Generative AI for Formative Feedback in Introductory Circuit Analysis: A Focused Narrative Review

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ABSTRACT

Generative artificial intelligence can provide explanations and comments on circuit solutions, but its educational value depends on how students interpret and use those responses. This focused narrative review examines the use of generative AI to help students identify and correct errors in introductory circuit analysis. Published sources were identified through OpenAlex searches, publisher records, and reference checking, with full-text assessment informing selection and synthesis. Twelve reports were selected for their relevance to circuit reasoning, feedback, or learner verification; an electronics-course perception study provides an explicitly adjacent comparison. Foundational research on formative feedback and self-regulated learning informs the interpretation. The synthesis addresses circuit representation and diagnostic accuracy, students' use of feedback, and the interpretation of educational outcomes. Technical evaluations show that input representation, reference information, and computational support shape the conditions under which responses are assessed. Classroom and tutoring reports describe opportunities for explanation, comparison, revision, and instructor intervention. The selected reports provide more direct evidence of perceived usefulness than of independently retained understanding. Observational grade associations and a historical-cohort comparison offer additional perspectives, although their designs limit causal interpretation. The review proposes teaching considerations that preserve students' initial reasoning, check the represented circuit, focus guidance on a specific difficulty, and require students to justify corrections. These considerations are derived from the literature and have not been evaluated as a combined intervention. The principal implication is that AI feedback should be judged through the accuracy of its diagnosis and the student's subsequent reasoning. Selective coverage, heterogeneous outcomes, and AI-assisted selection and extraction constrain the review's conclusions.

Keywords: Generative Artificial Intelligence; Formative Feedback; Circuit Analysis; Self-Regulated Learning; Engineering Education

INTRODUCTION

Feedback in introductory circuit analysis must connect physical relationships with the reasoning expressed in a student's solution. A wrong result may originate in a misidentified connection, an inconsistent current direction, an unsuitable equation, or an arithmetic error. These difficulties require different instructional responses. An explanation that corrects the final value without addressing the source of the error can leave the student's underlying interpretation unresolved. Conversely, a valid solution may use different reference directions or an alternative equation set from those in an instructor's worked answer. Effective guidance therefore requires attention to the circuit, the student's assumptions, and the purpose of the task.

Formative feedback provides information intended to improve learners' thinking or behaviour [1]. Its educational function extends beyond identifying whether an answer is correct. Hattie and Timperley distinguish feedback concerning a task, the processes used to perform it, and the learner's regulation of learning [2]. Nicol and

Macfarlane-Dick emphasise students' active role in assessing their work and generating internal feedback [3]. Carless and Boud similarly connect feedback literacy with making judgments and taking action [4]. Together, these perspectives suggest that the quality of an explanation and the student's use of that explanation should be examined together.

Generative AI introduces a conversational source of support into this feedback process. Students can request clarification, submit partial work, compare methods, or ask why a calculation fails. These possibilities are relevant to circuit courses, where intermediate steps often reveal more about understanding than the final answer. A broader review by Alwarafy considers large language models across electrical and computer engineering education, including programming, simulation, circuit design, and embedded systems [5]. The present article concentrates on feedback during foundational circuit problem solving, particularly the interpretation of connections, the application of Kirchhoff's laws, and the checking of node or mesh equations.

The instructional interpretation of these systems depends on the outcome measured. Model correctness, perceived usefulness, assisted completion, and independent understanding provide different kinds of evidence. Their relationship is central to deciding how generated comments should be used in teaching.

The review addresses one question: What does published research indicate about using generative AI to help students identify and correct errors in introductory circuit solutions? Its contribution is a critical interpretation of selected technical and educational reports through the concepts of feedback uptake and verification. The resulting teaching considerations are intended to inform instructors' decisions about student work, guidance, and assessment. They are presented as implications of the reviewed literature rather than as findings from a new classroom intervention.

REVIEW APPROACH

A focused narrative approach was adopted to examine a bounded instructional question. The emphasis is on explaining relationships between circuit representation, feedback use, and reported outcomes. Reporting was informed by the emphasis on a clear purpose, transparent literature identification, appropriate referencing, and scientific reasoning in SANRA [6]. SANRA was developed for narrative reviews in medicine; its general reporting principles informed this article, and no formal SANRA score was assigned.

Literature discovery used six OpenAlex searches, supplemented by publisher records and reference checking. The exact query strings submitted separately through the Works API search parameter were: "circuit analysis" "ChatGPT"; "circuit analysis" "large language model"; "electric circuits" "generative AI"; "circuit analysis" "tutor"; "electrical engineering education" "ChatGPT"; "circuit" "formative feedback" "generative". Adjacent quoted phrases were combined by implicit AND. Each query applied publication-date filters from 1 January 2022 to 31 October 2026. Focal sources were English-language journal articles or full conference papers with accessible full texts and verified publication identities. Published counterparts were verified when author manuscripts provided access.

Selection was purposive. Reports were retained when their evaluated outputs, tutoring interactions, or classroom activities illuminated circuit reasoning, feedback, or verification. Eleven reports address circuit analysis directly. One adjacent electronics-course study was retained specifically to clarify the interpretation of self-reported retention and critical thinking. Reports spanning wider course content were used only for relevant findings. Broad engineering leaderboards, digital-logic studies, industrial design applications, and unevaluated curriculum proposals were outside the synthesis. Foundational feedback literature and a broader engineering-education review supplied conceptual context.

For each report, attention was given to the task, AI support, evaluation unit, outcome, and limits of inference. Related publications were considered together, and incompatible model scores or participant totals were not pooled. Selection and extraction were AI-assisted. All retained references and substantive claims, including reported numerical values, were subsequently verified by a human author against the corresponding full texts. Study selection and extraction were not independently duplicated. This is a selective narrative synthesis, with

no claim of exhaustive coverage or systematic-review compliance. Table 1 identifies the twelve reports and their roles in the argument.

Critical Synthesis of the Evidence

To establish a clear foundation for the synthesis, Table 1 catalogues the twelve selected reports by their experimental settings, conceptual contributions, and methodological constraints. Rather than pooling disparate scores across incompatible benchmarks, the table categorises what each investigation demonstrates about circuit representation, feedback interactions, or student outcomes. Crucially, the final column identifies the principal interpretive boundaries of each study, including self-selection bias, small qualitative samples, and reliance on subjective satisfaction, to prevent conflating perceived utility or model correctness with measured, independent learning gains.

Table 1 Summary of reviewed studies, educational contributions, and methodological constraints.

Report	Evaluation and setting	Contribution to the review	Principal interpretive limit
Ogunfunmi [7]	Four illustrative ChatGPT circuit examples	Identifies reasoning failures relevant to checking explanations	Exploratory examples do not estimate general accuracy or learning
Horne [8]	50 Electric Circuits I students; manual and AI comparisons	Connects prompting, circuit interpretation, and student reflection	Perceptions and response summaries; inconsistent percentage reporting
Chen et al. [9]	283 submitted solutions to 119 circuit problems	Separates assessment of method, arithmetic, answers, completeness, and units	Reference-supported model assessment; no feedback-uptake outcome
Cao [10]	50 resistive circuits represented by textual netlists	Demonstrates the importance of representation and prompt conditions	Restricted circuit set without dependent sources; no learner evaluation
Rocha et al. [11]	135 student raters plus a technical response evaluation	Distinguishes perceived quality from technical correctness	Ratings of learning value are not measured learning gains
Chen et al. [12]	Circuit tutor deployment; 66 feedback responses	Describes problem-specific guidance and feedback on submitted work	Responses are not unique participants or achievement gains
Dhagat et al. [13]	132 enrolled students; 121 discussion participants	Documents guided error checking and reflection on AI use	Exploratory classroom evidence without an isolated AI learning effect
Knievel et al. [14]	Circuit-aware tutor; 12 dialogues from 9 students	Examines Socratic guidance and difficulties within interactions	Small qualitative dialogue sample; no achievement comparison
Müller et al. [15]	First-semester pilot with 18 students	Describes differing needs for entry-point guidance and calculation checking	Exam groups defined retrospectively; no untreated comparison
Xie et al. [16]	Circuit-analysis tables: 72 tutor users and 41 non-users	Relates engagement with tutoring to final course grades	Self-selected participation; observed associations are not causal effects

Report	Evaluation and setting	Contribution to the review	Principal interpretive limit
Zamora-Hernández et al. [17]	Five-week circuit course; cohorts of 32, 27, and 25	Compares course grades after adding AI-generated practice	Historical cohorts; reported group differences were nonsignificant
Habib [18]	Adjacent electronics course; 34 complete participants from 45 enrolled	Clarifies what perceived retention and critical-thinking ratings measure	Questionnaire outcomes; no objective retention or comparative scoring

Circuit representation and diagnostic accuracy

Circuit representation establishes the problem to which feedback refers. If a system identifies a connection incorrectly, subsequent equations can remain internally coherent while describing a different circuit. Ogunfunmi's exploratory examples illustrate limitations in generated circuit reasoning [7]. Horne's classroom report similarly describes inaccurate interpretations and calculations during students' comparisons of manual work with ChatGPT outputs [8]. These reports make the correspondence between a diagram and its description an instructional concern. An orderly sequence of calculations is insufficient evidence that the intended circuit has been analysed.

The assessment benchmark by Chen et al. provides a different evaluation boundary [9]. Its dataset contains 283 student solutions to 119 problems, with reference and student solutions converted into LaTeX. The model assesses completeness, method, final answer, arithmetic, and units using contextual information that includes the reference solution. This design is relevant to feedback because it distinguishes several possible difficulties in submitted work. It also shows why an assessment result must be interpreted in relation to its inputs: the evaluated task includes substantial support and does not require unrestricted interpretation of an unfamiliar circuit image.

Cao evaluated nodal analysis on fifty resistive circuits supplied as textual netlists [10]. The circuit set excluded dependent sources, and the evaluated prompting conditions supplied worked examples. Such an arrangement reduces some uncertainty associated with visual interpretation and makes the analytical task more explicit. Its results therefore concern performance under specified representations and prompting conditions. For teaching, the implication is that a circuit description should identify connections, component values, sources, and reference assumptions before a generated solution is treated as feedback on a student's work.

Rocha et al. compared response architectures that combined language models with differing amounts of retrieval and computational support [11]. Their evaluation distinguishes students' ratings from a complementary assessment of technical correctness. This distinction matters because an explanation's clarity or perceived learning value does not resolve whether its circuit analysis is sound. Across these reports, reliability depends on the represented problem and the support available to the system. Comparisons that overlook those conditions can overstate what a general conversational model has demonstrated.

Students' use of explanations and guidance

The circuit tutor described by Chen et al. provides open-ended help and feedback on submitted solutions, using problem-specific contextual material [12]. Its preliminary deployment collected sixty-six responses about the usefulness of homework feedback, of which 90.9% indicated helpfulness. The reported unit is a feedback response, so the percentage describes reception of the system rather than the proportion of students who achieved a learning gain. The design nevertheless illustrates how feedback can be directed towards method, arithmetic, completeness, and units while retaining the student's submitted work as context.

Dhagat et al. integrated generative AI into a foundational circuit course through demonstrations, activities involving error identification, and discussion of its advantages and limitations [13]. Of 132 enrolled students, 121 participated in discussion assignments. Student accounts included conceptual clarification and help with

starting problems, alongside correctness concerns and possible overreliance. The instructional significance lies in making AI use an object of examination. Students were asked to consider the tool's contribution and limitations within an existing course, rather than being expected to accept its output without interpretation.

Dialogue-based guidance also requires adaptation. The AITEE report analyses twelve dialogues from nine students in addition to technical evaluations of the system [14]. Its examples include productive conceptual guidance and difficulties associated with cognitive load. Repeated Socratic questions can become unhelpful when a learner lacks the prerequisite representation or concept needed to answer them. The dialogue evidence supports considering when to provide a direct explanation, a representation aid, or a more constrained question. It does not establish which combination produces the greatest subsequent achievement.

Müller et al. describe a first-semester pilot with eighteen students using a tutor configured with course materials [15]. Students in the higher examination-performance group more consistently used it to check calculations, whereas lower-performing students showed a greater need for initial guidance and declining engagement. The groups were formed retrospectively from examination results. The findings identify differences in observed use and support needs, while leaving the direction of influence unresolved. Together, the classroom reports suggest that access to explanations should be accompanied by guidance on how to question, apply, and check them.

Interpreting the educational outcomes

Evidence concerning achievement deserves separate consideration from response ratings. Xie et al. examined tutor use across Circuit Analysis and Signal Processing [16]. The circuit-specific analysis includes seventy-two users and forty-one non-users, with greater engagement associated with higher final course grades. Participation was voluntary, so prior achievement, motivation, and study habits could contribute to both engagement and grades. The reported associations provide a reason to investigate learning conditions more closely; they cannot isolate an effect of tutoring from the characteristics of students who chose to use it.

Zamora-Hernández et al. compared a five-week circuit course incorporating Wisdolia-generated practice with two historical cohorts [17]. The AI-supported cohort contained twenty-five students, compared with thirty-two and twenty-seven in the earlier groups. Although its mean course grade was descriptively higher, the reported comparisons did not identify statistically significant group differences (ANOVA $p = 0.237$; Kruskal-Wallis $p = 0.447$). These results neither establish superiority nor demonstrate equivalence. Differences between cohorts and the evolving instructional package also constrain attribution to the AI component.

The adjacent electronics study by Habib helps clarify another outcome distinction [18]. Thirty-four students completed manual-first and ChatGPT-assisted work on three problems involving diodes, transistors, and operational amplifiers, followed by a questionnaire. Accuracy, efficiency, retention, and critical-thinking assistance were rated as perceptions. The author explicitly acknowledges the absence of objective scoring of AI-generated versus manual answers. Accordingly, the retention item cannot be read as a delayed knowledge test, and correlations between ratings cannot establish changes in competence. These observations provide a methodological comparison, with no assumption of direct transfer to introductory linear-circuit learners.

Related reports also require careful interpretation. The assessment benchmark, preliminary tutor deployment, and later AI-Tutor evaluation belong to the same research programme [9,12,16]. They address different evaluation targets and are treated here as connected contributions. Their findings are not aggregated as independent replications. Across the selected literature, technical performance, perceived usefulness, interaction processes, and course achievement each contribute information, but no single category captures the complete formative-feedback process.

DISCUSSION AND TEACHING IMPLICATIONS

Feedback quality depends on the student's reasoning

The synthesis identifies a practical tension between the availability of explanations and the visibility of student understanding. A system can produce detailed material while leaving the instructor uncertain about what the learner has understood or changed. Formative-feedback theory directs attention towards that change [1-4]. In

circuit analysis, the relevant evidence includes a revised interpretation, a corrected equation, or a defensible explanation of why a previous step was unsuitable. Evaluating feedback through these actions gives technical accuracy a specific educational purpose.

Retaining an initial attempt is therefore a useful design consideration. A diagram annotation, branch-current assumption, or partial node equation gives a tutor or instructor evidence of the learner's starting point. It also allows a subsequent correction to be examined. The classroom comparisons and problem-specific tutoring reports provide examples of activities in which student work and generated explanations can be considered together [8,12,13]. Requiring an attempt is proposed here as a way to make reasoning visible; the selected studies do not establish a universal rule about the optimal timing of AI access.

Diagnosis should be sufficiently specific to support revision. A topology error requires reconsidering which nodes a component connects. An arithmetic error requires checking a calculation after the governing relationships are established. A units error may require relating the computed quantity to its physical meaning. The separate assessment dimensions used by Chen et al. provide a basis for distinguishing such difficulties [9,12]. A focused explanation can then address the relevant step without treating every incorrect final answer as the same problem.

The instructor's reference answer should also permit valid alternatives. A negative current can be consistent with the assumed reference direction, and different equation sets can describe the same circuit. The appropriate question is whether the assumptions and equations are physically consistent and meet any explicitly assigned method requirement. This is a circuit-analysis implication of the review, rather than an additional empirical finding. It guards against feedback that replaces a student's valid reasoning merely because its notation differs from a stored solution.

Verification should be an explicit learner activity

Verification requires more than obtaining a second answer. For a node equation, the learner can identify connected branches and explain the direction and sign of each term. For a numerical solution, substitution into the governing equations can reveal an inconsistency. Simulation can provide a further comparison when its topology, sources, and reference conditions correspond to the analysed circuit. These are proposed teaching actions based on the representational and feedback issues identified in the literature [7-10,13,14]. Agreement between outputs has instructional value when the student can explain the basis of that agreement.

Table 2 translates the synthesis into teaching considerations. It links a difficulty with a feedback focus and an observable verification action. The table is intended to support task design and discussion with students. Its actions are proposed implications and have not been tested together as an intervention.

Table 2 Teaching considerations derived from the reviewed evidence.

Difficulty	**Feedback focus**	**Learner verification**	**Basis**
Misread connection	Re-establish nodes, branches, values, and sources	Compare the description with the original circuit	[7,8,10]
Inconsistent equation	Examine one governing relationship and its assumptions	Explain the signs and branch terms in the revised equation	[2,9,12]
Numerical or units error	Check calculations after confirming the circuit model	Substitute the result and interpret its unit	[9,10,12]
Dependence on a complete answer	Direct guidance towards the student's partial attempt	Record the revised step and justify the change	[3,4,12,13]
Difficulty starting or persistent confusion	Adjust the specificity of explanation and questioning	State the next feasible step or request instructor help	[1,14,15]

Figure 1 illustrates a proposed closed-loop AI circuit feedback cycle derived from Table 2. Unresolved errors prompt renewed checking and revision under instructor oversight.

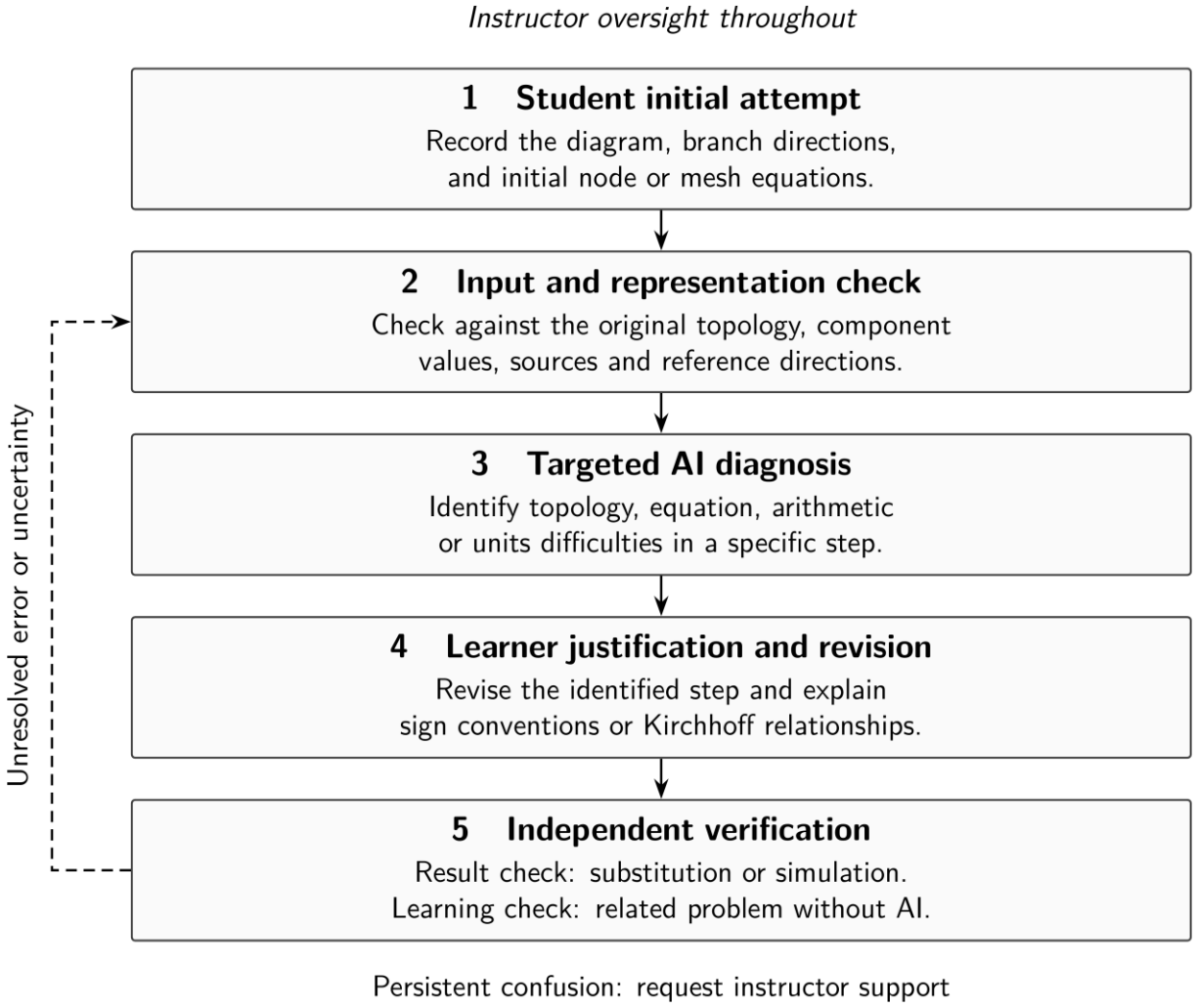

Figure 1 Proposed closed-loop AI circuit feedback cycle

The amount of assistance should respond to the learner's preparation. The observations in AITEE and the first-semester pilot suggest that sustained questioning can place demands on students who first need help identifying a circuit relationship [14,15]. A short explanation or explicitly bounded subtask may be appropriate before asking for independent revision. For learners who can already formulate the problem, feedback may instead focus on checking assumptions or explaining an inconsistency. These are conditional instructional judgments, supported by evidence of differing needs rather than by a comparative test of a single best prompting style.

Implications for introductory and diploma teaching

Introductory circuit courses provide opportunities to define clear tasks and prepare reference solutions. Instructors can identify the concepts a problem is intended to assess, determine which intermediate steps should remain visible, and specify how students should justify corrections. This preparation can also clarify the role of AI in homework, guided practice, and assessment. The contribution of a generated explanation then becomes assessable through its relationship to a stated learning task, rather than through its length or apparent confidence.

For sub-degree and technical and vocational education and training (TVET) programmes, including foundational engineering diplomas in Malaysia and comparable polytechnic settings, the proposed application is a bounded activity with explicit instructor oversight. A student might submit an initial interpretation, use guidance to revise one step, and explain the revision with reference to circuit principles. This activity aligns with the review's emphasis on feedback uptake and checking. Its effectiveness in these settings requires direct evaluation; it should

therefore be regarded as a literature-informed instructional approach rather than an empirically verified, institution-specific intervention.

Assessment can strengthen the distinction between supported completion and independent understanding. Retaining the initial attempt and revision allows instructors to inspect how feedback was used. A subsequent comparable problem, completed with less assistance, can provide additional evidence of understanding. A task with a changed topology is more informative about transfer than repeating an identical calculation. These assessment suggestions follow the conceptual emphasis on self-regulation and action [2-4]; they identify useful evidence to collect, without asserting that the present review has measured it

Limitations

The literature was selected to address a focused question and does not represent an exhaustive inventory. Discovery relied on OpenAlex and targeted source checking, with accessible English-language full texts. Relevant publications may have been missed. AI-assisted selection and extraction were not independently duplicated; subsequent human verification does not eliminate selection or interpretive bias. The publication cut-off also limits applicability to later systems and evidence.

The reports use different tasks, model configurations, representations, and outcomes. Technical examples, student ratings, dialogues, and course grades cannot be combined into a common estimate of educational effectiveness. Some sources were consulted through author manuscripts linked to verified publications, so differences from final versions remain possible. Inconsistent numerical reporting in parts of Horne's report limits precise quantitative interpretation [8]. The synthesis consequently emphasises documented activities and appropriately bounded findings.

Small samples, voluntary use, historical cohorts, and related research programmes constrain learning inferences. The adjacent electronics study contributes an outcome-measurement comparison rather than evidence specific to introductory linear circuits [18]. The proposed teaching considerations also remain unevaluated as a combined approach. These limitations support cautious interpretation of instructional possibilities and identify the kinds of evidence needed to examine their effectiveness.

CONCLUSION

Generative AI can participate in formative-feedback activities in introductory circuit analysis by providing explanations, commenting on submitted work, and supporting comparison and revision. The selected literature indicates that the represented circuit, the reference information available to the system, and the learner's preparation shape how this support should be interpreted. Technical correctness is essential, while the educational contribution also depends on the student's subsequent reasoning.

The central teaching implication is to connect guidance with visible learner action: interpreting the intended circuit, identifying a specific difficulty, justifying a correction, and checking the revised result. Existing reports provide evidence about response quality, perceptions, interactions, and some achievement associations. They provide limited grounds for attributing durable independent learning to AI feedback itself. The proposed teaching considerations offer a focused basis for instructional design and evaluation while retaining that distinction.

Ethics And Data Availability

This review recruited no participants and generated no new student dataset. The cited publications and study-characteristics table identify the evidence supporting the synthesis. The selection record and source-verification notes are retained with the review materials.

Use Of Generative Ai

Generative AI (ChatGPT) assisted literature discovery, source collation and selection, evidence extraction and synthesis, drafting, and language refinement. A human author verified all retained references, substantive claims,

and numerical values against the corresponding full texts. Responsibility for conceptual interpretation, editorial decisions, authorship, and final approval rests with the human author.

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REFERENCES

1. Shute, V. J. (2008). Focus on formative feedback. Review of Educational Research, 78(1), 153-189. https://doi.org/10.3102/0034654307313795
2. Hattie, J., & Timperley, H. (2007). The power of feedback. Review of Educational Research, 77(1), 81-112. https://doi.org/10.3102/003465430298487
3. 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
4. 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
5. Alwarafy, A. (2026). Large language models in electrical and computer engineering education: Opportunities, challenges and the road ahead. European Journal of Education, 61(3), Article e70761. https://doi.org/10.1111/ejed.70761
6. Baethge, C., Goldbeck-Wood, S., & Mertens, S. (2019). SANRA—a scale for the quality assessment of narrative review articles. Research Integrity and Peer Review, 4(1), Article 5. https://doi.org/10.1186/s41073-019-0064-8
7. Ogunfunmi, T. (2024). Exploration of generative AI tools for an electric circuits course. In 2024 IEEE International Symposium on Circuits and Systems (ISCAS) (pp. 1-5). https://doi.org/10.1109/ISCAS58744.2024.10558391
8. Horne, C. (2025). Leveraging AI chatbots to enhance student understanding of electric circuits. In 2025 IEEE Global Engineering Education Conference (EDUCON) (pp. 1-3). https://doi.org/10.1109/EDUCON62633.2025.11016290
9. Chen, L., Qin, Z., Guo, Y., Rohde, J., & Zhang, Y. (2025). Benchmarking large language models on homework assessment in circuit analysis. International Journal of Artificial Intelligence in Education, 35(5), 3294-3355. https://doi.org/10.1007/s40593-025-00501-w
10. Cao, Y. (2026). Large language models for nodal analysis in circuits education: An evaluation. In SoutheastCon 2026 (pp. 1-6). https://doi.org/10.1109/SoutheastCon63549.2026.11476570
11. Rocha, A., Ferreira, J., Oliveira, P. C., Alves, M., & Sousa, A. (2026). A tool-augmented agentic AI pipeline for reliable circuit-analysis tutoring with local language models. Computers, 15(10), Article 647. https://doi.org/10.3390/computers15100647
12. Chen, L., Xie, H., Rohde, J., & Zhang, Y. (2025). WIP: Large language model-enhanced smart tutor for undergraduate circuit analysis. In 2025 IEEE Frontiers in Education Conference (FIE) (pp. 1-5). https://doi.org/10.1109/FIE63693.2025.11328403
13. Dhagat, P., Cate, R., Najim, N., & Storksdieck, M. (2026). Understanding student perception and utility of generative artificial intelligence as a learning aid in a sophomore-level engineering course on electrical circuit analysis. In 2026 ASEE Annual Conference & Exposition Proceedings. https://doi.org/10.18260/1-2--61149
14. Knievel, C., Bernhardt, A., & Bernhardt, C. (2026). Recognition, retrieval, and response: The AITEE framework for Socratic tutoring in electrical engineering. IEEE Access, 14, 50109-50126. https://doi.org/10.1109/ACCESS.2026.3679269
15. Müller, J., Meier, A., Heinz, M., Göller, K., & Zyla, A. A. (2026). From cognitive overload to individualized learning: AI tutoring in electrical engineering. European Conference on e-Learning, 25(1), 371-380. https://doi.org/10.34190/ecel.25.1.5273

16. Xie, H., Chen, L., Rohde, J., Sun, W., & Zhang, Y. (2026). Leveraging RAG-enhanced LLMs for engineering education: Design and evaluation of AI-Tutor. In 2026 ASEE Annual Conference & Exposition Proceedings. https://doi.org/10.18260/1-2--59993
17. Zamora-Hernández, I., Rodriguez-Paz, M. X., González-Mendivil, J. A., & Palomares-Moctezuma, J. A. (2025). Integrating generative AI into a flipped learning model with a digital channel: Reinforcing theoretical understanding in circuit analysis. In 2025 International Conference on Education Technology and Computers (ICETC) (pp. 714-718). https://doi.org/10.1109/ICETC66579.2025.11387367
18. Habib, S. A. (2025). Exploring the efficacy of ChatGPT in an undergraduate electronics course through comparative analysis of circuit problem solving. In 2025 10th International STEM Education Conference (iSTEM-Ed) (pp. 1-6). https://doi.org/10.1109/iSTEM-Ed65612.2025.11129294