Multimodal Immediate Feedback (Audio/Video + LLM-based Code Reviewers) in Practice-Oriented Disciplines: Causal Analysis of Effects on the Pace of Skill Formation, Metacognitive Monitoring, and Sustained Engagement

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Abstract. ***Amid the rapid digitalization of higher education and the emphasis on practice-oriented trajectories, traditional feedback formats exhibit declining effectiveness. This study conducts a causal analysis of the impact of an integrated system of multimodal immediate feedback, combining expert audiovisual (A/V) commentary and automated reviews based on large language models (LLM), on key educational outcomes. The aim is to explicate the causal mechanisms through which the synergy of these modalities affects the pace of practical skill formation, the quality of metacognitive monitoring, and learners' sustained engagement. The methodological framework rests on synthetic causal analysis conducted on the basis of a systematic review of empirical studies from 2020–2025. The results indicate that the integrated system implements an effective two-loop architecture: the LLM loop provides rapid tactical correction, accelerating the acquisition of procedural skills, whereas the A/V loop initiates deep strategic reflection, enhancing metacognitive self-regulation. It is shown that this design comprehensively addresses students' basic psychological needs for competence, autonomy, and relatedness, which, in the logic of self-determination theory, serves as a causal driver of sustained engagement. The conclusions support the hypothesis of a synergistic effect that exceeds the sum of the influences of each modality taken separately. The material is of interest to researchers in educational technology, developers of intelligent tutoring systems, and instructors in practice-oriented disciplines.***

Keywords: multimodal feedback, large language models, skill formation, metacognitive monitoring, student engagement, causal analysis, practice-oriented learning, educational technology, audiovisual feedback, artificial intelligence in education

1.Introduction

The contemporary system of higher education is entering a bifurcation regime driven by two interrelated macro-trends: the rapid, exponentially paced integration of artificial intelligence (AI) technologies into educational practices and a paradigmatic shift toward graduating specialists with immediately applicable, practice-oriented competencies [1, 2]. The scale of this transformation is quantitatively verified: by estimates, global investment in AI for education will reach 23 billion USD by 2029, and by 2025, 87% of organizations worldwide will in one way or another adopt AI tools [3]. Against this backdrop, traditional models of pedagogical feedback-slow, text-centric, and poorly scalable-prove disproportionate to the dynamics and iteratively mastering complex practical skills (programming, engineering design, clinical diagnostics, etc.) [4].

In parallel, the academic field is actively searching for new feedback formats. Audiovisual expert feedback provided by instructors consistently demonstrates advantages: students perceive it as more personalized, detailed, and emotionally supportive relative to textual comments, which strengthens trust and increases motivation [4]. At the same time, the emergence of large language models has enabled the construction of automated reviewers that provide immediate, standardized, and scalable feedback on structured tasks, including program code analysis [7]. However, the existing body of research is fragmented: the effects of A/V and LLM approaches are evaluated predominantly in isolation, leaving unresolved the question of the causal mechanisms of their joint impact on cognitive, metacognitive, and affective learning outcomes.

Research **objective** - to conduct a causal analysis of the impact of an integrated system of multimodal instant feedback (A/V + LLM) on the rate of practical skill formation, the effectiveness of metacognitive monitoring, and the sustained engagement of students in practice-oriented disciplines.

The research hypothesis is that combining A/V and LLM feedback generates a synergistic effect that exceeds the sum of their separate effects, owing to the organization of dual-loop support: the LLM loop provides rapid tactical correction, whereas the A/V loop initiates deep strategic reflection.

The scientific novelty lies in the proposal and theoretical substantiation of a causal model that explains the nature of the synergistic influence of combined multimodal feedback on the cognitive, metacognitive, and affective components of educational outcomes.

2.Materials and Methods

The methodological framework of the study is based on a systematic literature review with an emphasis on empirical designs-experimental and quasi-experimental-featured in leading peer-reviewed journals and proceedings of authoritative conferences. A fundamental feature is the synthesis and interpretation of the data corpus through the lens of causal inference. In contrast to traditional practices in Educational Data Mining (EDM), where predictive models (for example, performance forecasting) dominate, the causal approach is aimed at identifying and explaining causal mechanisms. This makes it possible to move from documenting correlations (students receiving video feedback are more satisfied) to constructing well-substantiated causal chains (video feedback increases satisfaction because it satisfies the need for connection, which in turn strengthens engagement). Such a perspective is important for designing genuinely effective educational technologies, because it answers not the question what is happening? but the question why is this happening?

3.Results and Discussion

The analysis conducted made it possible to identify and theoretically substantiate a set of key causal mechanisms through which the integrated multimodal feedback system influences the learning process. These mechanisms clarify the observed effects: acceleration of skill acquisition, improvement in the quality of metacognition, and an increase in student engagement.

The fundamental basis of the effectiveness of the proposed system lies in constructing two mutually complementary feedback loops that operate at different temporal and cognitive levels and are aligned with the natural staging of skill acquisition. The development of any complex skill proceeds through sequential stages: cognitive (understanding the task), associative (procedural practice), and autonomous (automated performance with an emphasis on strategies) [5, 6, 20]. Effective feedback must be stage-appropriate, that is, matched to the learner's needs at each of these stages.

The integrated model implements this principle through a two-loop architecture (see Fig. 1).

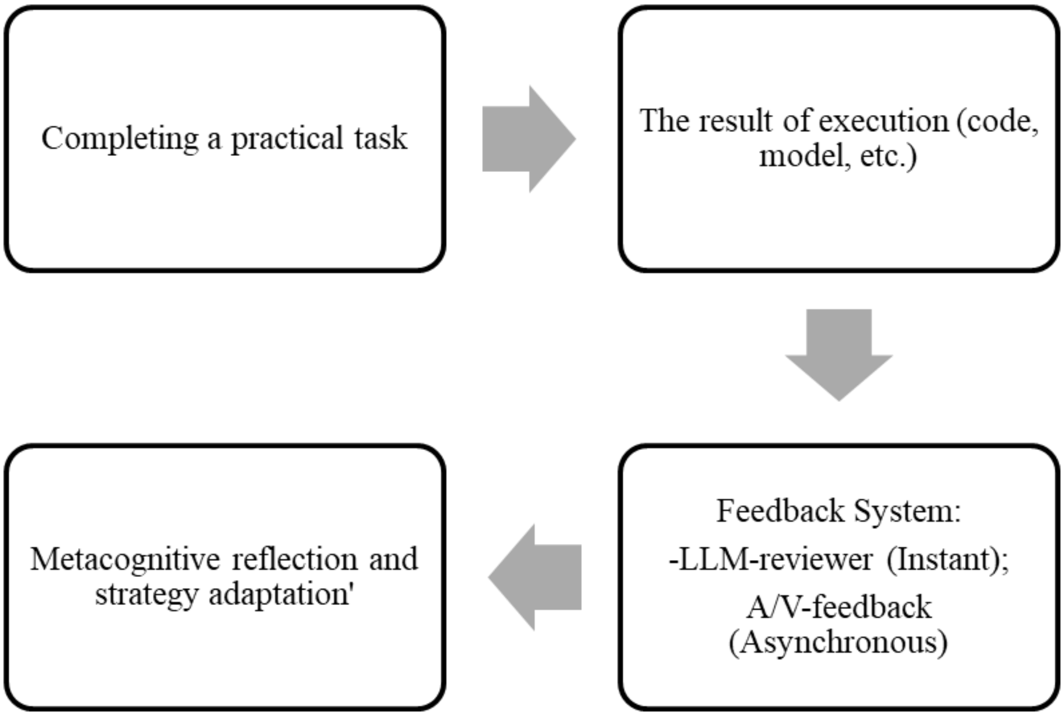

Figure 1: Conceptual causal model of double-loop feedback (compiled by the author based on [5, 6, 20]).

In the presented instructional model, two complementary feedback loops are engaged, providing multilevel regulation of the development of a professional skill: a tactical microcycle and a strategic macrocycle. Their coordination establishes a continuous transition from rapid adjustment of procedural actions to the deliberate reappraisal of problem-solving strategies.

The tactical microcycle (LLM-mediated) is initiated immediately after task completion and generates an automated review. This feedback is characterized by high speed and reproducibility and focuses on the formalizable components of the output: syntactic errors, logical inconsistencies, deviations from coding standards [7]. A high-frequency iterative loop is established action → immediate feedback → correction, optimal for the associative stage of acquisition. Minimizing the gap between an error and its correction prevents the consolidation of incorrect procedural schemas and accelerates the attainment of stable operational accuracy.

The strategic macrocycle (audio visually mediated) unfolds asynchronously - periodically, for example, every few days or at the end of a module - and provides a comprehensive expert assessment. In contrast to LLM-based feedback, this format has a holistic orientation: the focus shifts to the solution strategy, project architecture, the appropriateness and novelty of the chosen approaches, as well as other high-level aspects that are difficult to formalize [4]. The instructor's prosody, intonational and visual cues convey semantic nuances inaccessible to a purely textual channel, thereby modeling exemplars of expert thinking. A more extended cycle operates here result → expert feedback → deep reflection, stimulating the transition to autonomous mastery of the skill and the formation of professional judgment.

The coordinated action of micro- and macrocycles forms a multilevel learning ecosystem: the former ensures operational procedural correctness and regular calibration of actions, the latter provides strategic coherence, conceptual integrity, and transferability of solutions. This composition simultaneously reduces the risk of fossilization of errors and strengthens metacognitive skills, ensuring steady progression from mere correct execution to conscious and autonomous mastery.

Therefore, the integral effect of the system is determined not by the summative provision of two information streams, but by the construction of two heterogeneous yet temporally and cognitively aligned loops strictly matched to the hierarchical organization of the learning process.

The dual-loop model directly accelerates skill development through differentiated and optimized guidance at distinct phases of learning. The LLM reviewer acts as a tireless trainer, allowing the learner within a single session to make and promptly correct numerous microtactical errors-something that is practically unattainable when waiting for an instructor's review. As a result, the time required to bring basic procedures to the level of automaticity is markedly reduced. At the same time, expert A/V feedback prevents stagnation at the competence plateau: the student ceases to limit themselves to the correct execution of isolated operations and begins to perceive the coherent structure of activity. This channel triggers qualitative leaps in understanding, shifting attention from how to do to why exactly so. A comparative characterization of the modalities is presented in Table 1.

Table 1: Comparative characteristics of feedback modalities in the context of skill formation (compiled by the author based on [4, 7, 8, 16])

Parameter	LLM reviewer	Audio/Video feedback (Expert)	Synergistic effect
Speed	Immediate	Asynchronous (hours/days)	Immediate tactical + delayed strategic
Scalability	High (automated)	Low (requires expert time)	Optimal resource allocation: LLM for routine, expert for complex
Objectivity	High (rule-based)	Subjective (depends on the expert)	Combination of objective metrics and expert intuition
Personalization	Contextual (code)	Deep (personality, learning style)	Holistic personalization (accounting for both code and the student)
Emotional impact	Neutral/low	High (support, motivation)	Reduced frustration (LLM) + increased confidence (A/V)
Focus	Tactical (errors, syntax)	Strategic (approach, thinking)	Comprehensive coverage from micro- to macro-level

Metacognition thinking about thinking, represents a reflexive activity that includes two interrelated components: monitoring (assessment of the degree of one's own understanding and the dynamics of progress) and regulation (adaptation of learning strategies based on the results of monitoring) [17]. The integrated feedback system exerts a causal influence on both of these components (see Fig. 2).

1) Impact on monitoring: Accurate metacognitive monitoring is impossible without timely and objective indicators of one's own activity [18]. The LLM-driven tactical loop provides a continuous flow of such indicators: each instantaneous review serves as a calibration point that allows one to relate subjective confidence in the correctness of a solution to the actual state of affairs. As a result, the ability to soberly evaluate the quality of one's own work in real time is formed - the key core of effective monitoring.
2) Impact on regulation: Whereas LLM primarily strengthens the monitoring component, A/V feedback from the expert directly develops metacognitive regulation [15, 18]. Receiving the instructor's comments, the student obtains not only an indication of errors but also access to the very logic of expert reflection: which aspects are highlighted, how alternatives are weighed, and how an improvement strategy is constructed. This observable model of expert thinking is internalized, providing the learner with a repertoire of metacognitive strategies that can subsequently be applied autonomously to manage their own learning process.

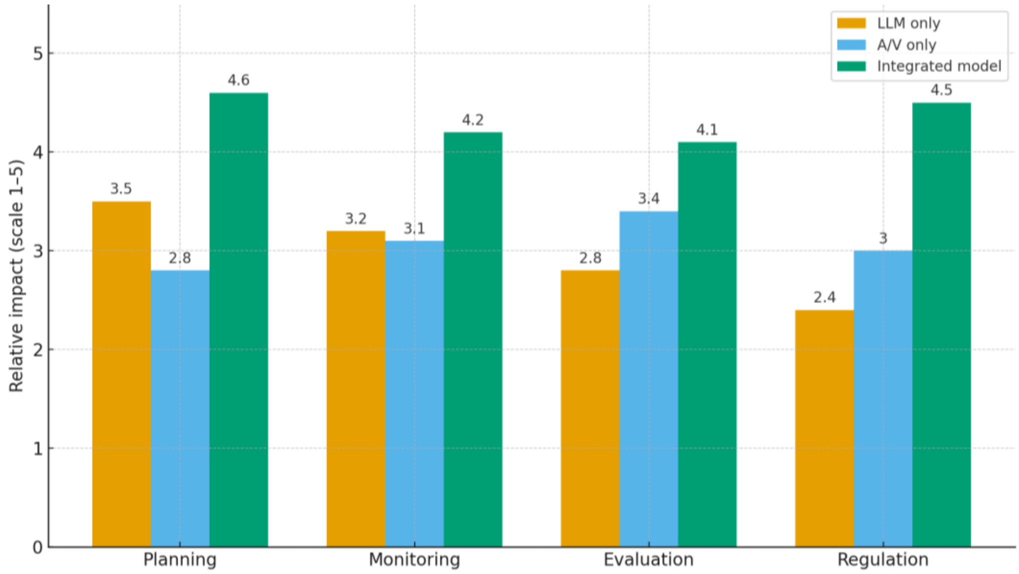

Figure 2: Comparative causal influence of feedback types on the phases of the metacognitive cycle (compiled by the author based on [14, 18, 19])

To clarify the causal mechanisms by which integrated feedback influences engagement, it is appropriate to draw on Self-Determination Theory (SDT). Within the SDT framework, intrinsic motivation and, consequently, sustained engagement arise when three basic psychological needs are satisfied: competence, autonomy, and relatedness [9, 10]. The integrated feedback model is fundamentally oriented toward coordinated influence on all three needs.

1. The need for competence - is satisfied to the greatest extent through the tactical LLM loop: the ability to obtain instant confirmation of the correctness of actions or promptly correct errors cultivates in the student a sense of control and visible progress, reduces frustration from getting stuck, and strengthens confidence in the student's own capabilities [13, 19].
2. The need for relatedness - is ensured by the strategic A/V loop: a personalized video or audio message from the instructor, addressed to the student by name and conveying empathy and support, creates a robust interpersonal bond; the student feels that they are not just one of many and that their efforts are noticed and valued [4, 12].
3. The need for autonomy - is realized through the system's flexibility and controllability: the student independently determines when and how often to consult the LLM reviewer for self-checking and can revisit A/V messages at a convenient time; such freedom in organizing one's own receipt of feedback strengthens a sense of responsibility and ownership toward learning.

Therefore, the increase in engagement is driven less by the amount of feedback than by its qualitative diversity, which makes it possible to holistically satisfy the fundamental psychological needs that underpin intrinsic motivation (see Fig. 3).

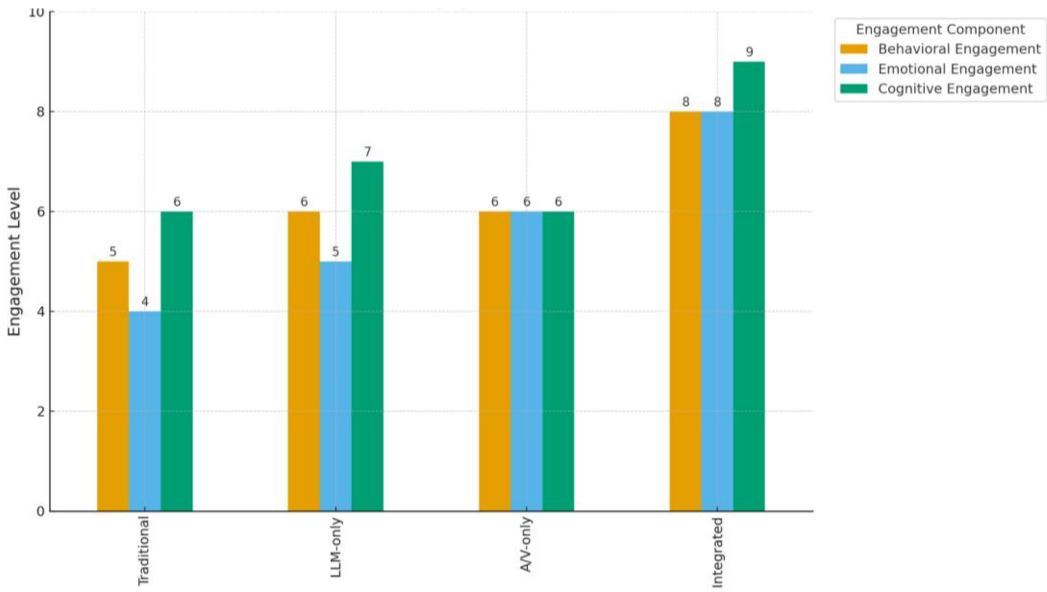

Figure 3: Predicted levels of student engagement components (on a scale from 1 to 10) (compiled by the author based on [14, 18, 19, 20]).

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Despite its promise, the deployment of an integrated multimodal feedback system is inevitably associated with a set of risks and barriers, necessitating rigorous analytical consideration and the design of mitigation mechanisms (see Table 2).

Table 2: Matrix of risks and barriers to the implementation of an integrated feedback system (compiled by the author based on [7, 11, 14, 15, 16])

Risk/Barrier	Description	Possible mitigation strategies
Cognitive overload	The student receives too much information from two sources simultaneously, which impedes processing.	Clear delineation of roles: LLM for tactics, A/V for strategy. Temporal separation of feedback delivery.
Conflicting feedback	LLM and expert recommendations may diverge, causing confusion.	Use the LLM as the first reviewer, whose conclusions are verified and supplemented by an expert in the A/V message.
Excessive dependence on LLM	Students may lose the ability to independently identify errors and debug code.	Implementation of pedagogical guardrails requiring the student to first explain their code before receiving assistance.
Ethical risks	Data privacy issues (transmitting code to third-party servers) and algorithmic bias.	Use locally deployed open LLMs. Conduct model bias audits. Clear data policy.
Technological and resource barriers	High implementation cost, the need for instructor training, and technical integration challenges.	Phased implementation starting with pilot groups. Development of professional development programs for instructors.

In summary, the integrated multimodal feedback system accelerates skill formation, strengthens metacognition, and increases engagement through the coordinated operation of two loops aligned with stages of mastery: a tactical microcycle with instantaneous LLM review prevents the consolidation of procedural errors and is optimal for the associative phase, whereas a strategic A/V macrocycle provides holistic expertise, models exemplars of professional thinking, and transitions the learner toward autonomous mastery. This dual-loop architecture is not reducible to the sum of channels but constitutes multilevel regulation: the LLM primarily enhances metacognitive monitoring, and A/V develops regulation; together they create a continuous cycle action-correction-reflection-strategy revision that increases the transferability of solutions and the quality of judgments. The rise in engagement is causally explained by satisfying the three basic needs of SDT: competence (through instantaneous indicators of progress), relatedness (through personalized empathic expertise), and autonomy (through controllability of the frequency and format of feedback), with the integrated model yielding the most balanced gains across behavioral, emotional, and cognitive components.

4.Conclusion

The conducted causal-explanatory analysis verified the initial hypothesis: an integrated system of multimodal and near-instant feedback, combining LLM-based automated reviews and personalized expert audio-video comments, exerts a synergistic rather than additive effect on key learning parameters in practice-oriented disciplines. The source of this effect is not the sum of the individual modalities, but the complex dual-loop architecture of pedagogical support that emerges from their coupling.

The key findings of the study are as follows:

1) The dual-loop organization accelerates skill formation: the rapid tactical LLM loop acts as a catalyst for the acquisition of procedural actions at the associative stage, whereas the asynchronous strategic A/V loop secures the transition to the autonomous stage, shaping elements of higher-level strategic thinking.
2) The integration amplifies metacognitive processes: the system develops metacognition in a coordinated manner, with the LLM providing objective indicators for accurate self-monitoring, and the A/V feedback modeling expert reflection required for effective self-regulation.
3) Sustained engagement is maintained through the satisfaction of basic psychological needs: the growth of intrinsic motivation is causally determined by the concurrent fulfilment of needs for competence (via the LLM), relatedness (through A/V), and autonomy (due to configurational flexibility), which aligns with the tenets of self-determination theory.

The practical significance of the work lies in the formulation of a scientifically grounded model for the design and implementation of next-generation, highly effective feedback systems. The results obtained may be used by developers of EdTech platforms to create more intelligent and pedagogically calibrated tools, as well as by instructional designers and instructors to critically reexamine and optimize their own practices, above all in courses oriented toward the formation of complex practical skills.

Prospects for further research are associated with the empirical validation of the proposed causal scheme. Long-term controlled experiments are required to quantify the magnitude of the synergistic effect and its impact on academic achievement and long-term skill retention. Additional interest lies in adapting the model to different subject domains (for example, medical simulations and creative disciplines) and to diverse learner groups, including persons with special educational needs.

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