

From Revision to Transfer: Longitudinal Effects of LLM Writing Feedback

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Abstract

Prior automated writing feedback systems have shown limited evidence of transferable writing development. This pilot longitudinal study examined whether repeated interaction with process-oriented LLM feedback improved independent writing performance over time. Results suggest positive transfer effects across novel writing tasks, supporting the potential developmental role of LLM-mediated feedback.

1 Introduction

Automated written feedback (AWF) systems have long been used to support scalable writing instruction and revision. Prior research has shown that AWF can improve immediate revision quality, particularly for lower-level linguistic features such as grammar, spelling, and mechanics (Wilson et al., 2014; McCarthy et al., 2022). However, evidence for broader transfer to subsequent independent writing performance has remained limited (Kellogg et al., 2010; Wilson et al., 2014).

Recent advances in large language models (LLMs) change this landscape by enabling more contextualized and process-oriented feedback targeting higher-order dimensions of writing, including organization, reasoning, evidence use, and rhetorical effectiveness. Several studies on modern LLM-powered AWF systems show the potential for providing richer forms of formative revision support beyond simple surface corrections (Deane et al., 2021; Wang et al., 2020; Liu et al., 2025; Buterfuss et al., 2022). Recent studies further suggest that actionable high-level LLM feedback may support transfer beyond immediate revision contexts (Attali et al., 2026; Lo et al., 2026).

At the same time, an important open question remains unresolved: whether repeated engagement with process-oriented LLM feedback supports longitudinal writing development over time. Existing AWF research has focused predominantly on im-

mediate revision outcomes or short-duration interventions, with relatively little work examining cumulative developmental effects across repeated independent writing tasks (Shi and Aryadoust, 2024).

To address this gap, the present study investigates whether sustained interaction with process-oriented LLM feedback supports longitudinal transfer in independent writing performance. We conducted a 10-week pilot intervention in which undergraduate students engaged in repeated writing and revision activities using an LLM-based Writing Tutor designed to provide iterative, targeted, high-level feedback in three core dimensions: persuasiveness/engagement, idea development, and coherence. Students also completed independent writing assessments on novel prompts without AI assistance, allowing us to evaluate transfer beyond immediate revision contexts.

The study was guided by the following research question: Does repeated engagement with process-oriented LLM feedback lead to greater improvement in independent writing performance over time than a comparison condition involving instructional videos? Results favored the Writing Tutor condition, with participants demonstrating greater improvement across writing assessments over time.

The contributions of this study are threefold. First, we provide preliminary evidence regarding the longitudinal effects of process-oriented LLM feedback on independent writing performance. Second, we extend prior AWF research beyond immediate revision outcomes by focusing explicitly on transfer across novel unsupported writing tasks. Third, we present a design for LLM-based writing support within a broader formative feedback framework emphasizing iterative uptake, revision, and developmental learning processes.

2 Background and Related Work

2.1 Feedback and Writing Development

Research on writing instruction has consistently identified feedback as one of the most powerful influences on student learning and achievement (Hattie and Timperley, 2007). In writing specifically, formative feedback supports development when it helps learners identify gaps between current and desired performance while also providing guidance for future revision and improvement (Parr and Timperley, 2010; Sadler, 1989). Effective feedback therefore extends beyond error correction by supporting learners in evaluating performance, engaging productively with feedback, and developing greater self-regulation as writers (Carless and Boud, 2018; Hattie and Timperley, 2007).

These theoretical perspectives are particularly relevant to AWF systems. Hattie and Timperley (2007) argue that feedback is most effective when it supports not only task correctness, but also process-level understanding and self-regulation. Likewise, Sadler (1989) emphasizes that effective formative feedback requires learners to understand standards of quality and to develop the capacity to close the gap between current and desired performance. From this perspective, many earlier AWF systems may have been constrained by the restricted instructional scope of the feedback they were capable of generating.

2.2 Research on Automated Written Feedback

AWF systems were originally developed to provide scalable writing evaluation and revision assistance in contexts where individualized human feedback is difficult to provide consistently at scale (Shi and Aryadoust, 2024; Wilson et al., 2014). Over time, AWF systems have expanded considerably in both scope and technical sophistication, encompassing automated writing evaluation platforms, intelligent tutoring systems, online writing assistants, and AI-based revision environments (Shi and Aryadoust, 2024). Nevertheless, much AWF research has historically focused on lower-level linguistic features such as spelling, grammar, mechanics, and lexical correctness (Shi and Aryadoust, 2024; Wilson et al., 2014). Reviews of AWF research likewise suggest that many systems remain primarily oriented toward surface correction rather than higher-order writing processes such as argumentation, organization, audience awareness, and rhetorical development (Fu et al., 2024; Shi and Aryadoust, 2024).

Although these systems frequently improve immediate revision quality, evidence for broader and more transferable writing development has remained mixed. For example, Wilson et al. (2014) found that students improved across revisions within a writing task when receiving automated feedback, but observed limited evidence of transfer to subsequent independent writing performance. Similarly, Kellogg et al. (2010) and McCarthy et al. (2022) reported improvements in local revision and editing behaviors without corresponding evidence of broader improvements in independent writing quality.

2.3 Process-Oriented AI Writing Support

Unlike earlier rule-based or feature-based systems, LLM-based AWF systems can generate contextualized and rhetorically-oriented feedback addressing higher-order dimensions of writing, including evidence use, coherence, organization, reasoning, and audience awareness. As a result, LLM-based feedback systems may increasingly function not only as mechanisms for automated correction but also as forms of instructional scaffolding supporting revision-oriented learning processes.

This shift is particularly important from the perspective of feedback literacy and learner uptake. Feedback research increasingly emphasizes that learning gains are influenced by learners' ability to interpret, evaluate, and act on feedback productively over time (Boud and Molloy, 2013; Carless and Boud, 2018). Prior research on automated writing systems has therefore attempted to move beyond surface correction toward more process-oriented forms of writing support. For example, scenario-based assessment environments have been used to support formative argument-writing instruction through richer task structures and automated writing indicators (Deane et al., 2021). Similarly, systems such as eRevise and eRevise+RF have demonstrated that NLP-based revision support can improve students' use of textual evidence, revision quality, and argumentative reasoning across drafts (Wang et al., 2020; Liu et al., 2025). Other recent work has explored higher-level AI-supported revision guidance intended to support writing and revision strategies rather than localized editing alone (Butterfuss et al., 2022). More broadly, recent reviews suggest that advances in generative AI may enable richer forms of formative writing support than were previously feasible in automated systems (Shi and Aryadoust, 2024).

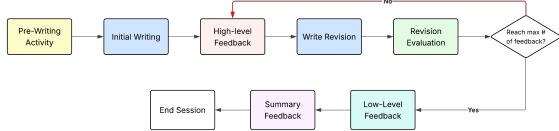


Figure 1: Writing Tutor flow.

Recent studies have provided initial evidence consistent with this possibility. Attali et al. (2026) found that actionable high-level LLM-generated feedback produced measurable improvements not only within revision cycles, but also on subsequent independent writing tasks, suggesting transfer beyond immediate draft revision. In a follow-up study, Lo et al. (2026) further demonstrated that repeated exposure to multiple high-level AI suggestions supported improved revision quality and transfer across writing tasks. Together, these findings suggest that process-oriented LLM feedback may support forms of transfer and learning that earlier AWF systems struggled to achieve.

At the same time, relatively little research has examined whether repeated interaction with AI-mediated feedback contributes to cumulative developmental gains over extended instructional periods. Existing AWF research has focused predominantly on immediate revision outcomes or short-duration interventions (Shi and Aryadoust, 2024; Wilson et al., 2014), leaving the longitudinal effects of process-oriented LLM feedback largely unexplored.

3 Methods

3.1 LLM-Based Writing Tutor

For this study, we used a previously developed LLM-based Writing Tutor (WT) (Lo et al., 2026) designed to support writing development through iterative feedback, revision, and reflection cycles. The system was developed in response to limitations identified in prior automated written feedback (AWF) systems, particularly their historical emphasis on surface-level corrective feedback and limited support for transferable writing development.

The tutor was implemented using a collection of LLM-based components responsible for generating feedback and supporting revision interactions. Most components, including prewriting support, higher-order feedback generation, uptake evaluation, and summary feedback, were built using GPT-4.1. Lower-level linguistic feedback addressing grammar, wording, and mechanics was generated

using a fine-tuned GPT-3.5 model optimized for writing feedback tasks. Figure 1 illustrates the overall interaction flow. Because the focus of the present study is on longitudinal learning outcomes rather than model development, we describe the system at a functional level and refer readers to Appendix 7.3 for representative interface examples.

The WT combined several forms of instructional support spanning the writing process. Before drafting, students engaged in prewriting activities intended to support idea generation, rhetorical framing, and planning. These activities encouraged students to clarify positions, organize arguments, and identify supporting evidence before composing full drafts.

Students then received both higher-order and lower-order LLM-generated feedback during drafting and revision. Higher-order feedback focused on dimensions such as organization, coherence, idea development, reasoning, evidence use, and rhetorical effectiveness. Rather than providing only evaluative comments or error identification, the LLM also generated targeted actionable suggestions linked to specific portions of student text. The feedback was designed to function as process-oriented instructional guidance intended to support substantive revision and reflection.

A central feature of the system was its iterative uptake-oriented feedback structure. After students revised their drafts, an evaluation component analyzed the revised text in relation to the original feedback, assessed the extent to which the revision addressed the targeted issue, and generated follow-up comments reflecting the quality of the uptake. In cases where revisions successfully addressed the issue, students received reinforcing feedback; in other cases, the system directed students toward unresolved conceptual or rhetorical weaknesses requiring additional revision. This iterative structure was intended to support the development of revision strategies and feedback uptake behaviors over time.

In addition to higher-order feedback, the tutor also included lower-level linguistic support targeting grammar, sentence clarity, wording, and mechanics. These lower-level suggestions were incorporated into the broader revision workflow as a separate stage following the higher-level feedback loops.

At the conclusion of each writing session, GPT-4.1 generated summary feedback synthesizing major strengths, weaknesses, and suggested areas for

continued improvement. The overall instructional design of the WT was informed by formative feedback theory (Hattie and Timperley, 2007; Parr and Timperley, 2010) and feedback literacy frameworks emphasizing iterative revision, learner reflection, and active uptake of feedback (Carless and Boud, 2018).

3.2 Study Design and Procedure

The study employed a 10-week longitudinal mixed within-/between-subjects design examining writing development across two genres: narrative and argumentative writing.

Participants were assigned to one of two between-subject conditions. Participants in the WT condition completed interactive AI-supported writing revision sessions using the Writing Tutor, whereas participants in the comparison condition completed instructional video activities during intervention weeks. Both groups completed the same assessment tasks and surveys at matched timepoints; the experimental manipulation occurred only during intervention sessions.

The study consisted of two five-week instructional blocks, one focused on narrative writing and the other on argumentative writing. Each block followed the same structure: an initial pretest writing assessment, three intervention sessions, and a final posttest writing assessment. Across the full study, participants therefore completed four independent writing assessment sessions and six intervention sessions. To reduce potential order and practice effects, the order of the narrative and argumentative instructional blocks was counterbalanced across participants.

Assessment sessions occurred during Weeks 1, 5, 6, and 10. During these sessions, participants completed timed independent writing tasks without AI assistance or intervention support. These assessments served as the primary outcome measures for evaluating longitudinal writing development.

During intervention sessions (Weeks 2–4 and 7–9), WT participants completed Writing Tutor activities involving drafting, revision, automated feedback, and uptake-oriented follow-up feedback. These sessions typically required approximately 20 minutes to complete, compared to approximately five minutes for assessment sessions.

Distinct prompts were used across sessions in order to minimize prompt memorization and encourage transfer across tasks (see Appendix for prompt examples). Narrative prompts focused

on themes such as personal experiences, hobbies, life lessons, and meaningful events, whereas argumentative prompts addressed topics including education, persistence, cultural preservation, generational learning, and language requirements.

3.3 Participants and Attrition

Participants were undergraduate students enrolled in writing-related courses at Arizona State University (ASU). Recruitment occurred through course announcements and university mailing lists. Participation was voluntary and conducted outside of students' regular coursework. Participants received compensation for completing study activities.

A total of 31 students initially enrolled in the study, including 20 participants assigned to the WT condition and 11 participants assigned to the comparison/control condition. Due to attrition over the 10-week intervention period, the final analytic sample consisted of 13 students who completed all required study sessions, including 8 participants in the WT condition and 5 participants in the control condition.

Completion rates were comparable across conditions. Participants in the WT condition completed the study at a rate of 40.0% (8/20), while participants in the control condition completed the study at a rate of 45.5% (5/11).

To evaluate whether attrition was systematically associated with treatment assignment or baseline writing ability, logistic regression analyses were conducted predicting completion status from experimental condition, baseline writing score, and their interaction. Baseline writing performance was operationalized using Week 1 assessment scores collected prior to the intervention. These analyses did not provide evidence that completion probability differed significantly as a function of condition ($p = .82$), baseline performance ($p = .43$), or their interaction ($p = .91$).

Although attrition was substantial, the absence of evidence for differential attrition reduces concern that the final analytic sample disproportionately favored stronger participants in the WT condition. Nevertheless, the modest sample size limits definitive conclusions regarding attrition mechanisms.

3.4 Measures and Statistical Analysis

Given the exploratory nature of the study and the modest completion sample, analyses focused primarily on estimating treatment effects and charac-

terizing uncertainty rather than relying exclusively on null-hypothesis significance testing.

The primary outcome measure was an automated writing quality score assigned to writing samples collected during the four independent assessment sessions using the Duolingo English Test writing scoring system, a state-of-the-art automated writing assessment framework described in Section 5.2 of the DET Technical Manual (Naismith et al., 2025). Assessments spanned both narrative and argumentative genres and were administered at pre- and post-intervention timepoints.

Because the study involved a small and unbalanced completion sample, linear mixed-effects models were subsequently used as the primary inferential framework. Mixed-effects modeling provided greater flexibility for repeated-measures data under conditions of imbalance and missingness. The primary mixed-effects model examined the interaction between experimental condition and assessment timepoint while including participant-level random intercepts to account for repeated observations within individuals.

In addition to inferential analyses, standardized effect sizes and estimated marginal means were computed to characterize the magnitude of observed differences between conditions. Participant-level change scores were calculated based on differences between pretest and posttest performance averaged across genres, and Hedges' g was used to estimate standardized group differences in improvement.

4 Results

4.1 Mixed-Effects Modeling

The model revealed a positive interaction between condition and pre/post assessment, indicating that participants in the WT condition demonstrated greater longitudinal improvement than participants in the control condition ($\beta = 0.587$, $SE = 0.320$, $t(37) = 1.83$, $p = .075$).

Estimated marginal means suggested divergent trajectories across conditions (see Figure 2). Participants in the WT condition increased from an estimated mean score of 1.12 at pretest to 1.44 at posttest, whereas participants in the control condition showed no improvement over the same period (0.99 at pretest and 0.49 at posttest). Consistent with this pattern, a difference-in-differences contrast estimated that WT participants improved by approximately 0.83 score units more than con-

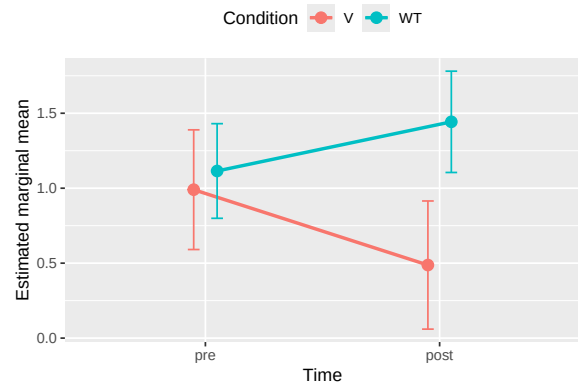


Figure 2: Estimated marginal means across pretest and posttest assessments for WT and control conditions.

trol participants over the course of the intervention ($t(37) = 1.83$, $p = .075$).

Given the pilot nature of the study and the modest completion sample, emphasis was placed on the magnitude and consistency of observed effects rather than conventional significance thresholds alone. Across analyses, the direction of the effect favored the WT condition.

4.2 Effect Sizes

To characterize the magnitude of observed differences independent of inferential significance testing, participant-level change-score analyses were also conducted. Standardized effect size estimation using Hedges' g yielded a moderate-to-large effect favoring the WT condition ($g \approx 0.89$).

Although confidence intervals were necessarily wide due to the modest completion sample, the magnitude of the estimated effect was notable for a pilot longitudinal intervention study involving unsupported transfer assessments on novel writing prompts.

5 Discussion

The present study investigated whether repeated engagement with process-oriented LLM-based feedback was associated with longitudinal transfer in independent writing performance. Results favored the Writing Tutor condition. Participants receiving LLM-based feedback demonstrated more positive longitudinal trajectories on independent writing assessments than participants in the comparison condition. Importantly, gains were observed on unsupported writing assessments and using novel prompts. The findings therefore suggest transfer beyond immediate revision contexts, an outcome that

has proven difficult to demonstrate in prior AWF research (Wilson et al., 2014). These findings also extend earlier studies of short-term transfer by suggesting that repeated AI-mediated feedback may support similar effects over longer instructional periods. Given the small sample size, these findings should be interpreted cautiously, but they provide preliminary evidence that repeated AI-mediated feedback may support longitudinal improvement in independent writing performance.

From a theoretical perspective, the findings are consistent with formative feedback frameworks emphasizing process-oriented guidance, self-regulation, and actionable revision support (Hattie and Timperley, 2007; Parr and Timperley, 2010). Unlike many earlier AWF systems focused primarily on surface-level correction, the WT intervention emphasized higher-order dimensions of writing such as organization, reasoning, evidence use, and rhetorical effectiveness, and incorporated iterative uptake-oriented feedback cycles intended to encourage reflection and substantive revision rather than localized editing alone. One possible interpretation of the observed longitudinal trends is that repeated interaction with this process-oriented feedback helped students develop revision-oriented strategies that transferred across writing contexts.

Several limitations substantially constrain interpretation of the findings. Most importantly, the final analytic sample was small due to considerable attrition across the 10-week intervention period. Although attrition analyses did not provide evidence for systematic differences in completion probability across conditions or baseline writing ability, the modest sample size limits statistical power and increases uncertainty around parameter estimates. The study should therefore be interpreted as a pilot investigation.

The study also had several additional limitations. The study focused on relatively short writing tasks collected within a controlled extracurricular context, and the extent to which the findings generalize to longer authentic academic writing tasks remains unclear. Furthermore, the present analyses focused exclusively on longitudinal writing outcomes and did not examine process-level interaction data, revision behaviors, or mechanisms of feedback uptake.

Despite these limitations, the present findings provide preliminary but convergent evidence that process-oriented LLM feedback may support longitudinal transfer in writing performance beyond immediate revision contexts. Although causal claims

cannot be made, the consistency of findings across analyses increases confidence in the results.

Future studies should therefore evaluate process-oriented LLM feedback using larger and better-powered longitudinal designs capable of examining both developmental outcomes and revision processes in greater detail. In particular, future work should investigate which forms of AI-mediated feedback most effectively support transferable writing development and which learner characteristics moderate responsiveness to iterative feedback systems.

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7 Appendix

7.1 Narrative Prompt Examples

What are some hobbies that you have? Which ones do you think you will have more time to enjoy in the next year? Suggest ways that these hobbies could change in the next five years.

Write about the last time you participated in a physical activity. What was the physical activity? Did it go well? What was the experience like? How did you feel before and after? Include specific details in your response.

7.2 Argumentative Prompt Examples

Do you think that hard work is enough, or does a person also need some talent to achieve difficult goals? Provide reasons to support your opinion.

Some people feel that food is one of the most important ways to represent and preserve a culture. What are your thoughts on this? Argue your position using specific examples from your experience or observations.

7.3 Screenshots of Writing Tutor Stages

1:58

×

1. Plan your writing

Answer the questions in the right panel to plan your writing.

2. Write about the topic

3. Read suggestion and revise your response

4. Resolve suggested edit(s)

5. Review the summary report

What are two or three hobbies you have right now?

Cooking, reading, weight training

Which one of these hobbies do you think you will have more time to enjoy in the next year?

Reading

What is one reason you expect to have more time for that hobby next year?

Because I'll probably cook less

How might that hobby change in the next five years?

CONTINUE

Figure 3: Prewriting stage of the Writing Tutor.

×

1. Plan your writing

Answer the questions in the right panel to plan your writing.

2. Write about the topic

3. Read suggestion and revise your response

4. Resolve suggested edit(s)

5. Review the summary report

What are two or three hobbies you have right now?

Cooking, reading, weight training

Which one of these hobbies do you think you will have more time to enjoy in the next year?

Reading

What is one reason you expect to have more time for that hobby next year?

Because I'll probably cook less

How might that hobby change in the next five years?

✓ Good job!

Great job! Your answers clearly identify your hobbies, future plans, and reasons, providing a strong base for your essay.

👍

👎

CONTINUE

Figure 4: Prewriting evaluation stage.

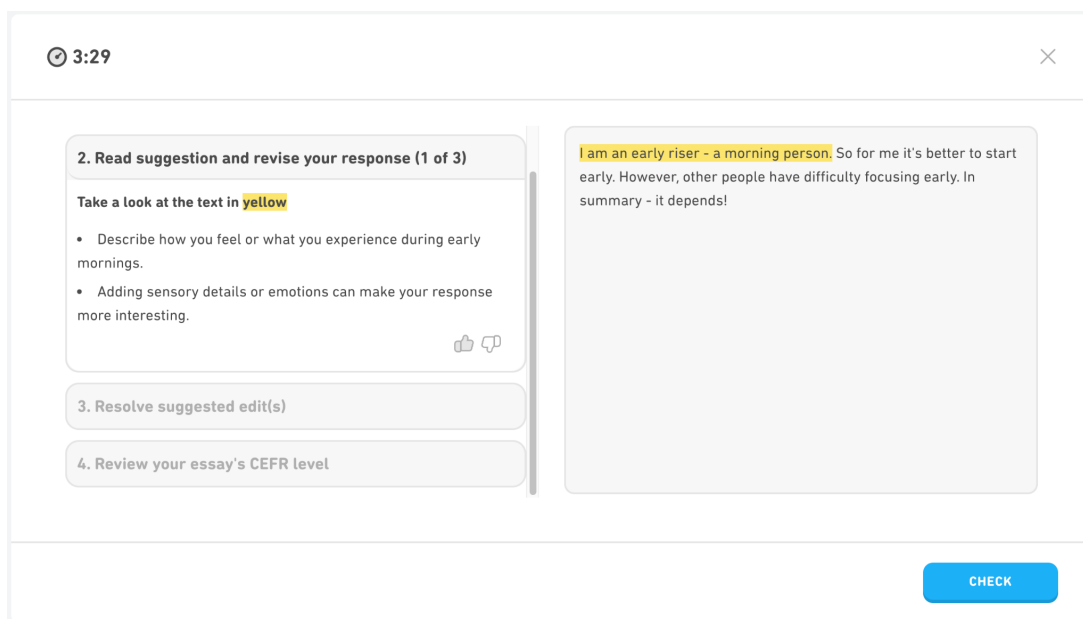


Figure 5: High-level feedback stage.

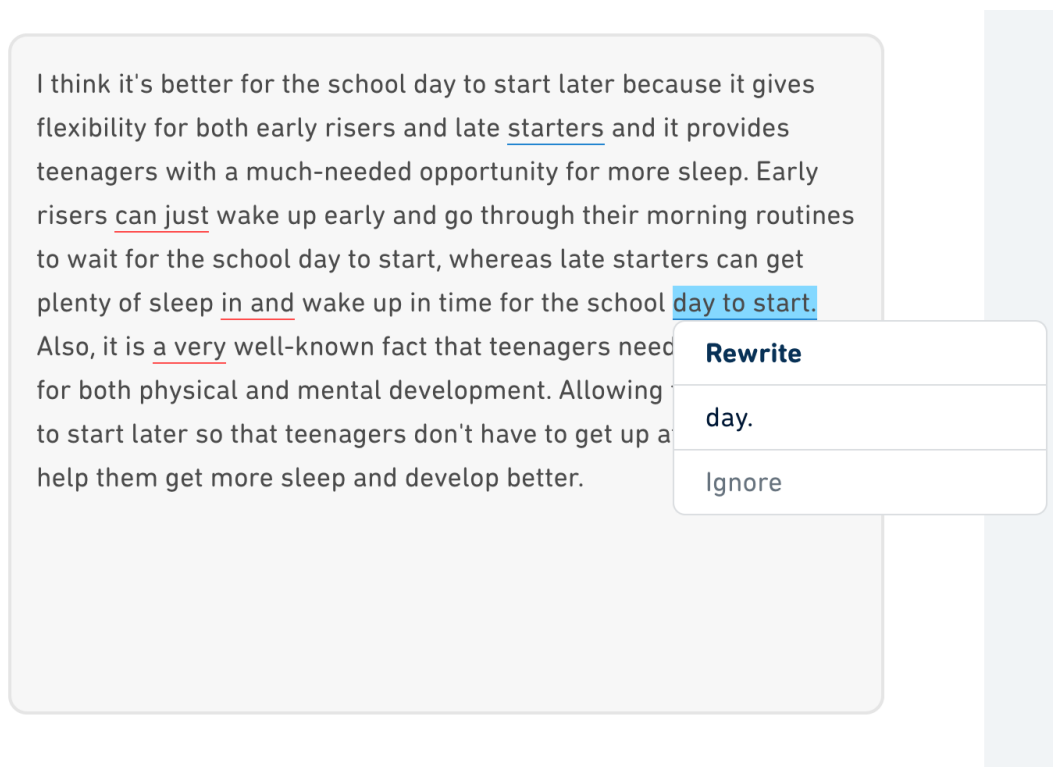


Figure 6: Low-level linguistic feedback stage.

🕒 5:00

✕

2. Read suggestion and revise your response (1 of 3)

Take a look at the text in **yellow**

- Describe how you feel or what you experience during early mornings.
- Adding sensory details or emotions can make your response more interesting.

👍🗨

3. Resolve suggested edit(s)

4. Review your essay's CEFR level

I am an early riser - a morning person. In the morning I feel more focused and tingling with expectation for the day. In contrast, in the afternoon and evening I feel quite tired. So for me it's better to start early. However, other people have difficulty focusing early. In summary - it depends!

✔️ **Good job!**

You added sensory details and emotions about how you feel in the morning, making your response more engaging.

👍🗨

CONTINUE

Figure 7: Revision evaluation and uptake feedback stage.

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5. Review the summary report

Thank you for your effort in writing and revising your essay. You maintained a clear focus on your hobby of cooking and developed your ideas in a thoughtful way. Although you received several suggestions to add more personal examples and reflections, you kept your essay consistent and well-organized. Writing is a process that takes time and practice, and you have shown dedication in expressing your thoughts clearly. In order to further improve your writing, you can focus on:

Grammar and Vocabulary: Your vocabulary is appropriate and varied, and your grammar is accurate throughout the essay. To further improve, you could incorporate more descriptive language or culinary terms to make your writing even more vivid and precise.

Development: Your essay addresses the prompt by discussing your current hobby, your plans for the next year, and possible changes in the next five years. However, the development could be strengthened by including specific examples, such as a favorite dish you enjoy cooking or a new recipe you want to try. Adding a personal reflection on how cooking makes you feel or what you hope to achieve would also make your essay more engaging and complete.

Coherence: The essay is logically organized, with each paragraph building on the previous one. You move smoothly from describing your current interest in cooking to your future plans and how the hobby might evolve. To further enhance coherence, consider using more transition words or phrases to connect your ideas even more clearly.

Engagement: While your essay is clear and informative, it could be more engaging by sharing a personal story or emotion related to cooking. For example, describing the satisfaction you feel after preparing a meal or a memorable cooking experience would help readers connect with your passion.

Your essay is at the CEFR level of C2.

Figure 8: Summary feedback stage.

Video 3: Ethos

Due Mar 21 at 11:59pm

Points 3

Questions 3

Available until Mar 29 at 11:59pm

Time Limit None

Instructions

Please watch Video 3: [Ethos](#)  and then answer the three questions that follow.

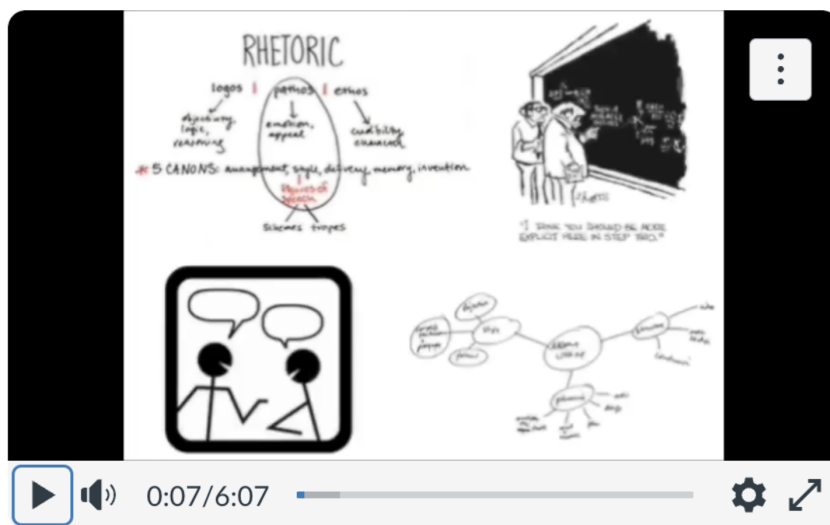


Figure 9: Comparison-group instructional video task.