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Wissal EL Fougour
Abdelmalek Essaâdi University, Morocco

Mohamed Erradi
Abdelmalek Essaâdi University, Morocco

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Personalized Feedback in Computer-Based Learning: A Systematic Review of Its Cognitive, Emotional, and Educational Impacts

Wissal EL Fougour, Mohamed Erradi

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Abstract

Feedback is an integral aspect of developing self-regulated learning in that it enables the student an opportunity for reflection, making changes, and learning. The computer-based feedback system supports this systematic review in exploring how improvement in academic performance, metacognitive reasoning, and emotional resilience has taken place in the cognitive and affective dimensions of feedback. Using the PRISMA standards and the PICOS framework, we synthesized findings from 22 studies to assess the effectiveness of these compared with more traditional methods of providing feedback. Results have demonstrated that there is a great enhancement in learning outcomes with personalized real-time feedback, which also reduces frustration, particularly in high-stress environments. Such systems adapt to meet the needs of each learner, developing critical thinking and emotional resilience with continued motivation. While computer-based feedback has shown strengths in terms of scalability and precision, limitations regarding creativity and a human touch raise the need for hybrid models that combine technological efficiency with educator support. This review places cognitive and affective feedback as major drivers of transformative learning in bridging the gap between the learner's aspiration and achievement.

Introduction

In education, feedback is a significant guide that enables learners to conduct their academic journeys with more clarity and less confusion. Much more than highlighting mistakes, good feedback reflects, develops strategies, and enables learners to change and perform. However, personalized and meaningful feedback is one of the biggest challenges in many Instructional settings due to large class sizes, diversified students' needs, and administrative loads for educators (Wang et al., 2022). Each of the factors often deprives learners from getting personalized feedback, that is critical to making substantial progress in learning.

Recent development in computer-based feedback systems holds great potentials that can address these long-standing challenges. Neural networks and Natural language processing can now provide real-time, personalized feedback based on meet the unique needs of individual learners according to Radhakrishnan et al. (2022). Performance feedback from these systems goes further in-depth to address vital issues concerning cognitive engagement, emotional resilience, and lifelong learning skills, important components of SRL. Some of the main approaches to developing self-regulated learning are to set goals, monitor progress, and evaluate strategies in pursuit of areas where one should improve.

Feedback plays an integral role here in solidifying learning strategies while guiding students on how to focus their efforts. According to Schmitz and Wiese (2006), self-regulated learning consists of three phases, the pre-actional phase, which involves setting goals and planning as learners prepare for activities; the actional phase, where plans are executed and progress is tracked; and the post-actional phase, dedicated to reflecting on achievements and identifying areas for growth. Effective feedback supports this process by addressing knowledge gaps and fostering emotional resilience, which is crucial for maintaining motivation to achieve learning objectives (Fong et al., 2019).

This systematic review, therefore, intends to make an exploratory analysis pertaining to the role of feedback in adaptive computer-based learning and its cognitive and emotional impact. Evidence on real-time personalized feedback is synthesized in an attempt to redefine approaches to bridging the gap between a learner's actual performance and his/her potential. In this context, feedback is not viewed as corrective in nature but, rather, an agent for lifelong development. How feedback, integrating technological innovation, cognitive principles, and emotional intelligence can catalyze transformative change by empowering learners to navigate an ever-changing world with flexibility, resiliency, and critical thinking at its core.

Method

A systematic review is the comprehensive and methodologically rigorous process of synthesizing existing literature in addressing clearly defined research questions with precision and scholarly depth. It has been defined as

> "*a review of a clearly formulated question that employs systematic and explicit methods to identify, select, critically appraise relevant research, and to collect and analyze data from the studies included in the review.*"

This review is aligned with the guidance provided by Kitchenham and Charters (2007), where an identified research gap and formulation of focused research questions lead into a detailed protocol containing inclusion and exclusion criteria, strategies for the search, and data extraction methodology. Then comes an extensive, systematic search through relevant databases so that the scoping of the existing studies regarding the specific subject becomes valid. A thorough screening of the retrieved studies, according to predefined eligibility criteria, was followed by the systematic synthesis and analysis of the findings.

The research questions that guided this systematic review are as follows:

1. RQ1: How do Personalized Feedback influence students' learning performance and self-regulation in adaptive computer-based systems?
2. RQ2: How does emotional and negative feedback affect frustration, motivation, and learning outcomes, particularly in high-stress learning environments?
3. RQ3: Do adaptive computer-based systems provide feedback that is as effective as, or more effective than, traditional teacher feedback in improving overall academic performance and learning strategies?
4. RQ4: How does the interaction between cognitive and emotional feedback influence the development of

students' metacognitive reasoning, including their ability to reflect and adapt learning strategies?

These questions provide important insights into the efficacy and influence of cognitive and emotional feedback mechanisms on learning outcomes, and they form the basis for investigating the intricate interactions between these mechanisms in adaptive learning environments.

The Versatility of the PICOS Framework Beyond Medicine

The PICOS framework allows research topics and methods to be organized in a systematic way, starting with the original PICO developed by Richardson et al. (1995). However, it was only after that the wide applicability of PICOS became realized; as noted by Nishikawa-Pache (2022), PICO and PICOS could generally apply in fields other than medicine—like technology, social sciences, and education—due to their adaptability and rigor. This systematic review applied the PICOS framework in the following manner.

Population: University students or health professionals undertaking learning or cognitive tasks.
Intervention: This study examines the immediacy of personalized or general performance feedback, including cognitive and emotional effects delivered via AI tools, chatbots, or learning analytics platforms.
Comparison: It compares conditions such as positive versus negative feedback, feedback versus no feedback, and different feedback modalities.

Outcomes

Primary outcomes: Motivation, academic performance, and self-regulation.
Secondary outcomes: Cognitive-emotional responses, including neurocognitive indicators such as ERP signals.
Study Design: Empirical studies of a quantitative, qualitative, or mixed-method design, RCTs, and neurocognitive experiments are all included in the scope.

This systematic review clarifies the applicability of the PICOS framework beyond conventional clinical settings. Its structured approach enhances transparency and reproducibility, hence making it feasible to analyze the inherent feedback mechanisms within adaptive learning systems and deepening our understanding of their importance within academic and professional development.

Search Strategy

A systematic search strategy is the basis of every systematic review; hence, finding all relevant papers requires exploring a variety of electronic sources. No single database or search engine contains all the literature that may be relevant to a given subject. Therefore, a search must be carried out in as many sources as possible to make the collection of research as complete as it can be. This systematic review has been conducted in accordance with guidelines developed by Kitchenham and Charters (2007), using structured search strings identified through a methodical extraction of keywords, synonyms, and variations in spelling for each of the PICOS elements: Population, Intervention, Comparison, Outcome, and Study Design. Boolean operators have been used; AND is used between differing elements to refine searches, and OR connects synonymous terms, making searches exhaustive and specific. The following search strings for this review are modified as such:

1. *Population:* ”students” OR ”professionals” OR ”university learners” OR ”healthcare providers”
2. *Intervention:* ”personalized feedback” OR ”immediate feedback” OR ”performance feedback” OR ”AI tools” OR ”learning analytics platforms”
3. *Comparison:* ”positive feedback” OR ”negative feedback” OR ”feedback versus no feedback” OR ”feedback modalities”
4. *Outcome:* ”motivation” OR ”academic performance” OR ”self-regulation” OR ”neurocognitive responses” OR ”ERP signals”
5. *Study Design:* ”quantitative studies” OR ”qualitative studies” OR ”RCTs” OR ”mixed-methods research” OR ”neurocognitive experiments”

A structured search strategy has been developed on the IEEE Xplore, Web of Science, ScienceDirect, and Scopus databases to make sure that the literature review covers all the aspects of the topic. PICOS elements were combined in an initial search using the Boolean ”AND”. This retrieved very few results, with a total of ten articles in Scopus. It was then decided to remove the element of Comparison in order to broaden the search and capture more relevant studies.

This removal of the Comparison element allowed capturing other studies under the same study’s objectives and/or scope. Of course, such an ability indicates the flexibility of structured methods in conducting systematic reviews in balancing between breadth and precision in a search so that relevant material can be effectively identified. Kitchenham and Charters (2007), instructed how to combine topic categories by the use of AND operators iteratively with the inclusion of synonyms and related phrases through OR operators. Since, as Brereton et al. (2007) noted, no single database contains all relevant research, we consulted multiple sources. We selected each database for its strengths:

– *IEEE Xplore:* Focuses on the most recent topics of interest in engineering, including artificial intelligence and machine learning, which are critical components of feedback systems.
– *ScienceDirect:* Offers a broad scope of subject areas, including education, psychology, and cognitive sciences.
– *Scopus:* Provides broad coverage and powerful search features to access diverse studies.
– *Web of Science:* High-quality, cross-disciplinary research from impactful journals.

Together, these databases provided the most comprehensive coverage so that the review could include only high-quality studies on educational technology and feedback systems.

Study Selection

Inclusion and Exclusion Criteria

The inclusion and exclusion criteria describe the types of study, intervention, population, and outcomes that are eligible for in-depth review, and those that are excluded. These criteria need to be specified in the report or article describing the review (Petticrew and Roberts,2006).

For this review, inclusion criteria focused on primary studies involving university students, interventions such as cognitive or emotional feedback, and outcomes related to motivation, academic performance, or self-regulation. Exclusion criteria included non-English papers, secondary studies, grey literature (e.g., theses or dissertations), and studies with incomplete data or irrelevant outcomes. These criteria ensure the review is methodologically sound and focused on the target population and interventions.

Table 1 provides a detailed overview of the step-by-step process for applying our selection criteria.

Table 1. Inclusion and Exclusion Criteria

Category	**Inclusion Criteria**	**Exclusion Criteria**
Population	University students, healthcare professionals, or participants in educational tasks.	Non-educational populations or those unrelated to feedback mechanisms.
Intervention	Studies involving personalized, immediate, or adaptive feedback (e.g., AI tools, chatbots).	Studies without interventions related to feedback or learning systems.
Study Design	Empirical studies such as RCTs, comparative studies, or quasi-experimental designs.	Non-empirical studies, reviews, grey literature (e.g., theses, books, abstracts).
Language	Articles published in English.	Non-English publications.
Time Frame	Articles published in the last 10 years (2014-2024) to ensure relevance to current practices.	Studies published outside the specified period.
Outcomes	Focus on motivation, academic performance, self-regulation, or cognitive-emotional outcomes.	Studies not addressing these outcomes or lacking clear data.
Publication Type	Peer-reviewed journal articles.	Conference abstracts, grey literature, or incomplete studies.

Database Extraction Process

Table 2 summarizes the articles retrieved from four digital libraries, totaling 2,678. Scopus contributed the majority (77.33%), followed by ScienceDirect (14.00%), Web of Science (4.93%), and IEEE Xplore (3.73%). This ensures broad coverage of relevant studies.

Table 2. Articles Retrieved from Digital Libraries

Digital Library	**Number of Articles**	**Percentage (%)**
IEEEExplorer	100	3.73
Science Direct	375	14.00
Scopus	2071	77.33
Web of Science	132	4.93
Total	2678	100.00

Extraction and Screening Process

Integration of a Semi-Automated Screening Tool in the Review Process

A semi-automated tool was developed in collaboration with the competencies of a software engineer to rank articles using predefined inclusion and exclusion criteria based on the PICOS framework, with a view to making the first stage of title and abstract screening more efficient. In this regard, each article had a relevance score associated with it, which gave justification to the content found within the title and the abstract. Articles associated with higher relevance scores would be scheduled for manual review. To ensure methodological accuracy, all system-generated outputs were independently verified through manual screening by the first author. Further details about the design and validation of the tool will be shared in the subsequent manuscript. This hybrid strategy enhanced the efficiency of the screening process while preserving the precision and reliability that a systematic review required.

Results

From 2,678 publications, 22 studies met the PRISMA-based inclusion criteria.(Haddaway et al., 2022), Exploring personalized feedback's impact on students' development in computer-based learning (see Figure 1 for the PRISMA flowchart).

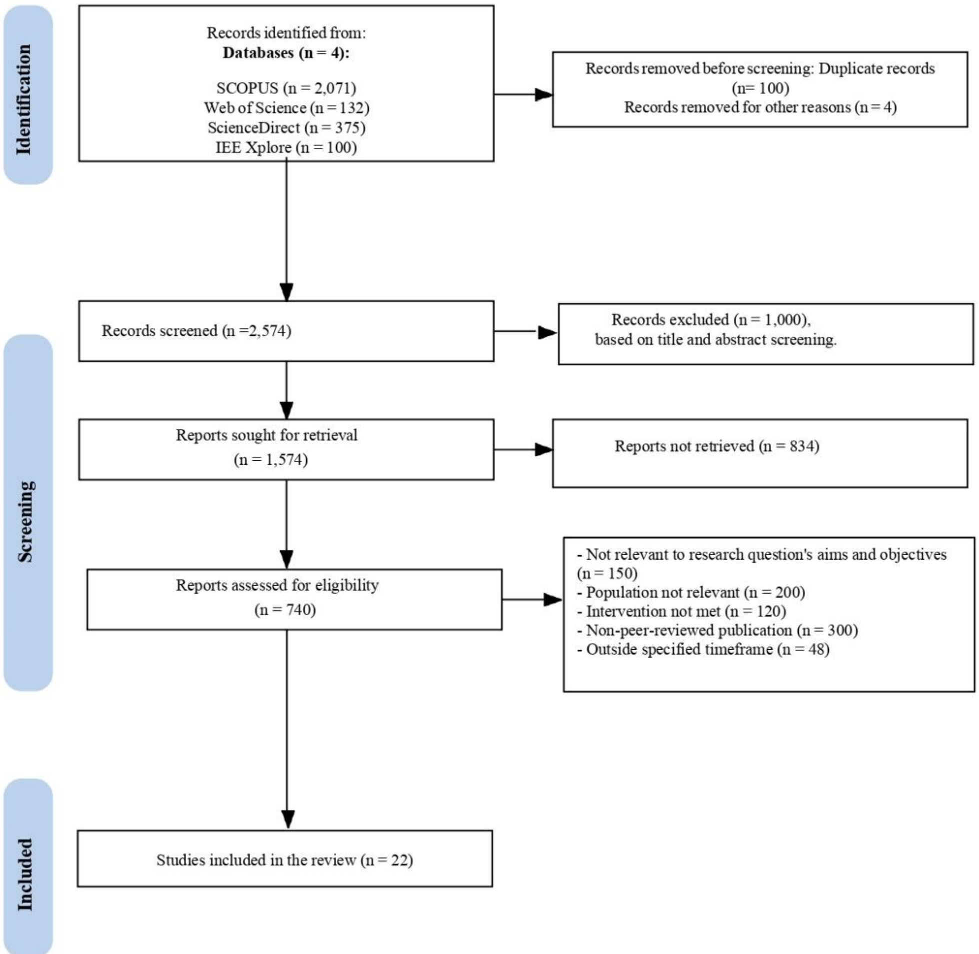

Figure 1. Flowchart of Selection Procedure

Study Coverage of Research Questions

A systematic analysis assessed how effectively the articles addressed research questions (RQ1–RQ4). Table 3 summarizes the focus of each issue in the 22 studies reviewed.

Table 3. Coverage of Research Questions by Reviewed Studies

Study	**RQ1**	**RQ2**	**RQ3**	**RQ4**
(Yang and Dorneich, 2018)	No	Yes	No	No
(Mahrous et al., 2023)	Yes	No	Yes	No
(Jukiewicz, 2024)	No	No	Yes	No
(Lim et al., 2021)	Yes	No	Yes	No
(Ortega-Ochoa et al., 2024)	No	Yes	Yes	Yes
(Naseer et al., 2024)	Yes	No	Yes	No
(Chryssafiadi et al., 2023)	Yes	No	Yes	No
(Marwan et al., 2022)	Yes	No	No	Yes
(Tuti et al., 2020)	Yes	No	Yes	No
(Wang et al., 2022)	Yes	No	Yes	Yes
(Bellhäuser et al., 2023)	Yes	No	Yes	No
(Theobald and Bellhäuser, 2022)	Yes	No	Yes	No
(Mejeh et al., 2024)	Yes	Yes	No	No
(Bulut et al., 2019)	Yes	Yes	Yes	Yes
(Say et al., 2024)	Yes	Yes	No	Yes
(Gonçalves et al., 2023)	Yes	No	Yes	No
(Kuklick et al., 2024)	No	Yes	No	No
(Clinton-Lisell, 2018)	Yes	No	No	No
(Demaidi et al., 2015)	Yes	No	No	No
(Woo et al., 2018)	No	Yes	No	No
(Li et al., 2022)	No	Yes	No	No
(Thuillard et al., 2007)	No	Yes	No	No
Percentage Coverage	68%	36%	50%	27%

Only papers that thoroughly answered a research topic were categorized as ”YES” in this review. Research that only partially addressed a research topic was classified as ”NO” in order to preserve uniformity and solid inclusion requirements. This method guarantees that studies that give full responses to a research question are clearly distinguished from those that just offer supplementary or partial insights.

Study Characteristics

Temporal Distribution of Included Studies

This review’s included studies’ temporal distribution is shown in Figure 2.

Although the first few years (2015–2020) exhibit a comparatively small number of publications, research activity clearly picks up from 2022 onward. This trend emphasizes how adaptive feedback systems are becoming more and more popular among academics in both the professional and educational fields.

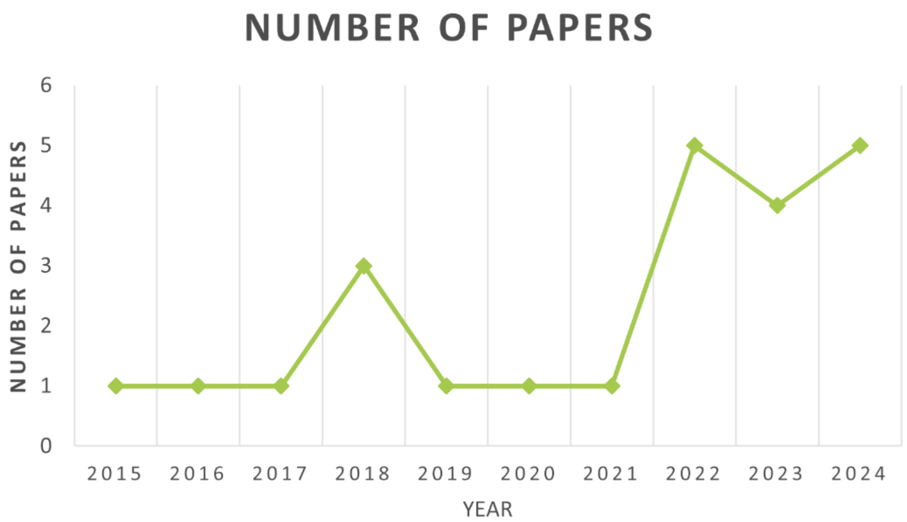

Figure 2. Temporal Distribution of Included Studies.

Geographical Distribution of Included Studies

The geographical distribution of the studies that were part of this systematic review is shown in Figure 3. The figure shows the countries where the study was carried out, with the United States producing the most studies, followed by Germany and Australia. This distribution sheds light on the widespread interest in computer-based feedback systems and how they affect education.

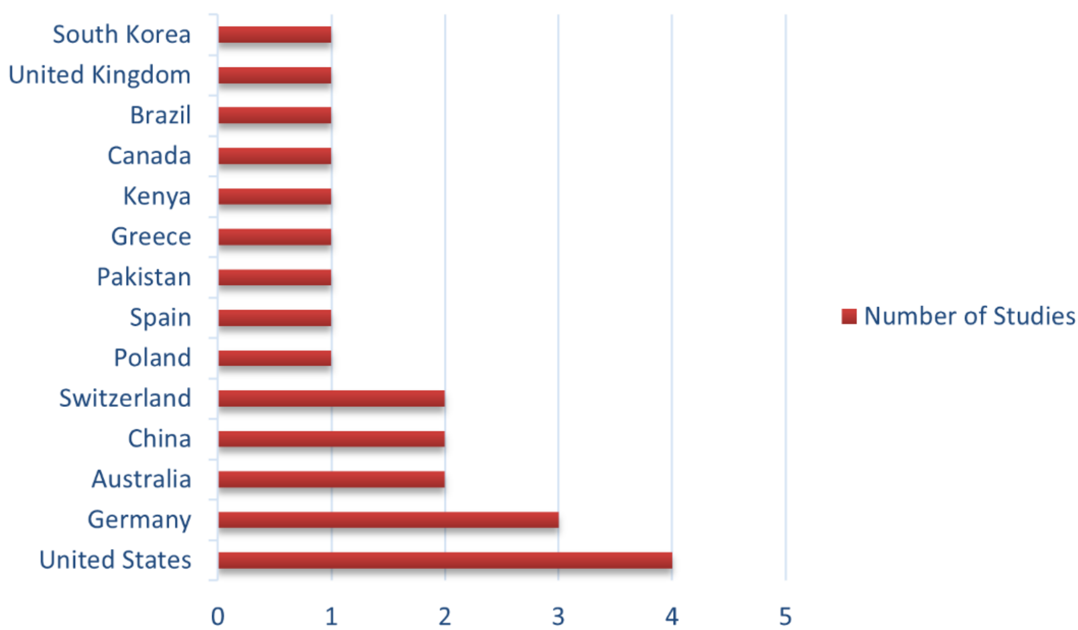

Figure 3. Geographical Distribution of Studies

Fields of Study Covered by Included Articles

Figure 4 presents the representation of the field of study from the included articles, broken down: Science, Technology, Engineering, and Mathematics (the largest category) including Social Sciences and Humanities, Education, and then Healthcare. That also shows, simultaneously, both the multidisciplinary and multidimensionality of studies focused on adaptive feedback.

The included studies' data were methodically gathered and then combined utilizing a narrative technique. By integrating the results of several research, this approach highlights important themes, patterns, and trends in literature. The narrative synthesis provides a thorough framework to examine and interpret the data, enabling a unified picture of the study landscape

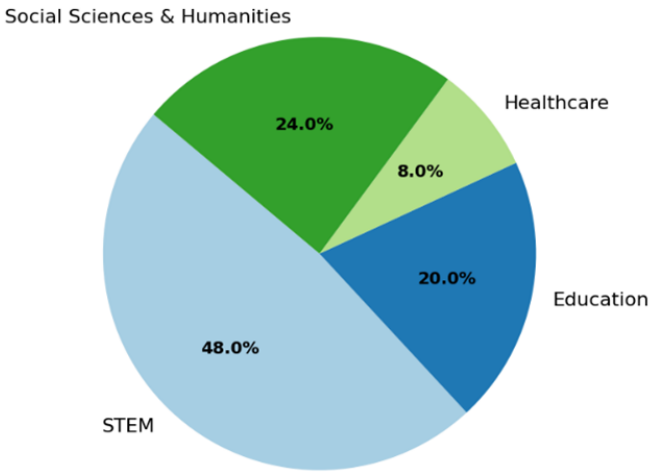

Figure 4. Distribution of Fields of Study among the Included Articles

(RQ1): How do Personalized Feedback influence students' learning performance and self-regulation in adaptive computer-based systems?

Personalized feedback has turned the role of adaptive computer-based learning systems from a rather passive mode of knowledge intake to an active and self-regulated learning process. It enhances academic performance and develops critical capabilities such as reflection, strategic adjustment, and learner autonomy through advice adapted to the needs of each learner. In its nature, feedback is dialogical, allowing students to be actively and meaningfully involved in their learning.

Of all the accompanying benefits of feedback, the most striking is flexibility. Real-time feedback-for instance, altering the difficulty of tasks by the student's progress-was found by Naseer et al. (2024) to carry an incredible 25% increase in academic improvements over conventional methods. These systems challenged students at their optimal engagement level, therefore fostering growth in their cognitive skills.

This was further extended by Tuti et al. (2020), who, in turn, proved that adaptive feedback systems enhance learning outcomes with a statistically significant effect size of 0.644 ($p < .001$). Feedback with reflection prompts challenged the students to reconsider their knowledge, refine their skills, and deepen their understanding of key concepts. Of particular relevance were some compact sessions that would maximize such effects through timely interventions to optimize such advantages of tailored feedback.

Adaptability guarantees relevance, while depth enables meaningful learning. Mahrous et al. (2023) discussed the transformative effect of elaborative feedback, which is especially important in dentistry education, where students demand extensive explanations for their mistakes. This kind of feedback promotes critical thinking and a more profound understanding. Lim et al. (2021) also echoed process-focused feedback, as posited in the COPES model by Winne and Hadwin (1998). It helped students reflect on their progress, review tactics with a view to reaching academic goals, and align efforts accordingly. This approach enhanced grades and encouraged a more deliberate and adaptable learning attitude.

In this regard, Theobald and Bellhäuser (2022) conceptualized the notion of transformational feedback through the integration of short-term assessments into long-term strategies. It provides an avenue for making the leap from current to intended performance less formidable for students by reducing procrastination while encouraging the development of skills like planning and iterative self-monitoring. Feedback herein will be viewed more as a growth map rather than a corrective tool. Likewise, in Bulut et al. (2019)'s study, 97% of the students used midterm feedback to prepare for final examinations, which is considered a long-term impact of feedback. Students preferred elaborate, deep, and prospective feedback because it enabled them to evaluate their progress themselves and make any adjustment in their strategy.

Information-seeking activity is also one kind of self-regulatory activity, especially essential for learning. It is thus an active approach by learners in addressing a particular knowledge gap through resources such as notes or textbooks. Again, Say et al. (2024), Butler and Winne (1995), and Zimmerman (2002) identify feedback as a catalyst for such an action, which is an approach viewed as a metacognitive signal that motivates learners to assess the current state of their knowledge on the issue and triggers the search for more knowledge. Marwan et al. (2022) highlighted that in feedback systems, mechanisms such as subgoal monitoring and progress indicators prompt students to reflect on their approach and make improvements that continually re-engage them in the work.

Differentiating Feedback Effectiveness Across Cognitive Levels and Learner Characteristics

What makes tailored feedback effective is that it can adjust to the task complexities as well as learners' individual characteristics. Indeed, Demaidi et al. (2018)provides strong evidence for this twofold approach by presenting that feedback aimed at both the learner's cognitive needs and their readiness significantly enhances effectiveness. Using Bloom's taxonomymy (Bloom et al., 1956), the study presents detailed and extensive feedback as a scaffolding mechanism for novice students, gradually leading them to understand basic concepts. On the other hand, brief and specific feedback is useful for advanced students because it would promote autonomy, increase self-regulatory abilities, and enable them to practice their strategies with minimal external support.

This tailored approach ensures that learners obtain the specific type of feedback most suited to their needs at the exact moment it is required. The present research also underlines the fact that feedback may have different degrees of effectiveness, depending on the cognitive demands of the tasks. In the case of relatively simple tasks that can be performed predominantly with basic knowledge and comprehension, personalized feedback is found to perform at a level equal to that of Knowledge of Results feedback (KOR), with no significant advantage of one method over the other.

When the tasks require more complex higher-order cognitive skills, such as in-depth analysis and critical thinking, it becomes clear that personalized feedback has a far better influence on learning outcomes. A notable 50% of students showed positive learning gains within the experimental group—a great success, given that only 25% of the students showed improvement in the KOR group (Demaidi et al., 2018).This specific finding points out and underlines the crucial and important role that feedback plays in fostering and encouraging critical thinking skills, as well as deep engagement with challenging and demanding material. It shows that the value of feedback increases even more and rises substantially with an increase in the cognitive demands and complexities of the task at hand.

(RQ2): Emotional and Negative Feedback: A Balancing Act in High-Stress Learning Environments

Emotional and negative responses act like pivotal elements in the molding of educational outcomes, where the influence of motivation and frustration level modulation is very strong in students who are under extreme compulsion to perform. However, this mechanism does not work the same with each student, while individual differences regarding prior knowledge and metacognitive skills, motivational and emotional states, and preferred learning strategies and styles are crucially important with respect to the way the feedback will be received, interpreted, and reacted to. For instance, students with more advanced metacognitive capabilities can make more useful inferences from ambiguous feedback; students with greater affective sensitivity may require that feedback also provide emotional sustenance. Additionally, whether or not feedback becomes a source of interest or frustration depends on motivation and prior knowledge.

Divergent findings from early studies provide a good example of the role of student differences. Following Yang and Dorneich (2018), highly frustrated students responded more positively to feedback framed as solutions, which they termed” negative-politeness” feedback. This approach’s ability to provide clarity and specific suggestions without adding additional emotional burden allows students to focus on task-related growth rather than feeling overwhelmed. By contrast, Ortega-Ochoa et al. (2024) found that emotionally adaptive feedback given through empathetic conversational agents was also highly effective. In particular, on complex tasks such as computer programming, these systems detected and transformed learners’ affective states, dramatically reducing frustration and increasing persistence. The delivery mode of feedback is also significant in diminishing or enhancing the emotional and motivating effects of feedback. A study by Thuillard et al. (2022) showed that negative feedback from automated systems was perceived by students as more objective and neutral than that from human teachers, who often managed to provoke suspicion or blame. This objectivity meant that” the student could focus on how he could improve, not on the emotional burden of being criticized.” This emotional resilience comes at a price, however: while performance may remain intact, over time, negative feedback will undermine intrinsic motivation as well as emotional well-being. On the other side, Mejeh et al. (2024) address that negative feedback is uncomfortable but can be one of the most powerful motivators if it instigates students to reflect upon their strategies and practice effective self-regulation. Indeed, balanced feedback-turning out to be somewhat clear, emotionally sensitive, and full of insights-emerges as the most effective strategy under high-stress learning conditions.

The Neuroscience of Feedback: A Blueprint for Effective Learning Systems

To design feedback tools, one needs to understand how the brain processes feedback and shapes a learner's ability to regulate emotions, refine strategies, and achieve goals. Feedback is not an instructional method but rather a direct intervention into the neural pathways of the brain. Negative feedback has been called an error signal since it makes learners aware of their mistakes; besides, the emergence of these negative signals can be effective for prompting behavior modification as well. If it is inadequately administered, however, negative feedback will provoke overactivation of the amygdala—the affective processing site in the brain—resulting in frustration, anxiety, and low concentration and retention (Dolcos and McCarthy, 2006). Feedback, to become effective, has to offset these affective perturbations by engaging the DLPFC responsible for both emotional regulation and constructive learning (Goldin et al., 2008 ; Drabant et al., 2009).As to whether or not feedback itself causes more emotional strain and promotes further learning, everything depends on its quality. For example, Li et al. (2018) checked that clear and executable feedback turned on the DLPFC so that one was able to govern emotional reactions by reorganizing the means. In that respect, clear feedback also engages the P300 response, a neurological pattern of updating reflecting the efficiency by which brains process feedback and reorganize actions. On the other hand, too vague or overly critical feedback leaves learners uninformed and encourages frustration and disengagement. Woo et al. (2015) emphasized that confirmatory feedback, which only indicates correctness, evokes emotional responses via the amygdala. In contrast, feedback offering explanation and corrective guidance develops emotional resilience, promotes cognitive focus, and sustains motivation in the presence of challenges.

These insights into the brain underline that educational tools should also be aligned to the feedback processing of the brain. Adaptive technologies, such as PCAs (empathic pedagogical conversational agent), have provided great promise in providing dynamically adjusting feedback to the emotional states of the learners, given the importance of persistence and engagement toward challenging tasks. By embedding neuroscientific principles into feedback strategies, embedding emotional sensitivity alongside cognitive clarity provides systems with an empowering means for learners to surmount the obstacles toward the attainment of durable success.

(RQ3): Do adaptive computer-based systems provide feedback that is as effective as, or more effective than, traditional teacher feedback in improving overall academic performance and learning strategies?

In the expanded offerings of higher learning, personalized feedback represents a fundamental requirement confronting an expanding series of complications. Large class sizes, further complicated by heterogeneity among students' learning needs and limited instructor availability, make it very difficult for traditional mechanisms of feedback to be effective. Intrinsically important, these often fall short relative to the expanding need for precision, adaptability, and timeliness. This is where adaptive computer-based systems have come into play—frontiers now offering scalable, individualized feedback solutions for improved learning outcomes that truly meet the diverse needs of the learners.

Adaptive systems are increasingly supported by an increasing volume of empirical evidence. For instance, in one controlled experiment, Naseer et al. (2024) found that students receiving AI-generated feedback outperformed those receiving traditional instruction by 25% ($p < .001$), a large gain that reflects a greater degree of alignment between feedback and learner progress. Another such example is provided by Chrysafiadi et al. (2023), regarding fuzzy-based ITS, which mentions a large improvement in students' performance, with learners using ITS outperforming those receiving traditional feedback. Such findings reveal the potential of adaptive systems to track individual learning trajectories more sensitively than could be the case in a static approach.

One of the most encouraging benefits of adaptive systems is their power to develop self-regulated learning (SRL). Evidence from the work of Theobald and Bellhäuser (2022)identified that real-time feedback, together with forward-looking strategies, created transformative feedback that garnered drastic differences in planning, self-monitoring, and reducing procrastination—all core facets of SRL. These students not only derived SRL benefits but also demonstrated improved final examination performance, hence their long-term academic benefit. In this manner, it has been noted by Bellhäuser et al. (2023) that adaptive systems best facilitate particular key metacognitive skills such as setting goals, managing time, and maintaining a preplanned, structured study schedule. In large-scale learning settings, where it is frequently unfeasible to provide customized feedback from educators, adaptive feedback systems appear as a highly scalable and economical substitute that maintains pedagogical integrity. It has been demonstrated that these methods foster critical abilities required for lifelong learning while also improving academic achievement. Adaptive systems creatively overcome the drawbacks of conventional teaching methods by customizing input to meet the individual cognitive and emotional requirements of every learner. In addition to encouraging more student autonomy, this individualized method improves the standard of training as a whole.

Adaptive systems address not only intellectual barriers to learning but also emotional ones. Bulut et al. (2019) argue that computer-generated feedback, unlike face-to-face feedback—which can be perceived as an ego threat—is neutral and nonjudgmental. As a result, students are more likely to respond constructively to computer-mediated feedback, free from the risk of embarrassment or defensiveness. The most significant benefit for students who are sensitive to negative feedback is the development of emotional neutrality. It turns the potentially discouraging occasion into a worthwhile chance for development and progress. It is not always true that the source of feedback—whether it be computer or human—affects the performance results. According to Thuillard et al. (2022), there was not a noticeable distinction in task performance between computer-generated and human-generated feedback. As an exception, negative feedback from a computer led to higher idea generation in ideation tasks, explained through the" increased motivation" mechanism of (Sauer et al., 2019). These findings underpin the fact that feedback is effective not only with respect to its source but also with respect to the way it is communicated and perceived. For this reason, clarity, relevance, and engagement by learners should be important considerations at the design stage if adaptive systems are to achieve maximum effectiveness.Adaptive systems range from enhancing creativity to technical skills. For instance, Mahrous et al. (2023) proved AI-driven feedback effective in dental education, with dynamic and interactive presentation of feedback that developed substantially higher cognitive and practical competencies.

Wang et al. (2022) examined the effectiveness of SVVR-AWE (Spherical Video-based Virtual Reality and Automatic Writing Evaluation) approach in writing- intensive courses and recorded significant improvements in originality, coherence, and content structuring. These studies show the flexibility of such systems in meeting a wide range of teaching demands and contexts.

At the same time, even though these systems boast a lot of advantages, they are not suggested to replace educators but rather to supplement them. Ortega-Ochoa et al. (2024) predict that in the very near future, empathetic chatbots will join other AI platforms handling regular feedback roles, therefore allowing educators to take up more responsible tasks like mentorship, development of critical thinking, and deploying sophisticated teaching strategies. In this way, the collaboration will enrich and variegate educational experiences, combining technology's precision and scalability with human educators' nuanced expertise.

(RQ4): How does the interaction between cognitive and emotional feedback influence the development of students' metacognitive reasoning, including their ability to reflect and adapt learning strategies?

Metacognitive monitoring, defined as being aware of and controlling cognitive processes, for example, detecting errors in one's own thinking (Fernandez-Duque et al., 2000), is an important skill for university students to have when faced with complex academic tasks. Feedback can play a pivotal role in enhancing this skill through increased retrospective awareness, which enables learners to reduce biases and make their self-assessments more accurate. As noted by Beyer (2002) ; Labuhn et al.(2010) ; Nederhand et al.(2019), task-to-task feedback not only supports academic achievement but also helps to promote both self-regulation and reflection, even in low-stakes environments where extrinsic motivators are absent (Kuklick et al., 2023).

Indeed, feedback mechanisms, especially those related to calibration biases such as under- and overconfidence, common challenges usually seen in poorly performing students as encircled by the Dunning-Kruger effect (Kruger and Dunning, 1999), are vital in developing reflective practices. Such mechanisms make the learner aware of his lapses in performance and develop deeper cognitive engagements toward the creation of better learning strategies. It is based on these that dynamic interaction between cognitive and affective feedback proves to be a critical factor in metacognitive reasoning development. Cognitive feedback, as explained, permits the learner to make critical analyses of his/her approach and refine them. In that case, there would be a better understanding of both task demands and one's own capabilities. Emotive feedback, on the other hand, will create conditions that keep anxiety low and motivation high, self-reflective in nature. In corroboration, as seen from (Ortega-Ochoa et al., 2024; Wang et al., 2022), critical thinking and adaptive learning are jointly nurtured by these two kinds of feedback. According to Wang et al. (2022), it has been outlined that the SVVR-AWE framework effectively improves reflective and adaptive capacity in learners.

Moreover, timeliness in feedback provision is fundamental to furthering metacognitive calibration. Timely feedback, important in helping learners identify and reduce biases in their ways of thinking, develops better self-regulation skills and enhances their adaptive learning capabilities (Nederhand et al., 2019). Therefore, strategically placed feedback mechanisms have great potential for fostering richer metacognitive and reflective practices in various educational settings.

Feedback for enhancing metacognition is further supported by the work of Say et al. (2024), who illustrate the efficiency of a different approach: score-only feedback. Unlike (KR + EF), which customarily gives reasons and corrected answers, score-only feedback prompts students to look more closely at their work themselves and interact more intensively with their fellow students. While students may complain because there are no 'right' or 'wrong' answers to guide them, this type of feedback prompts reflection and self-evaluation skills that are foundational to the development of practical competencies like self-regulation, problem-solving, and critical thinking. Most importantly, score-only feedback better equips students for professional practice in flexible, self-directed professions like nursing Say et al. (2024). Moreover, reframing assessment as a stimulus to metacognitive engagement and not merely the production of answers better prepares students for the challenges they will face throughout their academic and professional careers.

Discussion

More than improving academic achievement, this systematic review underlines how individualized and adaptive feedback in education can be seen as an important driver of much deeper cognitive and emotional development. How feedback may respect each learner's unique starting point, cognitive capabilities, and emotional states while it supports self-regulation, comprehensive insight, and agency can be considered a core element of such a transformation process. One key conclusion of this review is that the effectiveness of individualized feedback is complex. For instance, Gonçalves et al. (2017) show that detailed teaching enables students with limited pre-instructional knowledge to overcome conceptual obstacles and thus relate better to challenging material. The finding is in agreement with the long-held concept in pedagogy that real learning does not necessarily take place when learners are corrected but when they are made capable of taking responsibility for their growth. Adaptive systems, such as those examined in work by Chrysafiadi et al. (2023), bring this concept to life with feedback that dynamically adjusts in concert with a learner's progress. These systems nurture not only better performance but also habits of reflection and adjustability that will serve students well long after formal education is left behind.

The efficiency of feedback has always been married to its duality of function: serving both as an immediate corrective and as a scaffolding mechanism for sustaining long-term development. Clinton-Lisell (2024) illustrates very clearly that elaborative feedback, especially that which is afforded reasoning and contextualization, builds the cognitive structures needed for deep learning. Yet again, this review also points out that not all learners gain equally from an equivalent amount of detail: Whereas novices, who are making their way through unfamiliar conceptual landscapes, may need detailed step-by-step guidance, more advanced learners may need only brief, strategic cues that respect their autonomy. These subtleties make it differ and introduce complexity in the design of a feedback system: besides having to be tuned for specific cognitive demands, it also has to take into consideration the fact that on the path toward mastery, learners shift from dependency to autonomy. Apart from this complex dimension, there is an added emotive dimension of feedback. In high-stress learning environments, such as programming or problem-solving, these emotionally adaptive systems have proved themselves strong in diffusing frustration and building resilience.

As Yang and Dorneich (2018) point out, ”negative-politeness” feedback might be direct and solution-focused, serving to diminish emotional obstacles and enabling learners to address issues with actionable improvements. The interest from Thuillard et al. (2022) reflects this neutrality, pointing out a remarkable paradox: even if perceived objectivity may reduce defensiveness, increasing focus on the process will be somewhat muted by the reduction in human-related empathy; consequently, the motivations and relationships pertinent to learning go without reinforcement. The future of feedback lies in the balance of tapping the precision of artificial intelligence while concurrently retaining human-like emotional interaction. This approach not only sustains intrinsic motivation and engagement but also fosters metacognitive reasoning based on the cognitive/emotional interplay.

Feedback that combines clarity with emotional awareness urges learners to reflect on their strategies and change their approach. For example, static feedback with hints provides learners with immediate, actionable advice while steadily increasing their independence in order to fortify the major metacognitive skills associated with planning, self-monitoring, and adaptive thinking—skills well aligned with real-world problem-solving (Wancham and Tangdhanakanond, 2020). Moreover, feedback approaches, such as score-only feedback, investigated by Say et al. 2024, show that discomfort, if carefully managed, is productive in getting learners to engage in their work both deeply and critically. Comparison of adaptive feedback systems with traditional teacher-led methods emphasizes the scalability and precision of the former. Technologies such as fuzzy-based intelligent tutoring models (Chrysafiadi et al., 2023) afford the opportunity for improving academic performance by cutting down inefficiencies in studies and thus having learners focus their efforts on specific areas of actual need.

To be sure, those systems have limitations. Yet, the findings bear considerable implications beyond the immediate academic scene toward professional development and lifelong learning. This would call for hybrid models, for which adaptive systems handle the routine feedback, so that the educator can concentrate on the development of higher-order thinking and creativity. The implications from these findings carry important implications that go far beyond the walls of the academic setting and bear great importance for professional development and lifelong learning. The feedback practices that balance cognitive challenge with emotional support are just as relevant in the workplace as they are in the classroom. Adaptive systems designed with neuroscientific principles in mind—like engaging the prefrontal cortex to achieve emotional regulation—will restructure training programs to increase employees' abilities to respond resiliently and adaptively to complex tasks. The iterative, reflective nature of good feedback provides a structure not only for academic success but for excelling in any field that requires ongoing development.

Limitations

This review acknowledges its limitations. Although adaptive systems have promise for facilitating self-regulated learning, their long-term impact on learners' independent functioning in a no-scaffolding condition is also poorly explored. Future studies should focus on hybrid models combining computer- and human-based feedback to serve a wide variety of learners in and between disciplines. Furthermore, the sample used a semi-automated screening instrument to expedite the review process using the PICOS model for abstract extraction. Inwards of substantial upscaling efficiency, the tool has not yet been thoroughly validated and is not publicly available. Its reliance on abstracts made it subject to manual supervi-sion to guarantee the inclusion of all relevant studies. Regular rechecks of system-generated results confirmed its accuracy. Future developments will center in the development of the full text screening ability, refinement of algorithms and tool validation, with a view to publish both tool design and application of systematic reviews.

Conclusion

This systematic review highlights the key importance of computer-based feedback systems towards the achievement of self-regulated learning (SRL) by engaging in cognitive and affective domains as well. In a synthesis of 22 studies, it emphasizes how adaptive feedback systems can substantially enhance academic performance, metacognitive thinking, and emotional resilience in contexts that are inherently diverse and high-pressure. Nevertheless, the present investigation also demonstrates significant limitations that deserve deeper exploration. Future research should explore the continuing effect of these systems on the autonomy and flexibility of learners, specifically, whether and to what extent dependence on outside feedback helps or hinders autonomous learning. Additionally, the possibility of hybrid feedback models, combining the reliability of technology with the intuitiveness of human guidance, continues to be an intriguing direction to promote creativity and more meaningful learner involvement. Research that includes underrepresented fields of study and heterogeneous learner profiles will be essential in establishing the generalizability of such findings. As education evolves, there is an exciting opportunity in the integration of personalized feedback systems. Through further exploration of their cognitive and affective aspects, future developments can reshape feedback as a dynamic, learner-driven instrument that empowers students to thrive in an increasingly adaptive and ever-changing world.

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Author Information

Wissal EL Fougour

https://orcid.org/0009-0000-8637-1985

Abdelmalek Essaâdi University

Morocco

Contact e-mail: *wissal.elfougour@etu.uae.ac.ma*

Mohamed Erradi

https://orcid.org/0009-0003-5507-1578

Abdelmalek Essaâdi University

Morocco

Appendix A. Summary of Included Studies

This table highlights the key characteristics and findings of the included studies, emphasizing their diverse approaches, populations, and objectives. It highlights the effects of computer-assisted feedback systems on different aspects of learning, from cognitive growth to emotional toughness, academic outcomes, and involvement. The constraints that have been described in each study offer very important clues for future research directions.

Table. Summary of Included Studies

Authors	Population	Design	Objective	Key Findings and Limitations
Yang & Dorneich (2018)	40 university students	Within-subject	Explore etiquette strategies to reduce frustration and improve learning.	Positive politeness improved satisfaction: frustration affected performance. **Limitations:** Limited to math tasks; no long-term impacts.
Mahrous et al. (2023)	73 dental students	RCT	Assess AI-based software for RPD design.	Improved grades; positive student perceptions. **Limitations**: Limited sample size; potential novelty effect influencing engagement; no long-term assessment of learning outcomes.
Marcin Jukiewicz (2024)	67 Cognitive Science students	Within-subject	Evaluate ChatGPT's ability to grade programming tasks and provide feedback.	Strong correlation between ChatGPT and teacher grades; ChatGPT stricter but consistent. **Limitations:** Cost of using ChatGPT API, occasional grading inconsistencies (hallucinations), need for teacher intervention.
Lim et al. (2021)	784 biology students	Quasi-experimental	Evaluate the impact of learning analytics feedback on SRL and academic performance.	Improved academic performance and SRL; experimental group had better final grades. **Limitations:** Non-randomized design; potential unaccounted variables.
Ortega-Ochoa et al. (2024)	196 students in Distributed Systems	Quasi-experimental	Evaluate empathic chatbot feedback on learning, motivation, self-	Empathic feedback effective as teacher feedback; significantly influenced metacognitive reasoning. **Limitations:** Results

			regulation, and metacognitive reasoning.	based on self-reported data; limited feedback scenarios.
Naseer et al. (2024)	300 university students	Mixed-methods	Explore personalized learning using deep learning techniques.	25% improvement in grades; higher engagement and satisfaction metrics; platform interaction rates were higher in the experimental group. **Limitations:**Integration challenges with the curriculum, technical glitches, and pedagogical adjustments for educators.
Chrysafiadi et al. (2023)	140 undergraduate students	Quasi-experimental	Evaluate the effectiveness of fuzzy-based ITS for computer programming.	Improved recommendation accuracy, reduced interaction time, increased learner performance. **Limitations:** Results specific to programming; generalizability untested.
Marwan et al. (2022)	50 undergraduate students	Between-subject	Evaluate an adaptive immediate feedback system for programming.	AIF improved performance, task completion, and persistence. **Limitations:** Specific to block-based programming; small sample size.
Tuti et al. (2020)	572 healthcare providers in low-income countries	RCT	Evaluate adaptive feedback in a mobile game for neonatal emergency care training.	Adaptive feedback significantly improved learning gains. **Limitations**: High dropout rates; limitations in Bayesian Knowledge Tracing.
Wang et al. (2022)	76 English major students	Quasi-experimental	Evaluate AWE and SVVR integration in EFL writing performance.	Improved writing performance, motivation, self-efficacy, reduced anxiety. **Limitations:** Short duration, small sample size.
Theobald & Bellhäuser (2022)	244 university students	Experimental (within- and between-subjects)	Evaluate effects of daily adaptive feedback on SRL, motivation, and	Improved SRL strategies and exam grades. **Limitations:** Self-reports prone to bias; no non-diary control

			performance.	group.
Bellhäuser et al. (2023)	194 university students	Randomized Field Experiment	Investigate adaptive feedback on SRL strategies.	Improved goal setting, planning, self-efficacy, and schedules. **Limitations**: Based on self-reports; limited to short-term behavioral changes.
Mejeh et al. (2024)	33,undergraduate students	Mixed-methods	Examine adaptive feedback impact on SRL components.	Improved planning, monitoring, emotional regulation**.** **Limitations**: Small sample size; no control group.
Bulut et al. (2019)	776 pre-service teachers	Quasi-experimental	Evaluate ExamVis impact on learning outcomes.	Improved final exam scores; immediate feedback reduced review rates. **Limitations:** Focused on multiple-choice; limited generalizability.
Say et al. (2024)	1,082 nursing students	Mixed-methods	Investigate score-only feedback on SRL strategies and satisfaction.	Promoted metacognitive engagement; reduced satisfaction. **Limitations:** Non-randomized; survey tool lacked validation.
Gonçalves et al. (2017)	64 computing students	Case study	Evaluate instructional feedback in a PM (Project Management) tool.	Enhanced project planning accuracy and engagement. **Limitations**: Limited feedback prominence; narrow PM knowledge coverage.
Kuklick et al. (2023)	439 university students	Experimental between-subjects	Effects of error message complexity on cognition, metacognition, and motivation.	Elaborated feedback improved correction; KR feedback negatively impacted motivation. **Limitations:** Context-specific results; limited long-term evaluation.
Clinton-Lisell (2024)	390 college students	Experimental	Feedback type and placement effects on e-textbook learning.	Elaborative feedback improved scores; no difference in performance across annotation locations. **Limitations:** Limited to one textbook excerpt.
Thuillard et al. (2022)	149 university students	Experimental	Effects of human vs. computer feedback on stress	Negative feedback induced stress; computer feedback less emotionally impactful.

			and performance.	**Limitations:** Limited generalizability; short-term effects only.
Demaidi et al. (2018)	88 undergraduate students	Pre-/post-test design	Evaluate personalized feedback using OntoPéFeGe.	Improved performance for students with low prior knowledge. **Limitations:** Focused on computer networking topics; no long-term effects.
Li et al. (2018)	18 undergraduate students	Experimental	Neural responses to feedback valence in rule acquisition tasks.	Informative feedback processed in P300 time window; valence processed across epochs. **Limitations:** Small sample size; feedback order effects.