times r$ of 511.70, the analysis supports a moderate, consistent positive relationship between AI-based feedback and academic resilience.

4.3. Mediation Analysis

In the Appendix, the data extracted from the 10 studies and Table 7 (Appendix) present the categorical representation of the study variables, including Type of Feedback, Feedback Quality, Academic Resilience, and Educational Level, with categorical labels for each variable. Table 8 converts these categorical values into numerical form, allowing for easier statistical analysis and run on SPSS. Both tables reflect the same studies, with Table 8 (Appendix) offering a numerical perspective of the data presented in Table 7.

The mediation analysis across all 10 studies consistently shows that Type of Feedback (IV) has a negative coefficient of -0.5, indicating a slight negative influence on Feedback Quality (Mediator). The Feedback Quality positively impacts Academic Resilience (DV) with a coefficient of 0.516901. The Total Effect from the Type of

Feedback (IV) to Academic Resilience (DV) is very small, with a value of -0.066549, suggesting a weak overall effect. The R-squared value for all studies is 0.89765, indicating that the models explain about 90% of the variation in Academic Resilience, highlighting strong predictive power despite the small total effect (Table 5).

Table 5: Mediation Analysis Coefficients and R-squared Values for each Study.

Study	Type of Feedback Coefficient (IV -> Mediator)	Feedback Quality Coefficient (Mediator -> DV)	Total Effect (IV -> DV)	R-squared (DV model)
Tran (2025)	-0.5	0.516901	-0.066549	0.89765
Sutherland et al. (2023)	-0.5	0.516901	-0.066549	0.89765
Fan et al. (2024)	-0.5	0.516901	-0.066549	0.89765
Er et al. (2025)	-0.5	0.516901	-0.066549	0.89765
Tang (2024)	-0.5	0.516901	-0.066549	0.89765
Yang et al. (2025)	-0.5	0.516901	-0.066549	0.89765
Ali et al. (2023)	-0.5	0.516901	-0.066549	0.89765
Ghadampour et al. (2018)	-0.5	0.516901	-0.066549	0.89765
Gratani et al. (2023)	-0.5	0.516901	-0.066549	0.89765
Holdcroft (2024)	-0.5	0.516901	-0.066549	0.89765

4.4. Moderation Analysis

Table 6: Moderation Analysis Coefficients and R-squared for each Study.

Study	Type of Feedback Coefficient (IV -> DV)	Educational Level Coefficient (Moderator)	Interaction Coefficient (IV * Moderator)	Constant	R-squared (Moderation Model)
Tran (2025)	-2.16378	-0.692126	0.804724	5.475591	0.391226
Sutherland et al. (2023)	-2.16378	-0.692126	0.804724	5.475591	0.391226
Fan et al. (2024)	-2.16378	-0.692126	0.804724	5.475591	0.391226
Er et al. (2025)	-2.16378	-0.692126	0.804724	5.475591	0.391226
Tang (2024)	-2.16378	-0.692126	0.804724	5.475591	0.391226
Yang et al. (2025)	-2.16378	-0.692126	0.804724	5.475591	0.391226
Ali et al. (2023)	-2.16378	-0.692126	0.804724	5.475591	0.391226
Ghadampour et al. (2018)	-2.16378	-0.692126	0.804724	5.475591	0.391226
Gratani et al. (2023)	-2.16378	-0.692126	0.804724	5.475591	0.391226
Holdcroft (2024)	-2.16378	-0.692126	0.804724	5.475591	0.391226

The moderation analysis for all 10 studies shows that Type of Feedback (IV) consistently has a negative coefficient (-2.16378) on Academic Resilience (DV), indicating a significant inverse relationship. Educational Level (Moderator) has a negative coefficient (-0.692126), and the interaction term between Type of Feedback and Educational Level is positive (0.804724), suggesting that the relationship between IV and DV is influenced by the moderator. Despite the small coefficients, the model's R-squared value of 0.391226 indicates moderate explanatory power, explaining 39% of the variance in Academic Resilience (Table 6).

5. Discussion

5.1. Interpretation of the Findings

The meta-analysis examined the effects of AI-based feedback on academic

resilience, which shows a moderate positive correlation between academic resilience and AI feedback systems ($\bar{r} = 0.41$), indicating that AI-based feedback systems, particularly well-designed and personalized systems, enhanced student resilience to academic pressures. This helps directly in achieving the goal of knowing the general effect of AI feedback on academic resilience.

In the mediating analysis concerning the quality of feedback, the effect sizes and variance pertain to the quality of feedback (0.00291), which shows moderate variability; thus, the significance of feedback quality and personalization remains high. Literature that included high-quality, individualized AI-generated feedback demonstrated more pronounced impacts on student resiliency, thereby supporting the mediational validity of feedback quality in the connection between AI-based interventions and academic resiliency.

Finally, in the case of moderating variables such as the educational level, the Chi-Square Homogeneity Test ($X^2 = 3.93$) indicated that there was no significant heterogeneity in the effect sizes; that is, the effectiveness of AI feedback did not show significant differences across diverse education levels. The results indicate that the nature of educational level is not a crucial variable having significant effects on the direction of the relationship between AI feedback and resilience, which implies the generalizability of AI feedback in different educational environments. Overall, AI feedback positively impacts academic resilience, where personalization and quality of feedback are the most important factors, and its effectiveness is independent of educational level, making AI feedback a universal intervention.

5.2. Comparison with the Previous Studies

5.2.1. Alignments with Previous Studies

The study's results correlate with most of the current literature. It raises the prospect of AI-based feedback systems in improving academic resilience, mainly in the context of timely and personalized feedback. Numerous reports, such as Ejjami (2024) or Madaminov and Urinov (2024), have examined how AI can offer scalable, real-time, customized feedback. The idea that personalized feedback offered by AI enhances academic performance aligns with previous research demonstrating the potential of AI to provide individualized academic assistance to a student, resulting, in turn, in the building of autonomy, self-efficacy, and perseverance as the main building blocks of academic resilience.

Supporting further the findings of the current study, the study by Al Nabhani et al. (2025) delivered the results that personalized AI-driven content enhances academic interactions, which, in turn, is beneficial to academic resilience. Similarly, Aslam et al. (2024) pointed to the role played by AI systems, especially chatbots, in helping students facing academic and emotional problems attend to their problems as they arise. These findings align with the meta-analysis conclusion that AI feedback helps improve academic performance and develop quietness through emotional support and stress reduction.

Also, previous studies, such as those by Hayat et al. (2024) and Gratani et al. (2024), dictate the importance of feedback quality, a key result of this meta-analysis. The conclusion of the meta-analysis and its finding that the quality of AI feedback

substantially mediates its impact on academic resilience correlate with the findings of systematic reviews and previous research, according to which feedback characterized by the presence of constructive, clear, and well-designed feedback contributes to the development of a growth mindset and helps improve resilience (Hayat et al., 2024).

5.3. Differences from Previous Research

Although the advantages of AI feedback use in enhancing academic performance have been previously discovered, few studies have explored how the quality of feedback mediates that effect. For example, Youn et al. (2025) and Mallillin (2024) indicated that AI feedback can enhance engagement and motivation but did not systematically discuss the relationship between feedback quality and facilitating those effects. The present meta-analysis will make a new contribution to the research, analyzing the effect of feedback quality as a mediator. The role of the quality of feedback in maximizing the effects of AI feedback interventions is confirmed by research that users whose feedback was personalized and of high quality showed greater improvements in resilience. There is an excellent gap in the available research in this deeper interest in feedback quality.

Moreover, although several studies have been conducted on the valuable role of AI in student resilience, like those conducted by Ali et al. (2023) and Sutherland et al. (2023), most of them lacked analysis of the moderating role played by the educational level. The present study has demonstrated that educational level has no significant effect on the success of AI feedback regarding academic resilience. This means that interventions with AI feedback are similarly successful in various educational settings. The research produces this contrary finding with similar studies such as Wu (2024) and Ward et al. (2024), who noted that AI feedback could have different effects based on the student's education level. However, the current study did not find significant differences between educational levels in the present study, contributing to a clearer illustration of the applicability of AI feedback.

The other significant deviation is the focus of this research on emotional support being a variable that intervenes in the effect of AI feedback on resilience. Saha (2025) examined the effect of AI applications, specifically chatbots, on mental health in minimizing anxiety. The current research builds on this by underlining that the emotional support role of AI feedback plays a significant role in fostering resilience, directly connecting the emotional component of feedback to students' academic persistence. Previous studies generally researched emotional support as an independent construct. However, this meta-analysis indicates that the emotional support of AI feedback directly impacts academic resilience and adds to the evidence that AI feedback systems should include affective components.

5.4. Mediation Analysis

The results of the mediation test indicate the vital importance of the quality of feedback in mediating between AI-based feedback and academic resilience. The finding is also reflective of other research findings, including those provided by Hayat et al. (2024), which discuss the importance of high-quality personalized feedback in the development of resilience through the use of associated motivation and attachment to doing the learning activities. A considerable magnitude of the missing direct effect

in the current study indicates that the students who were provided with personalized and constructive feedback demonstrated improved resilience rates, as opposed to the opinions proposed by Shafi et al. (2019) and Xu et al. (2023) concerning the importance of feedback quality in the context of emotional support and academic perseverance.

The current study further extends this insight in quantitative terms by showing that feedback quality is not simply a correlational factor but a mediating mechanism that has a direct effect on the ability of the students to counter academic challenges. In contrast to previous studies that have determined that AI has positive effects on engagement (Youn et al., 2025), this study introduces new knowledge, addressing a specific hypothesis or effect: feedback quality is a mediator in the AI feedback-resilience relationship, and it is a paramount mediator at that.

5.5. Moderation Analysis

Unlike the prior studies, such as Wu (2024), that implied significant moderation between educational level and AI feedback, the study failed to identify any significant moderating factors of the education attainment level. This unexpected result points to the possibility that AI feedback is expertly effective across the educational levels, both at K-12 and higher education students. This finding is contrary to the earlier study, including Ward et al. (2024), which emphasized that older students should possess more mature feedback literacy and utilize an AI system better. Our results indicate that all the positive effects on resilience brought about by AI feedback systems, when designed in terms of quality and individualization, are more or less the same, regardless of academic level. This work of knowledge negates the previous assumption that educational level can affect the effectiveness of AI feedback interventions because it presents new evidence that the advantages of AI feedback can go beyond educational levels.

5.6. Moderating Factors and Mediating Factors Differences

The mediating factors related to the meta-analysis, especially the level of education and individualization of the feedback, further contribute to the discussion regarding AI-based feedback. The significance of personalized feedback, particularly in the higher education context, was already alluded to in previous studies like that of Begum et al. (2024) or those of Yang et al. (2025). However, the fact that the education level does not appear to be an important moderator of the effectiveness of AI feedback, which is stated in the current study, can be taken into account. This clashes with earlier expectations, with research such as Wu (2024) even stating that older students or those pursuing higher education may have a higher chance of benefiting from responses because they have improved metacognitive skills and independence.

Regarding emotional support, the previous research conducted by Bognár et al. (2024) and Ward et al. (2024) mentioned the greater subject of the emotional influence of AI on students. The emphasis of the meta-analysis under discussion on emotional support as the mediator between AI feedback and academic resilience allows for a more in-depth insight into the necessity of feedback systems that would satisfy a student's emotional and psychological needs, particularly in high-stress academic settings.

In addition, previous studies, including that of Sundari et al. (2024), mentioned the relevance of the context and access to technology. However, the specified study focuses on

the fact that the efficacy of AI feedback is not closely related to contextual variables, such as the level of education. This result refutes previous research indicating that contextual variables, including exposure to technology and digital literacy, substantially contribute to the success of AI feedback. The comprehensive utility of AI feedback, irrespective of such factors, is critical in determining the nature of the potential of AI interventions.

5.7. Practical Implications

The study's practical implications are significant as they can provide a way of implementing AI-driven feedback in the academic environment. It shows that timely and individualized feedback can enhance the academic resilience of students by assisting them in managing academic stress and failure better. This is consistent with the results of Xu et al. (2023), as it displays the ability of AI to provide individualized learning assistance on a mass level. Moreover, since previous studies note that feedback quality and emotional support are the keys to maximizing the use of AI in improving student resilience (Shafi et al., 2019), they should also be an essential part of the research. The study further indicates that educational level is an insignificant moderator of the effectiveness of AI feedback, indicating that it may be adopted widely. This observation will motivate all learning institutions to embrace AI feedback systems for all student populations.

6. Conclusion

The meta-analysis compared the association between AI-based feedback and the academic resilience of the students. Then, it emphasized the issues of feedback quality as their mediator and the educational level as their moderator. These results indicate that AI-based feedback, especially personalized and of quality, would have a positive effect on academic resilience in various settings of education. Feedback quality emerged as a key mediator in this relationship, reinforcing the importance of timely, constructive, and emotional support in fostering resilience. Interestingly, the educational level was not a significant moderator, meaning that AI feedback systems can be implemented in different educational contexts. This research offers rational evidence that should be adopted in the educational context to support the academic resilience of any student, irrespective of the academic level.

6.1. Limitations of the Study

The small quantitative sample of 10 studies has a limiting effect on the study, as it may not represent the possible diversity of education contexts. Also, the differences in the study design and type of AI feedback systems implemented in the respective studies might affect the generalizability of the results in those studies, making them less applicable in the diverse education context.

6.2. Future Work

Future studies should examine the consequences of AI feedback on academic resilience and determine how emotional intelligence contributes to AI feedback systems. Furthermore, the influence of contextual variables, including socioeconomic status and cultural divergence, should be studied on the efficiency of AI interventions that target resilience.

References

- Adams, A.-M., Wilson, H., Money, J., Palmer-Conn, S. & Fearn, J. (2020). Student engagement with feedback and attainment: the role of academic self-efficacy. *Assessment & Evaluation in Higher Education*, 45(2), pp. 317-329. doi: <https://doi.org/10.1080/02602938.2019.1640184>
- Ahmad, D., Latif, I., Arafah, B. & Suryadi, R. (2024). Defining the Role of Artificial Intelligence in Improving English Writing Skills Among Indonesian Students. *Journal of Language Teaching and Research*, 15(2), pp. 568-578. doi: <https://doi.org/10.17507/jltr.1502.25>
- Al Nabhani, F., Hamzah, M. B. & Abuhassna, H. (2025). The Role of Artificial Intelligence in Personalizing Educational Content: Enhancing the Learning Experience and Developing the Teacher's Role in an Integrated Educational Environment. *Contemporary Educational Technology*, 17(2), pp. ep573. doi: <https://doi.org/10.30935/cedtech/16089>
- Ali, R. S., Syarifah, P. N., Rohmah, Y. & Perdhana, M. S. (2023). Understanding the Academic Resilience of Students in Managing Coursework Responsibilities and The Rationale behind The Usage of ChatGPT. *Proceedings of International Conference on Psychological Studies (ICPsyche)*, 4(1), pp. 30-42. doi: <https://doi.org/10.58959/icpsyche.v4i1.21>
- Alsaiani, O., Baghaei, N., Lahza, H., Lodge, J., Boden, M. & Khosravi, H. (2024). Emotionally Enriched Feedback via Generative AI. *arXiv preprint arXiv:2410.15077*. doi: <https://doi.org/10.48550/arXiv.2410.15077>
- Aslam, S., Faisal, O. & Kamal, H. (2024). Analyzing AI's Role in Promoting Diversity and Inclusivity within Educational Systems, Addressing different Learning Styles and Needs. *Review of Applied Management and Social Sciences*, 7(4), pp. 1099-1113. doi: <https://doi.org/10.47067/ramss.v7i4.446>
- Begum, S., Vimochana, M., Arunadevi, V., Dhivya, A. C. A., Vuyyuru, V. A. & Faizal, M. M. (2024). Using AI for Personalized English Writing Feedback on Educational Platforms. In *2024 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAQSA)* (pp. 1-6). IEEE. doi: <https://doi.org/10.1109/ICAQSA64000.2024.10882334>
- Bognár, L., Ágoston, G., Bacsá-Bán, A., Fauszt, T., Gubán, G., Joós, A., et al. (2024). Re-Evaluating Components of Classical Educational Theories in AI-Enhanced Learning: An Empirical Study on Student Engagement. *Education Sciences*, 14(9), pp. 974. doi: <https://doi.org/10.3390/educsci14090974>
- Briscoe, H., Olson, C. & Prior, M. (2023). Dealing Confidently with Feedback: The Impact of a Grow Your Academic Resilience Workshop. *Journal of Learning Development in Higher Education*, (28). doi: <https://doi.org/10.47408/jldhe.vi28.1019>
- Dann, C., Redmond, P., Fanshawe, M., Brown, A., Getenet, S., Shaik, T., et al. (2024). Making sense of student feedback and engagement using artificial intelligence. *Australasian Journal of Educational Technology*, 40(3), pp. 58-76. doi: <https://doi.org/10.14742/ajet.8903>

- Ejjami, R. (2024). The Future of Learning: AI-Based Curriculum Development. *International Journal for Multidisciplinary Research*, 6(4), pp. 1-31. doi: <https://doi.org/10.36948/ijfmr.2024.v06i04.24441>
- Er, E., Akçapınar, G., Bayazit, A., Noroozi, O. & Banihashem, S. K. (2025). Assessing student perceptions and use of instructor versus AI-generated feedback. *British Journal of Educational Technology*, 56(3), pp. 1074-1091. doi: <https://doi.org/10.1111/bjet.13558>
- Fan, Y., Tan, S. & Lim, G. Y. W. (2024). EAP teacher feedback in the age of AI: Supporting first-year students in EFL disciplinary writing. *Australian Journal of Applied Linguistics*, 7(3), pp. 1943. doi: <https://doi.org/10.29140/ajal.v7n3.1943>
- Gabriel, S. (2024). Generative AI and Educational (In) Equity. *Proceedings of the International Conference on AI Research, ICAIR 2024*, 4(1), pp. 133-142. doi: <https://doi.org/10.34190/icaire.4.1.3153>
- Ghadampour, E., Abbase, M., Yoosfvadh, M., Hassanvand, B. & Hosseini, H. (2018). The Effect of Corrective Feedback (Written and Verbal) of Teachers in the Formative Evaluation on Educational Resiliency and Meaning of Education of Students. *Psychological Achievements*, 25(2), pp. 21-38. doi: <https://doi.org/10.22055/psy.2019.20909.1736>
- Gjermeni, F. & Prodani, F. (2024). AI and Student Engagement: A Comparative Analysis. *Interdisciplinary Journal of Research and Development*, 11(3), pp. 195-195. doi: <https://doi.org/10.56345/ijrdv11n326>
- Glory, J. S., Nalina, E. & Prasad, D. (2023). Enhancing Holistic Education through AI-Integrated Learning Environments: A Comprehensive Framework. In *2023 International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE)* (pp. 1-5). IEEE. doi: <https://doi.org/10.1109/RMKMATE59243.2023.10369203>
- Gratani, F., Screpanti, L., Giannandrea, L., Scaradozzi, D. & Capolla, L. M. (2024). Personalized Feedback in University Contexts: Exploring the Potential of AI-Based Techniques. In G. Casalino, R. Di Fuccio, G. Fulantelli, P. Raviolo, P. C. Rivoltella, D. Taibi, & G. A. Toto (Eds.), *Higher Education Learning Methodologies and Technologies Online* (pp. 440-454). Springer Nature Switzerland. doi: https://doi.org/10.1007/978-3-031-67351-1_30
- Hayat, M. H., Awan, S. F., Munir, M. & Storay, D. (2024). Study how AI can Provide Timely and Constructive Feedback to Students, Fostering a Growth Mindset and Resilience. *International Journal of Social Science Archives (IJSSA)*, 7(3), pp. 1266-1275. Retrieved from <https://www.ijssa.com/index.php/ijssa/article/view/552>
- Herb, A. & Lloyd, C. (2024). The Future of Feedback: Exploring the Use of Generative AI in Formative Assessment. In T. Cochrane, V. Narayan, E. Bone, C. Deneen, M. Saligari, K. Tregloan, & R. Vanderburg (Eds.), *Navigating the Terrain: Emerging frontiers in learning spaces, pedagogies, and technologies* (pp. 141-142). ASCILITE Publications. doi: <https://doi.org/10.14742/apubs.2024.1386>
- Holdcroft, C. (2024). Can Generative AI Improve the Standardisation of Student Feedback Across a Business School Faculty? In L. Uden & D. Liberona (Eds.), *Learning Technology for Education Challenges* (pp. 364-376). Springer Nature Switzerland. doi: https://doi.org/10.1007/978-3-031-61678-5_26

- Kurd, S. A., Memon, S. S. & Sahito, J. K. M. (2023). Exploring the Mediating Effect of Student Motivation on the Relationship between ESL Teacher's Feedback and Undergraduate Academic Outcomes and Satisfaction from the Public Sector Universities in Jamshoro. *Al-Aijaz Research Journal of Islamic Studies & Humanities*, 7(3), pp. 1-17. doi: <https://doi.org/10.5281/zenodo.10514498>
- Madaminov, N. & Urinov, M. (2024). The Capacity of AI in Education System Towards in Acquiring the Innovative tested Models to Enhance the Learning Experience. In *2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)* (pp. 556-560). IEEE. doi: <https://doi.org/10.1109/ICACITE60783.2024.10616926>
- Mallillin, L. L. D. (2024). Artificial Intelligence (AI) Towards Students' Academic Performance. *Innovare Journal of Education*, 12(4), pp. 16-21. doi: <https://doi.org/10.22159/ijoe.2024v12i4.51665>
- Nazaretsky, T., Mejia-Domenzain, P., Swamy, V., Frej, J. & Käser, T. (2024). AI or Human? Evaluating Student Feedback Perceptions in Higher Education. In R. Ferreira Mello, N. Rummel, I. Jivet, G. Pishtari, & J. A. Ruipérez Valiente (Eds.), *Technology Enhanced Learning for Inclusive and Equitable Quality Education* (pp. 284-298). Springer Nature Switzerland. doi: https://doi.org/10.1007/978-3-031-72315-5_20
- Olson, C., Briscoe, H. & Prior, M. (2022). Grow your academic resilience. *Journal of Learning Development in Higher Education*, (25). doi: <https://doi.org/10.47408/jldhe.vi25.975>
- Saha, S. (2025). The Role of AI-Powered Chatbots in Reducing Student Anxiety in Online Learning Environments. *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*, 13(3), pp. 155-163. doi: <https://doi.org/10.22214/ijraset.2025.67066>
- Shafi, A., Middleton, T., Millican, R. & Templeton, S. (2019). Developing Academic Buoyancy and Resilience Through the Assessment Feedback Process. In *British Education Studies Association Annual Conference*. Retrieved from <https://eprints.glos.ac.uk/id/eprint/7033>
- Su, W., Qi, Q. & Yuan, S. (2022). A Moderated Mediation Model of Academic Supervisor Developmental Feedback and Postgraduate Student Creativity: Evidence from China. *Behavioral Sciences*, 12(12), pp. 484. doi: <https://doi.org/10.3390/bs12120484>
- Sundari, M. S., Penthala, H. R. & Nayyar, A. (2024). Transforming Education through AI-Enhanced Content Creation and Personalized Learning Experiences. In S. Tripathi & J. Rosak-Szyrocka (Eds.), *Impact of Artificial Intelligence on Society* (pp. 98-118). Chapman and Hall/CRC. doi: <https://doi.org/10.1201/9781032644509-7>
- Sutherland, S. C., Machado, T., Mahajan, S., Mohaddesi, O., Matuk, C., Smith, G., et al. (2023). Exploring the Role of AI-Generated Feedback Tangential to Learning Outcomes. In *2023 IEEE Conference on Games (CoG)* (pp. 1-8). IEEE. doi: <https://doi.org/10.1109/CoG57401.2023.10333239>
- Tang, X. (2024). An Empirical Study on the Effects of AI-Generated Feedback on English Writing. *International Journal of Educational Science and Theory*, 3(9), pp. 18-23. doi: <https://doi.org/10.26789/ijest.v3i9.2010>

- Tran, T. T. T. (2025). Enhancing EFL Writing Revision Practices: The Impact of AI- and Teacher-Generated Feedback and Their Sequences. *Education Sciences*, 15(2), pp. 232. doi: <https://doi.org/10.3390/educsci15020232>
- Tubino, L. & Adachi, C. (2022). Developing feedback literacy capabilities through an AI automated feedback tool. In S. Wilson, N. Arthars, D. Wardak, P. Yeoman, E. Kalman, & D. Y. T. Liu (Eds.), *Reconnecting relationships through technology. Proceedings of the 39th International Conference on Innovation, Practice and Research in the Use of Educational Technologies in Tertiary Education* (pp. e22039). ASCILITE Publications. doi: <https://doi.org/10.14742/apubs.2022.39>
- Wallis, R. P. (2017). *Undergraduate Students' Experiences and Perceptions of Dialogic Feedback Within Assessment Feedback Tutorials* (Doctoral dissertation, University of Brighton). Retrieved from https://cris.brighton.ac.uk/ws/portalfiles/portal/4756726/R.P.Wallis%20for%20UOB%20Printers%20copy%20final%20version_.pdf
- Wang, S. (2025). Hybrid models of piano instruction: How combining traditional teaching methods with personalized AI feedback affects learners' skill acquisition, self-efficacy, and academic locus of control. *Education and Information Technologies*, 30(9), pp. 12967-12989. doi: <https://doi.org/10.1007/s10639-025-13359-1>
- Ward, B., Bhati, D., Neha, F. & Guercio, A. (2024). Analyzing the Impact of AI Tools on Student Study Habits and Academic Performance. *arXiv preprint arXiv:2412.02166*. doi: <https://doi.org/10.48550/arXiv.2412.02166>
- Widono, S., Saddhono, K., Nurhasanah, F., Nugraheni, A. S. C. & Legowo, B. (2024). A Strategic Design of Personalized Based Learning System for Improving the Experience of Outcome Based Education. In *2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)* (pp. 1149-1154). IEEE. doi: <https://doi.org/10.1109/ICACITE60783.2024.10616811>
- Wood, J. (2022). Making peer feedback work: the contribution of technology-mediated dialogic peer feedback to feedback uptake and literacy. *Assessment & Evaluation in Higher Education*, 47(3), pp. 327-346. doi: <https://doi.org/10.1080/02602938.2021.1914544>
- Wu, X.-Y. (2024). Artificial Intelligence in L2 learning: A meta-analysis of contextual, instructional, and social-emotional moderators. *System*, 126, pp. 103498. doi: <https://doi.org/10.1016/j.system.2024.103498>
- Xu, W., Meng, J., Raja, S. K. S., Priya, M. P. & Kiruthiga Devi, M. (2023). Artificial intelligence in constructing personalized and accurate feedback systems for students. *International Journal of Modeling, Simulation, and Scientific Computing*, 14(01), pp. 2341001. doi: <https://doi.org/10.1142/S1793962323410015>
- Yang, C., Wei, M. & Liu, Q. (2025). Intersections between cognitive-emotion regulation, critical thinking and academic resilience with academic motivation and autonomy in EFL learners: Contributions of AI-mediated learning environments. *British Educational Research Journal*. doi: <https://doi.org/10.1002/berj.4140>
- Youn, C. H., Salam, A. R. & Rahman, A. A. (2025). AI-Driven Tools in Providing Feedback on Students' Writing. *International Journal of Research and Innovation in Social Science*, 9(3s), pp. 58-67. doi: <https://doi.org/10.47772/IJRISS.2025.903SEDU0006>

Appendix

1. Variance of Effect Sizes (S^2_{r}):

Formula:

$$S^2_{\text{r}} = \frac{\sum (r_i - \bar{r})^2}{k}$$

We'll compute the squared deviations of each effect size from the mean (0.409), sum them, and divide by the number of studies ($k = 10$).

2. Sampling Error Variance (S^2_{e}):

Formula:

$$S^2_{\text{e}} = \frac{1 - \bar{r}^2}{N}$$

Where:

- $\bar{r} = 0.409$
- $N = \frac{1252}{10} = 125.2$

3. Population Variance (S^2_{p}):

$$S^2_{\text{p}} = S^2_{\text{r}} - S^2_{\text{e}}$$

4. 95% Credibility Interval (CI):

$$CI = \bar{r} \pm 1.96 \cdot \sqrt{S^2_{\text{p}}}$$

5. Chi-Square Test for Homogeneity:

$$\chi^2 = \frac{S^2_{\text{r}}}{S^2_{\text{e}}} \cdot (k - 1)$$

1. Weighted Average Effect Size ($\bar{r}$):
0.409 – moderate positive relationship (already calculated)
2. Variance of Effect Sizes (S^2_{r}):
0.00291 – shows modest variability among effect sizes
3. Sampling Error Variance (S^2_{e}):
0.00665 – expected variability due to sampling
4. Population Variance (S^2_{p}):
-0.00375 – *negative*, which is not interpretable and typically suggests the observed variance is entirely due to sampling error
5. 95% Credibility Interval:
Not computable – because population variance is negative, the interval becomes undefined. This further reinforces the conclusion that most of the variability is likely due to chance.
6. Chi-Square Homogeneity Test (χ^2):
3.93 with 9 degrees of freedom — this is below the critical value (~16.92), indicating no significant heterogeneity among effect sizes.

Table 7: Categorical Representation of Study Variables: Type of Feedback, Feedback Quality, Academic Resilience, and Educational Level.

Study	Type of Feedback (IV)	Feedback Quality (M)	Academic Resilience (DV)	Educational Level (Moderator)
Tran (2025)	Hybrid (AI + Teacher)	4 (High Quality)	3.5 (Scale from 1 to 5)	2 (Undergraduate)
Sutherland et al. (2023)	AI	3 (Moderate Quality)	3.0	3 (Postgraduate)
Fan et al. (2024)	AI	2 (Low Quality)	2.8	1 (K-12)
Er et al. (2025)	Teacher	5 (High Quality)	4.2	2 (Undergraduate)
Tang (2024)	AI	4 (High Quality)	3.8	3 (Postgraduate)
Yang et al. (2025)	AI	4 (High Quality)	4.0	2 (Undergraduate)
Ali et al. (2023)	AI	3 (Moderate Quality)	3.3	1 (K-12)
Ghadampour et al. (2018)	Teacher	5 (High Quality)	4.5	2 (Undergraduate)
Gratani et al. (2023)	Hybrid (AI + Teacher)	4 (High Quality)	3.9	3 (Postgraduate)
Holdcroft (2024)	AI	3 (Moderate Quality)	3.4	3 (Postgraduate)

Table 8: Numerical Representation of Study Variables: Type of Feedback, Feedback Quality, Academic Resilience, and Educational Level.

Study	Type of Feedback	Feedback Quality	Academic Resilience	Educational Level
Tran (2025)	2	4	3.5	2
Sutherland et al. (2023)	1	3	3.0	3
Fan et al. (2024)	1	2	2.8	1
Er et al. (2025)	0	4	4.2	2
Tang (2024)	1	4	3.8	3
Yang et al. (2025)	1	4	4.0	2
Ali et al. (2023)	1	3	3.3	1
Ghadampour et al. (2018)	0	4	4.5	2
Gratani et al. (2023)	2	4	3.9	3
Holdcroft (2024)	1	3	3.4	3