Optimizing guiding feedback through pedagogical agents and generative artificial intelligence

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Abstract: Feedback is a central factor in supporting students' learning processes. In digital learning environments, informative tutoring feedback (ITF) strategies can be employed to support students with formative feedback without revealing correct solutions. For mathematical tasks, the ITF-strategy *guiding feedback* was conceptualized. It aims to provide learners with error-specific hints and offers them the possibility to solve tasks step-by-step. Initial studies on the use of guiding feedback demonstrated positive cognitive, motivational, and metacognitive effects. However, the findings also suggested that many students did not engage sufficiently with the feedback. To address this issue, this article proposes an optimization of guiding feedback involving the integration of pedagogical agents to provide the feedback to students and the use of generative artificial intelligence (GenAI) to support the generation of error-specific information. This article introduces the concept of the optimized feedback strategy, explains its potential to enhance students' engagement with feedback, and illustrates it through examples.

Keywords: informative tutoring feedback, computer-based learning, artificial intelligence, mathematics education, students' engagement, emotions

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1 Introduction

In technology-enhanced learning environments, informative tutoring feedback (ITF) strategies can be implemented to provide formative feedback to learners. These strategies offer elaborated feedback that supports students during task completion without revealing correct solutions (Narciss, 2012). They are grounded in the idea that human tutors frequently guide learners by helping them identify mistakes, rather than providing immediate solutions. ITF-strategies foster students' ability to recognize and correct their mistakes independently (Narciss, 2008). They confirm the correctness of a response after successful task completion and encourage learners to reattempt tasks for further practice.

Especially for mathematical tasks, the ITF-strategy *guiding feedback* was created using the Moodle-plug-in STACK (Razeghpour, 2024a). As part of guiding feedback, students' responses are analyzed for common error causes to provide them with error-specific information. For this purpose, typical incorrect responses are defined in advance to compare them with students' answers. Given the wide range of potential error sources and the necessity to define them in advance, it is not always possible to identify the underlying causes of students' errors. In such instances, students are given the opportunity to enter so-called task loops, in which they work through the task step-by-step.

Two empirical studies demonstrated the positive effects of guiding feedback in higher educational settings (Razeghpour, 2024b; Razeghpour & Rolka, 2026). However, these studies also identified areas for improving the feedback strategy. Specifically, it was assumed that some learners did not engage deeply enough with the feedback, as they continued to make errors in subsequent similar tasks despite having received feedback. Active feedback processing—defined as intensive engagement with feedback—is essential for achieving positive effects (Narciss, 2012; Rezat, 2021). It is therefore likely that even stronger effects could have been realized if students had engaged more intensively with the feedback.

To foster students' deeper engagement with guiding feedback, this theoretical article delineates a technical and didactical advancement of this feedback strategy. The paper first reviews existing empirical research regarding guiding feedback (see Chapter 1.1). Subsequently, it discusses the use of pedagogical agents (see Chapter 1.2) and Generative Artificial Intelligence (GenAI) (see Chapter 1.3) as potential approaches to improve feedback strategies. Building on these foundations, the article presents the optimized conceptual framework of guiding feedback, illustrated through two visualizations (see Chapter 2). The paper concludes with a summary of the refined concept and a discussion of potential directions for future research (see Chapter 3).

1.1 Previous research on guiding feedback

In the context of two studies, cognitive, motivational, and metacognitive effects of guiding feedback were investigated. As part of an experimental study (Razeghpour & Rolka, 2026), 64 students from science-related disciplines participating in a mathematics course were divided into two groups and completed a total of five digital tasks for which they received different ITF–strategies. One group received guiding feedback, while the comparison group was provided with an alternative ITF-strategy called *summarizing feedback*. In contrast to guiding feedback, summarizing feedback provided learners with detailed explanations outlining a possible solution process when the cause of an error was unclear. Although these explanations offered guidance, the final solution was deliberately withheld. Findings indicated that guiding feedback led to significantly greater improvements in students' performance, self-efficacy, and calibration compared to summarizing feedback.

In a field study (Razeghpour, 2024b) involving 222 engineering students, it was found that working on tasks with guiding feedback did not necessarily lead to an increase in students' self-efficacy. Rather, it contributed to more realistic self-assessments overall. This conclusion was drawn from comparisons between groups of students who completed different numbers of tasks with guiding feedback. While self-efficacy did not differ significantly between the groups, significant differences in performance were observed. Students who did not complete any tasks demonstrated the lowest performance levels and strongly overestimated their own abilities. In contrast, students who completed all available tasks achieved the highest performance and assessed their abilities with greater accuracy.

Alongside the many positive effects of guiding feedback, both studies also pointed out aspects of the feedback strategy that could be improved. It is assumed that some students did not engage sufficiently with the feedback, as they corrected their answers but were unable to correctly solve similar tasks afterwards. However, feedback can only be effective when students engage with it actively (Jonsson, 2013; Timms et al., 2016). In this regard, students' feedback processing is a crucial motivational factor that must be continuously fostered, enabling students to recognize the underlying causes of their errors and improve their performance (Narciss, 2008; Timms et al., 2016).

One possible explanation for some students being less engaged could be the lack of a personalized connection to the feedback. Another reason could be that the automatic evaluation of students' answers was not always able to identify the underlying causes of their errors, making it difficult for students to correct their mistakes directly. A more accurate diagnosis of error sources might have led students to perceive the feedback as more useful and thus engage with it more deeply. However, this is a challenging problem, as it is not possible to anticipate all potential error causes in advance (Sangwin & Köcher, 2016). In particular, computational errors are highly diverse and combinations of errors may occur, further complicating the design of the evaluation algorithm.

Overall, guiding feedback appears to be an effective approach for promoting cognitive, motivational, and metacognitive areas of learning. However, the findings also indicated potential for further improvement. There is a need to foster deeper student engagement with feedback to fully leverage its instructional value. A possible approach to address this could be the integration of pedagogical agents to establish a personal connection and GenAI to support the generation of error-specific feedback.

1.2 Pedagogical agents

A possible approach to communicate feedback to learners can be the use of pedagogical agents. These are virtual characters that take the role of a learning companion by usually interacting with students through spoken language, text, or gestures (Kim et al., 2007). Frequently, these agents appear as animated figures that simulate social presence by exhibiting human-like characteristics such as facial expressions, voice, or body language (Schroeder et al., 2013).
Several studies suggested that the use of pedagogical agents may be linked to a range of positive outcomes. It has been shown that the integration of pedagogical agents can enhance learners' motivation (Guo & Goh, 2015; Liew et al., 2017; Y. Wang et al., 2023) as well as their academic performance (Castro-Alonso et al., 2021; Y. Wang et al., 2023; Woolf et al., 2010). Furthermore, students working on mathematical tasks featuring pedagogical agents exhibit greater persistence, as indicated by an increased tendency to reattempt tasks following incorrect responses (Neugebauer et al., 2024). In addition, the use of pedagogical agents has been shown to enhance learners' positive emotions (Ba et al., 2021; Lang et al., 2024; Lawson & Mayer, 2022; Y. Wang et al., 2023). These positive emotions, in turn, are particularly beneficial for fostering deeper engagement with feedback (Lawson et al., 2021). From a theoretical perspective, this relation can be explained by the control-value theory of achievement emotions (Pekrun et al., 2007). According to this theory, achievement emotions are directly tied to achievement-related activities or their outcomes. Positive achievement emotions are expected to promote deep learning strategies, enhance engagement, and support self-regulation (Isen, 2001; Wolters, 2003). In contrast, negative achievement emotions tend to encourage surface-level processing and may hinder learning (D'Mello & Graesser, 2012). Consequently, integrating pedagogical agents may not only enhance learners' emotional experiences but also lead to improved feedback processing.
To deliberately foster positive emotions, the facial expressions of pedagogical agents should be carefully selected during their design. It is advisable to display cheerful expressions only in specific situations, such as when a correct answer is provided.

Excessive use of positive facial expressions may otherwise lead to reduced empathy, as well as diminished motivation and performance (Schneider et al., 2022; Yang et al., 2024), since overly frequent or inappropriate deployment of positive expressions undermines the agents' credibility.

1.3 Using GenAI for education

GenAI is a rapidly evolving subfield of AI focused on the automated creation of content such as text, images, and videos (e.g., Andersen et al., 2025; Kumar et al., 2025; Naghdy, 2025). By identifying patterns in large-scale training data, GenAI systems apply probabilistic methods to generate coherent and context-sensitive outputs. These systems are increasingly being deployed across a variety of domains, including healthcare (Levin et al., 2024), finance (Chan & Choi, 2025), and education (Belkina et al., 2025).

In the context of education, one promising application is the use of GenAI to analyze students' responses to digital tasks (Awang et al., 2025; Khazanchi et al., 2025; Opesemowo & Adewuyi, 2024). Several studies in mathematics education have shown positive cognitive (S. Wang et al., 2023), motivational (Azevedo et al., 2024), and metacognitive (Awang et al., 2025) effects when GenAI was employed to assess students' answers and generate feedback. The results of these studies clearly indicate that GenAI can adapt to students' individual learning processes and therefore can support the identification of students' error causes.

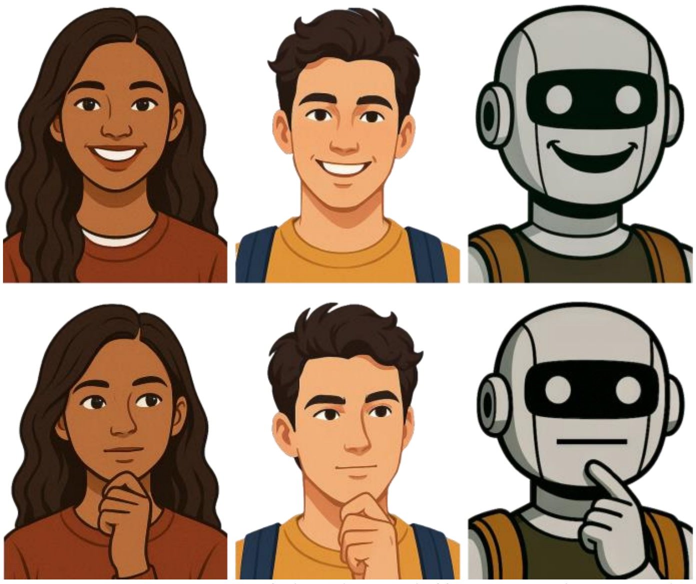
Improved identification of error causes offers the advantage that students can receive more targeted and specific feedback on their mistakes. This increased specificity is likely to enhance the perceived relevance of the feedback, which in turn may encourage students to engage with it more deeply and reflect more intensively on their errors (Leighton, 2019; Molloy & Boud, 2014).

2 Optimizing guiding feedback

As outlined in the introduction, two studies (Razeghpour, 2024b; Razeghpour & Rolka, 2026) identified spots for enhancing guiding feedback. This chapter draws on the stated possibilities related to the integration of pedagogical agents and GenAI to optimize guiding feedback.

For the provision of feedback, three different versions of agents were created, each featuring two distinct facial expressions (see Figure 1). They display a cheerful expression in case of correct answers (see Figure 1, above), whereas a thoughtful expression is shown for incorrect responses (see Figure 1, below). This design aims to enhance the credibility of the feedback, as supported by the theoretical findings (Schneider et al., 2022; Yang et al., 2024).

Figure 1. Choice of pedagogical agents



Note. Presentation of the three different pedagogical agents and their two facial expressions.

Learners are given the opportunity to select one of these three agents who support them during their task completions within their Moodle course. The available options include a female, a male, and an android (default setting). The agents' youthful appearance is intended to foster a friendly and collegial relationship between learners and their digital companion, thereby promoting social closeness and personal connections. This approach is supported by empirical findings indicating that peer teaching can be a particularly effective instructional method (Asare et al., 2025; Lim et al., 2020). Furthermore, the agent is designed to foster positive emotions through its varying expressions, thereby encouraging deeper engagement with the feedback (D'Mello & Graesser, 2012; Pekrun et al., 2007) as stated in the introduction.

A hybrid approach was adopted for implementing GenAI in guiding feedback, which differs from existing approaches by not relying entirely on the AI system to generate feedback (Awang et al., 2025; Azevedo et al., 2024; S. Wang et al., 2023). Instead, the algorithmic framework of STACK, along with its underlying computer algebra system, continues to play a central role in the evaluation process. This setup allows the provision of predefined feedback stored within STACK in cases where the response is correct or a typical error can be detected, without the need to invoke GenAI. However, if the error causes cannot be identified based on the evaluation algorithms embedded in STACK, GenAI is employed to analyze students' responses and infer potential explanations, which are then communicated to the learners. Students are subsequently given the opportunity either to revise their answers by using the feedback or to enter the task loop, enabling them to address the task through structured sub-steps.

The use of GenAI aims to enhance the identification of error causes by maintaining the existing detection mechanisms and applying GenAI analysis only in cases where the cause cannot be identified. This improved error detection has the potential to increase students' feedback processing, as learners with partially correct answers, whose error causes remained previously undetected, are no longer forced to rework the entire task in sub-steps. Instead, they receive targeted hints regarding their errors, enabling a direct correction of their responses.

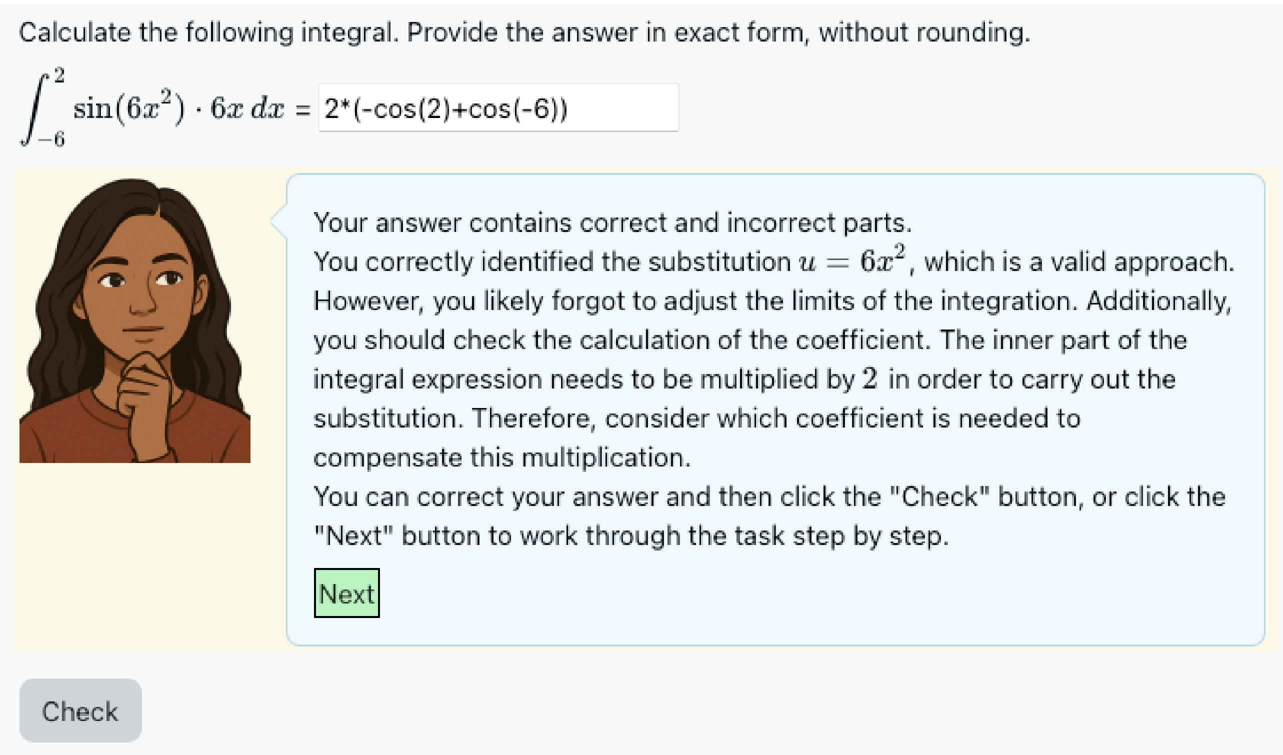
For the generation of the feedback, the GenAI was instructed to be a mathematics expert analyzing students' responses and providing error-specific feedback. This prompt was designed to align with the characteristics of ITF-strategies. Especially, the correct solution should not be revealed, and steps that were already correct should be highlighted.

As a GenAI model, Qwen 3 is currently used. Qwen 3 is an open-source GenAI model developed by Alibaba Cloud. It is based on neural networks and has been trained on extensive text data. In July 2024, Qwen was ranked as the leading Chinese GenAI model in various benchmarks and placed third globally behind the top models from Anthropic and OpenAI (Jiang, 2024). To ensure that learners are always provided with feedback, additional models have been integrated as backup solutions. This guarantees that, in the case of server outages, the system automatically switches to alternative GenAI models.

The optimized version of guiding feedback was implemented in an illustrative demo using a task involving the computation of a definite integral. For this purpose, two students' responses from a mathematics course at a German university were examined (see Figures 2 and 3). In each case, the answers were incorrect, but the STACK algorithm was unable to identify a specific source of error, which triggered the activation of the GenAI system. The two examples were not part of a formal study. As this is a theoretical article, they are not intended to provide empirical evidence of the tool's effectiveness but rather serve illustrative purposes. An empirical validation would require studies that systematically examine both the feedback provided by the tool and how students engage with it.

In the first case (see Figure 2), it was recognized that a suitable substitution was likely chosen. However, the limits of integration were apparently not adjusted accordingly. Furthermore, the GenAI identified that the coefficient was determined incorrectly. To support students' error correction, a hint was provided to guide them toward determining the coefficient correctly without explicitly revealing it.

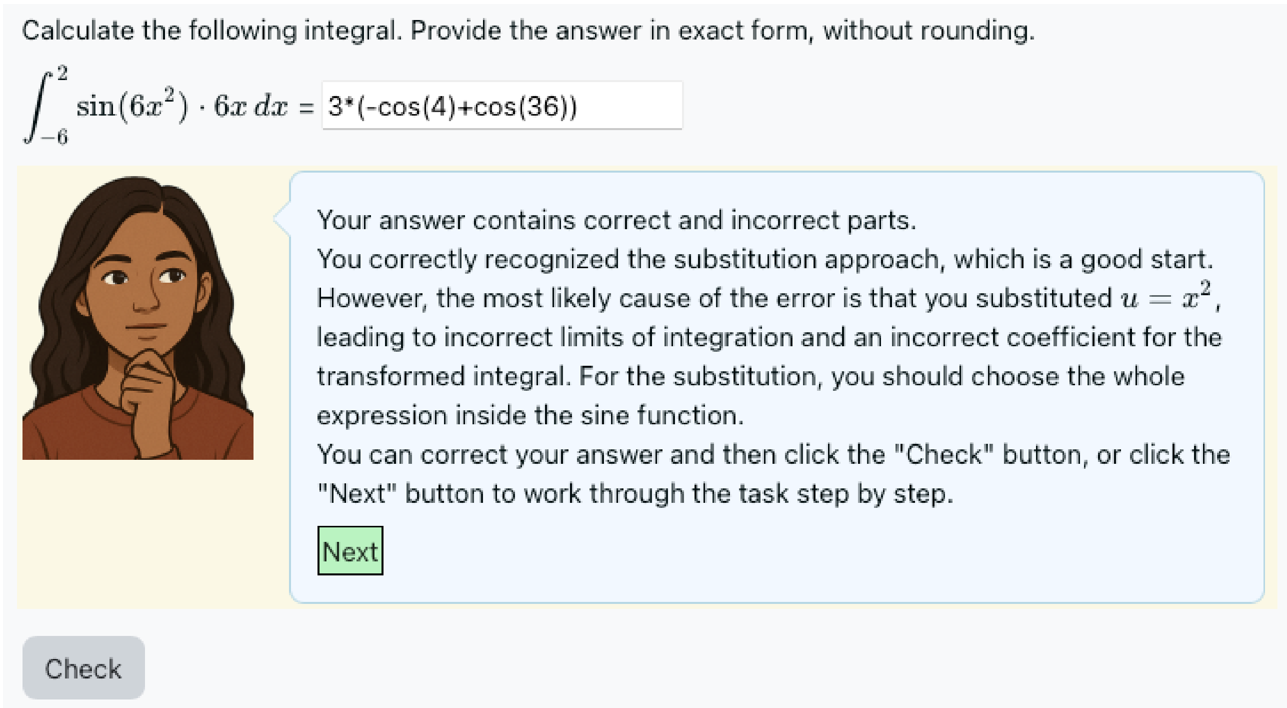
Figure 2. Example of feedback by GenAI (No. 1)



Note. An incorrect solution was entered in the input field. The feedback indicates that the limits of the integral were forgotten to be adjusted and that the coefficient was determined incorrectly.

In the second case (see Figure 3), it is recognized that the substitution approach was again most likely chosen correctly. However, the incorrect input is attributed to the use of an unsuitable substitution. This identification is particularly noteworthy, as the choice of substitution affects both the coefficient and the limits of integration. The underlying source of this error could only have been detected through the combined interpretation of both parameters.

Figure 3. Example of feedback by GenAI (No. 2)



Note. An incorrect solution was entered in the input field. The feedback indicates that the substitution was chosen incorrectly.

Overall, in both cases, the GenAI system was able to generate targeted error-specific feedback that would not have been available to students through the previous version of guiding feedback.

3 Conclusion and outlook

Building on previous studies (Razeghpour, 2024b; Razeghpour & Rolka, 2026) indicating that some students did not engage sufficiently with guiding feedback, this article presents an approach to further optimize this feedback strategy. For this purpose, pedagogical agents were used to provide feedback to learners. These agents aim to establish a personal connection—particularly through their visual design—in order to foster positive emotional connections and encourage deeper engagement with the feedback. Furthermore, GenAI was employed to enhance the identification of error sources, enabling learners who submit partially correct answers with unclear error causes to directly correct their answers instead of reworking the entire task step-by-step. This approach is expected to promote students' feedback processing.

The examples presented in this article demonstrate the strengths of the optimized feedback strategy. Even when identifying the cause of an error requires analyzing multiple parameters simultaneously, the GenAI model was able, in the presented examples, to accurately recognize the error cause and generate targeted, error-specific feedback tailored to students. It should be noted that the depicted incorrect responses (see Figures 2 and 3) could, in principle, also have been detected using the existing capabilities of STACK if they were explicitly anticipated during the task design phase. The primary advantage of integrating GenAI, however, lies in its ability to handle such cases without the need for a prior specification. Given the diversity of possible error sources, it is infeasible to anticipate all potential error causes in advance.

A limitation of this optimization approach is that, due to its probabilistic nature, GenAI may occasionally misidentify the underlying cause of an error. Because these models rely on statistical patterns rather than a true understanding of logic, they can produce explanations that sound confident but are factually incorrect. This creates a risk for the learning process, as students might adopt incorrect concepts as truth. Consequently, learners should be encouraged to engage critically with the feedback they receive, treating the AI as a starting point for reflection rather than an infallible source of truth.

To draw more robust conclusions about the effectiveness of the optimized feedback strategy, further quantitative and qualitative research is required. In particular, students' interactions with feedback should be examined to verify that the intended goal of fostering deeper engagement is being achieved. This article constitutes a first step by presenting the technical background of the tool and its didactical foundation as a basis for future empirical research on its motivational effects.

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