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HUMAN-IN-THE-LOOP AI COACHING IN ONLINE EDUCATION: COMBINING AUTOMATED FEEDBACK WITH HUMAN MENTORSHIP

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Abstract:
This article examines the organization of feedback in online education under conditions of increasing enrollment and limited opportunities for individualized instructional support. The study focuses on the distinction between automated error detection and the pedagogical interpretation of learning outcomes. Automated feedback provides rapid and consistent analysis; however, its application is associated with the risks of standardized responses, interpretive inaccuracies, and a disconnect between error identification and meaningful revision. The analysis identifies a consistent pattern: the greatest improvements in learning occur not at the moment feedback is received but during its incorporation into an iterative cycle of revision and refinement. Based on these findings, the article proposes a Human-in-the-Loop model in which automated feedback and instructor mentoring are treated as interdependent components of a unified educational process. The model describes the transition from initial diagnosis to pedagogical interpretation, revision, and continuous adjustment of the learner's educational trajectory. The practical significance of the study lies in clarifying the role of instructors within scalable online learning environments. The findings may be applied to the design of educational programs, the organization of mentoring practices, the development of feedback systems, and the preparation of instructors to work effectively with automated educational technologies.

Keywords: online education, automated feedback, mentoring, personalized learning, pedagogical interpretation, text revision

1. Introduction

Online education enables large numbers of students to participate in learning regardless of geographical location; however, as enrollment increases, so does the instructional workload, particularly with respect to providing individualized feedback (Banihashem

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et al., 2024). As a result, the time required to evaluate student work increases, feedback often becomes less detailed, and students experience longer delays before receiving recommendations for improvement. Under these conditions, automated feedback systems are increasingly adopted because they can rapidly identify common errors, monitor learning progress, and support the continuous delivery of formative feedback (Alghamdi & Alghizzi, 2025).

Nevertheless, automated feedback cannot fully replace the role of the instructor. Although such systems are effective in performing initial assessments and detecting recurring learning difficulties, they are considerably less capable of interpreting the substantive content of student responses, accounting for individual levels of prior knowledge, identifying the underlying causes of errors, or providing personalized instructional support (Kestin *et al.*, 2025). Consequently, growing attention has been given to approaches in which automated systems perform the initial diagnostic stage, while instructors interpret the generated recommendations, refine them when necessary, and assist students in shaping their subsequent learning trajectory (Doyle *et al.*, 2025).

The aim of this study is to develop and theoretically substantiate an original Human-in-the-Loop AI Coaching model for online education that explains the principles of integrating automated feedback with human mentoring while preserving, rather than replacing, the professional role of the instructor.

To achieve this objective, the following research tasks were formulated:

- summarize contemporary approaches to automated feedback and mentoring in online education;
- identify the advantages and limitations of automated feedback;
- demonstrate the instructor's functions in interpreting, adjusting, and monitoring automated recommendations;
- analyze data characterizing the effectiveness of hybrid feedback models.

It is hypothesized that the most effective learning outcomes in online education are achieved when automated feedback is combined with instructor mentoring. The automated system rapidly identifies common errors and generates initial recommendations, while the instructor evaluates their appropriateness, helps students understand the underlying causes of learning difficulties, refines the proposed directions for revision when necessary, and supports the subsequent learning process.

The scientific novelty of this study lies in the development of an original Human-in-the-Loop AI Coaching model that describes the distribution of functions between automated feedback and the instructor in online education. Within the proposed framework, artificial intelligence performs the initial analysis of learning outcomes, whereas the instructor is responsible for interpreting the generated recommendations, providing individualized learner support, guiding the revision of completed assignments, and adjusting the learner's subsequent educational trajectory.

2. Materials and Methods

The present study was conducted as a narrative review with an analytical synthesis of the literature. The analysis covered publications addressing automated feedback, intelligent tutoring systems, personalized learning, instructor mentoring, assessment of learning outcomes, teacher professional development, and the application of artificial intelligence in educational settings.

The literature search was performed using the Google Scholar, SpringerLink, and MDPI databases. The following search terms and their combinations were used: Human-in-the-Loop AI Coaching, AI feedback, automated feedback, teacher feedback, human mentorship, online education, personalized learning, AI tutoring, formative assessment, feedback engagement, learning analytics, teacher professional development, AI-assisted assessment, and artificial intelligence in education. Boolean operators (AND and OR) were applied to refine the search strategy. Publications published between 2024 and 2025 that reported experimental, analytical, or review-based evidence on automated feedback, personalized learning, and models of interaction between instructors and artificial intelligence systems were considered eligible. Studies focusing exclusively on the technical development of algorithms without examining educational processes, as well as publications that did not address the role of instructors or mentors in interpreting feedback, were excluded.

An initial search identified 32 publications. After assessing their relevance to the objectives of the study, 15 sources were selected for the final analysis. These publications provided the most comprehensive evidence on automated feedback, human mentoring, the professional role of instructors, personalized learning, and the combined use of artificial intelligence and pedagogical support. The selected literature was used to compare different approaches to feedback organization, analyze empirical findings, and develop the proposed Human-in-the-Loop AI Coaching model.

The methodological framework combined comparative and thematic analyses of the selected publications, followed by conceptual modeling. In the first stage, the respective functions of automated feedback and human mentoring were identified. These functions were subsequently compared with regard to response speed, personalization, interpretation of learning outcomes, pedagogical support, and feedback quality assurance. In the final stage, the findings were synthesized into an original conceptual model describing the sequence of interactions among the automated system, the instructor, and the learner within a unified feedback process.

The principal limitation of the study is the heterogeneity of the reviewed literature. The selected publications differ with respect to educational levels, academic disciplines, artificial intelligence tools, research designs, and approaches used to evaluate feedback effectiveness. Nevertheless, the analyzed studies revealed consistent patterns regarding the implementation of automated feedback in online education, which provided the basis for the development of the proposed conceptual model.

3. Results and Discussion

The effectiveness of feedback in online learning is determined by the extent to which it influences the subsequent revision of student work. This relationship is particularly evident in writing tasks, where revision simultaneously affects multiple dimensions, including language accuracy, internal coherence, argumentation, and overall organization. In this context, the number of completed revisions serves as an indicator of both student engagement and the degree to which feedback is integrated into the revision process (Alnemrat *et al.*, 2025). Table 1 presents differences in revision activity across various feedback approaches.

Table 1: Frequency of Revision Types Following Different Feedback Conditions (Tran, 2025)

Feedback Condition	Local Revisions (%)	Global Revisions (%)	Total Revisions (%)
Teacher-generated feedback	39.8	60.2	100.0
AI-generated feedback	44.5	55.5	100.0
Teacher + AI feedback	31.7	68.3	100.0
Self-correction	52.4	47.6	100.0

The distribution of revisions indicates that different feedback modalities primarily influence the nature rather than the overall amount of text revision. During self-review, local revisions predominate, whereas the proportion of global revisions remains minimal. This suggests that students mainly correct errors they are able to identify independently. More complex issues, such as insufficient argumentation, weaknesses in logical coherence, or organizational flaws, are considerably more likely to remain unaddressed. The introduction of external feedback substantially changes this pattern. Instructor comments shift the focus from isolated textual elements to the overall conceptual organization of the work. As a result, students revise not only individual expressions but also the relationships among claims, supporting arguments, and the overall structure of the text (Walter, 2024). Consequently, the nature of revision itself changes. Its value is determined not by the number of corrections but by the extent to which those revisions improve the substantive quality of the written work.

Automated feedback occupies an intermediate position. The proportion of global revisions increases compared with self-review but remains lower than that observed when automated feedback is combined with instructor comments. This pattern appears consistent with the characteristics of automated systems. Although automated feedback effectively identifies problematic sections of a text, it rarely provides sufficient guidance for their deeper conceptual revision. As a result, many revisions remain localized, with students concentrating on addressing individual system-generated comments rather than reconsidering the coherence and structure of the work as a whole (Fajardo-Ramos *et al.*, 2025).

The most substantial changes are observed when both sources of feedback are used in combination. Under this condition, the proportion of global revisions reaches its highest level, whereas the relative share of local corrections decreases. This pattern

cannot be explained simply by the accumulation of two streams of comments. Rather, it reflects a change in the overall logic of the revision process. The automated system identifies a broad range of potential problems, while the instructor helps determine which of them require meaningful conceptual revision. As a result, students shift their attention from correcting isolated inaccuracies to strengthening argumentation, improving organizational structure, and enhancing the internal coherence of their academic writing (Navío-Inglés *et al.*, 2025).

A further pattern emerges when all four feedback conditions are compared. As the progression moves from self-review to automated feedback, then to instructor feedback, and finally to the combined feedback model, the proportion of global revisions increases consistently, while local corrections become progressively less dominant. Importantly, this shift occurs gradually, without abrupt changes between adjacent conditions. This finding suggests that different feedback models differ primarily in the depth of subsequent text revision rather than in their ability to initiate revision itself. A similar tendency has been reported in previous studies, where the quality of feedback has been associated with its capacity to stimulate substantive revision of academic work rather than merely the correction of isolated errors (Farhood *et al.*, 2025).

The next group of findings concerns the role of the instructor. In this context, the critical issue is the extent to which information generated after a teaching session leads to meaningful changes in instructional practice. This question is particularly relevant in online education, where digital learning environments capture substantially more information about teaching and learning processes than conventional classroom settings. Table 2 presents the outcomes associated with different approaches to automated feedback designed for instructors.

Table 2: Effects of automated feedback choice and instructor professional development (Demszky *et al.*, 2025)

AI Feedback Condition	Student Attendance, Sessions	Assignments Completed	Significance
Feedback topic choice, entire treatment group	+0.112	No significant effect	$p < 0.05$
Choice + completed training modules	+0.260	+0.176	$p < 0.01$ / $p < 0.05$
Choice + accessed GPTeach	+0.265	+0.226	$p < 0.01$ / $p < 0.01$
Choice + modules vs. control + modules	+0.147	+0.118	$p < 0.05$ / $p = 0.131$
Choice + GPTeach vs. control + GPTeach	+0.216	No data	$p < 0.05$

The findings indicate that automated feedback alone is not sufficient to produce meaningful changes in instructional practice. The weakest effects are observed when

instructors receive only an analytical report. While such reports help identify characteristics of their teaching, they provide limited guidance for improving it. A different pattern emerges when feedback is incorporated into professional learning activities. In this context, analytical information serves not merely as a diagnostic tool but as the basis for practicing and refining new pedagogical strategies.

The differences between the instructional conditions reveal another important pattern. The most substantial improvements occur not immediately after instructors receive automated recommendations but after these recommendations are implemented in instructional modules or practice-based training environments. This shifts the focus from evaluating completed teaching sessions to preparing for future instruction. Under these circumstances, automated feedback functions not as the endpoint of analysis but as the starting point for improving instructional practice.

The distribution of educational outcomes is also noteworthy. Student attendance responds more rapidly to instructional changes than assignment completion. This difference appears consistent with the nature of these outcomes. Decisions to attend classes are influenced primarily by the quality of ongoing interaction with the instructor, whereas assignment completion reflects more stable patterns of learning behavior. Modifying such patterns requires a longer period of adaptation, and consequently the corresponding effects become evident more gradually.

A comparison of the findings presented in both tables reveals a common sequence. In neither case does the greatest effect occur immediately after automated feedback is received. At the student level, the next stage involves the revision of written work, whereas at the instructor level it involves the refinement of teaching practice. In both contexts, the automated signal serves only as the initial trigger. The most substantial improvements emerge when it is incorporated into a subsequent cycle of revision, regardless of whether the process concerns the improvement of academic writing or the enhancement of instructional practice.

Automated feedback offers a clear advantage in terms of speed. It rapidly identifies errors and immediately returns comments to learners. Its limitations become evident, however, once interpretation is required. At this stage, the system can no longer serve as a fully reliable guide. It detects deviations from learned patterns but cannot always determine whether those deviations actually represent errors. Consequently, correct responses may occasionally be classified as incorrect (Lan & Zhou, 2025). This limitation is particularly apparent in open-ended tasks, where multiple logical approaches may be equally valid. Students may therefore be instructed to revise responses that are already appropriate or, conversely, reinforce weaknesses by following recommendations that are formally correct but pedagogically inappropriate. Under such circumstances, feedback ceases to function as a neutral source of information. Instead, it begins to influence students' reasoning processes and may unintentionally distort them.

A second limitation concerns causal interpretation. Automated systems indicate which aspects of a response fail to satisfy predefined criteria but rarely explain why these deficiencies occur. Weak argumentation, gaps in logical reasoning, and inadequate

conceptual understanding may produce similar system-generated outputs despite requiring fundamentally different instructional interventions. Without identifying the underlying cause, revisions often remain superficial: wording changes, whereas the conceptual structure remains unchanged. An additional limitation is the inability of most systems to incorporate longitudinal learner information. Automated feedback typically does not account for previous assignments, recurring misconceptions, or individual patterns of progress. Each submission is treated as an isolated event, resulting in feedback that consists of disconnected comments rather than a coherent developmental sequence. Furthermore, biases embedded in training data may influence evaluations of writing style and argument quality. Data privacy also remains an important concern because the analysis of student work requires the transfer and processing of educational data. Collectively, these limitations constrain the effective implementation of automated feedback within educational practice (Yusuf *et al.*, 2025).

The greatest limitation of automated feedback becomes evident in relation to student motivation. Educational feedback extends beyond correcting errors; it also acknowledges learner effort, encourages persistence, and supports sustained engagement. Current automated systems are unable to establish this type of pedagogical relationship. Although they can generate neutral or even supportive comments, these interactions rarely develop into meaningful and enduring educational dialogue. Consequently, a clear distinction emerges. Automated feedback increases the speed and frequency of instructional support, but it does not create the pedagogical connection that characterizes effective human mentoring.

Against this background, the role of the instructor is no longer merely supportive. The issue is not simply the assessment of assignments but the organization of the entire learning process. The instructor selects the comments that are truly important and removes those of secondary importance. This reduces informational noise. As a result, the student works not with a collection of isolated signals but with a sequence of actions. The next stage is interpretation (Kong *et al.*, 2025). The same comment may indicate different underlying problems. Without this step, feedback remains formal; with it, it becomes an instrument for meaningful text revision.

Experience from online platforms demonstrates that scalability does not require eliminating the instructor. It is achieved through the flexible organization of instructor participation, including mentor allocation, adaptation of instructional formats, and adjustment of schedules. This is not an additional service layer but a way to preserve personalization in the context of large student cohorts. Within this model, the instructor works not with the text itself but with the learner's educational trajectory. The instructor identifies recurring mistakes, recognizes where students encounter persistent difficulties, and modifies the instructional strategy accordingly. No automated system is currently capable of performing this function (Wang, 2024).

The distinction becomes even more apparent in situations characterized by uncertainty. In academic writing, there is no single correct solution; rather, there is a range of acceptable alternatives. Automated systems tend to rely on fixed criteria,

whereas instructors acknowledge this variability and work within it. They evaluate the strength and consistency of students' argumentation. This naturally defines the distribution of responsibilities. Repetitive operations can be delegated to automated systems, whereas work involving meaning and interpretation remains the responsibility of the instructor. It is precisely this aspect that determines the quality of learning. Figure 1 illustrates the sequence in which automated feedback and instructor mentoring are integrated into a unified educational cycle.

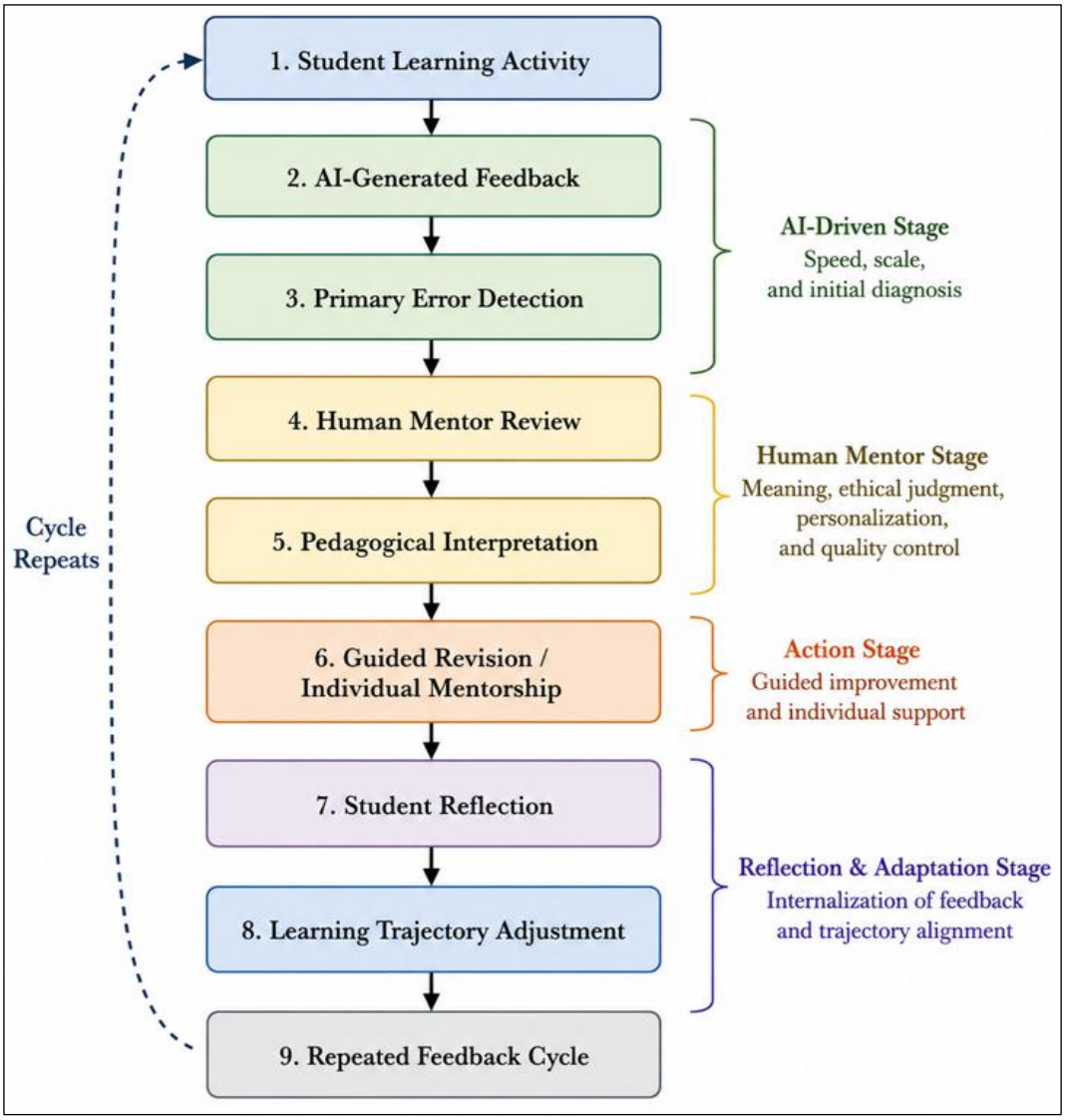

Figure 1: Human-in-the-Loop AI Coaching Model in Online Education (Developed by the Author)

The effectiveness of the proposed model is determined by the sequence of transitions between its stages. In this framework, the order of operations functions as a mechanism in itself. When this sequence is disrupted, discontinuities emerge. Feedback signals lose their priority, subsequent actions are not implemented, improvements fail to be consolidated, and they are not carried forward into the next learning cycle. Under such

conditions, feedback no longer shapes the structure of the learning process and is reduced to a series of isolated interventions.

The proposed framework addresses these discontinuities by integrating all stages into a coherent sequence. The initial automated component creates a dense layer of primary diagnosis and shortens the interval between task completion and feedback delivery. This increases the system's sensitivity to errors and improves the likelihood that learning difficulties will be detected. However, the principal effect emerges at the subsequent stage, when the generated feedback undergoes pedagogical interpretation. At this point, a hierarchy of actions is established. Some recommendations are assigned higher priority, others are modified or lose their significance. As a result, cognitive overload is reduced and a structured process of revision is created.

The nature of revision also changes. The revision process no longer consists of isolated responses to individual comments. Instead, the text is revised through broader conceptual units involving argumentation, logical coherence, and overall organization. This transformation is consistent with the findings demonstrating that combined feedback increases the proportion of global revisions. Consequently, the proposed model influences the depth of revision rather than merely its intensity.

The resulting improvements are consolidated through the introduction of a reflective stage. Changes are evaluated by comparing the initial and revised versions of the work, thereby linking current learning activities with previous experience. This process generates a cumulative learning effect. Revisions cease to represent isolated corrections and instead become transferable strategies that can be applied to subsequent learning tasks.

The final stage involves the adjustment of the learner's educational trajectory. Information obtained during the revision process is used to determine the next instructional step. As a result, learning ceases to follow a standardized sequence and instead becomes responsive to the learner's current level of development. Taken together, these mechanisms explain the observed pattern. The greatest improvements occur only after feedback is incorporated into a complete revision cycle. The proposed model enables the transition from simple error identification to systematic conceptual revision, which constitutes the principal source of its practical effectiveness.

3. Conclusion

The present analysis demonstrated that the effectiveness of feedback in online education is determined not by the speed with which recommendations are generated or by their quantity, but by their capacity to initiate a structured process of task revision. Automated feedback provides timely and consistent diagnostic information; however, by itself it neither determines the direction of revision nor establishes a coherent framework for improving academic work.

The principal outcome of this study was the development of a model that conceptualizes feedback as a cyclical process consisting of initial diagnosis, pedagogical

interpretation, guided revision, and subsequent adjustment of the learner's educational trajectory. Within this framework, automated analysis and instructor mentoring form an integrated functional system in which each stage establishes the conditions for the next. The practical significance of the proposed model lies in clarifying the role of the instructor within scalable online learning environments. Effective learning depends on an appropriate distribution of responsibilities. Automated tools strengthen the diagnostic component of the feedback process, whereas instructors establish priorities, interpret the underlying causes of errors, and guide the subsequent progression of learning. This configuration enables the transition from simple error detection to systematic conceptual revision.

The findings support the proposed hypothesis that the greatest educational benefits are achieved when automated feedback is incorporated into a structured cycle of revision rather than used as an isolated intervention. The coordinated sequence of diagnosis, interpretation, and application creates a sustainable mechanism for supporting learning and provides the foundation for the effectiveness of the Human-in-the-Loop AI Coaching model in online education.

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Conflict of Interest Statement
The author declares no conflicts of interest.

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Timofei Rogov is an EdTech entrepreneur and online education producer with extensive experience in developing and scaling digital learning projects in the Commonwealth of Independent States (CIS). He is the founder of Vysshiy Ball, an online platform for preparing students for Russia's OGE and EGE examinations, which was acquired by Skillbox in 2019. He has also produced large-scale online educational courses featuring public figures. His professional and research interests focus on the development of online education, the scalability of digital learning platforms, accessibility of distance learning, and the application of educational technologies to improve learning experiences.

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