Using Learning Analytics to Support Secondary School Students' Writing with Generative AI

Ho Yin Fong[1], Chun Lai[1], Xinyu Li[2], Carol K. K. Chan[1], Dragan Gašević[2] and Xiao Hu[3]

[1]*The University of Hong Kong*
[2]*Monash University*
[3]*University of Arizona*

Abstract
Generative artificial intelligence (GenAI) carries mixed blessings for writing, supporting writing process and performance but also inducing potential risks for plagiarism, overreliance, and metacognitive laziness. Learning analytics dashboards (LADs) may help address these pitfalls by visualizing students' interaction behaviors with GenAI and hence enhancing their metacognitive awareness during the writing process. However, few studies have explored the extent to which GenAI-empowered LADs may shape students' self-regulation on GenAI usage. Based on 46 secondary school students' logged behaviors on a GenAI-enhanced writing platform during an argumentative writing task, this study examined the reliability of using GenAI for automated classification of students' GenAI prompts and investigated whether the GenAI-empowered LAD of students' GenAI interaction behaviors might influence their GenAI usage patterns. The study revealed a high level of reliability of GenAI automated classification of GenAI prompts. It also showed that the GenAI-empowered LADs had the potential to reduce plagiarism and increase learning-oriented interaction with GenAI. The findings suggest that LADs may serve as a viable solution to enhance secondary school students' effective interaction with GenAI.

Keywords
Learning Analytics Dashboard, Writing with Generative AI, Secondary School Students

1. Introduction

The use of Generative artificial intelligence (GenAI) in writing has drawn immense research attention, and the generated insights have been synthesized in recent meta-analytic and synthetic review studies [1, 2]. These studies highlight that GenAI holds great potential for second language writing and creates new opportunities for enhancing students' writing process [3]. Yet, they also pinpoint various pitfalls and challenges, including over-reliance, plagiarism risks, and the loss of critical thinking as students tend to treat AI models as content generators [1, 2, 4]. Given this mixed blessing, it is urgent to boost students' ethical, critical, and strategic use of GenAI, especially among secondary school students who are still developing their regulation and metacognitive competence [5, 6].

Learning Analytics Dashboards (LADs) provide a potential solution to meet these challenges. LADs visualize students' behavioral data in accessible and actionable ways, which may potentially raise students' metacognitive awareness in the learning process [7, 8]. Yet, there is limited research on the effects of LADs on secondary school students' use of GenAI for writing. Moreover, with its generative capacities, GenAI has the potential to empower LADs [9, 10]. While existing studies have mainly used GenAI-empowered LADs to enhance students' performance, few studies have explored whether GenAI-empowered LADs might change students' GenAI usage patterns. In this research, we address these research gaps by studying the extent to which a GenAI-empowered LAD system that visualizes students' GenAI usage patterns during writing might shape students' adaptive use of GenAI tools.

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hyfoscar@hku.hk (H. Y. Fong); laichun@hku.hk (C. Lai); xinyu.li1@monash.edu (X. Li); ckkchan@hku.hk (C. K. K. Chan); dragan.gasevic@monash.edu (D. Gašević); xiaohu@arizona.edu (X. Hu)

2. Background work

2.1. GenAI for English Writing

Previous studies have shown that GenAI not only can enhance students' writing performance but also contribute to their writing development [1, 2]. However, the efficacy of GenAI depends essentially on students' ability to interact effectively with GenAI. For instance, in a study of using ChatGPT to provide essay improvement suggestions, students expressed the desire for support on prompt literacy [11]. Moreover, [12] found that, although students valued ChatGPT's usefulness in initiating ideas and providing individualized writing assistance, they expressed concerns about plagiarism and hallucination issues that require constant prompt modifications.

Furthermore, one consistent concern highlighted in existing literature is learners' over-reliance on and misuse of AI tools, resulting in the loss of personal (authorial) voice in writing and hindering the development of independent writing skills [13, 14]. [15] raised a significant concern about learner over-reliance of GenAI feedback and associated metacognitive laziness, characterized by limited efforts in internalizing and applying feedback in learning, which may "prompt short-term task performance improvements and long-term skill stagnation" (p. 19). Thus, there is an urgent need to explore how students can be supported to reduce shallow processing and instead engage in monitoring and adjusting usage patterns with GenAI that can benefit not only short-term writing performance but also long-term writing development.

2.2. GenAI Usage Patterns

GenAI usage patterns were directly associated with student learning from interaction with GenAI. For instance, [16] discovered that students who held a resistive or receptive approach against GenAI, either by refusing to use GenAI or blindly consuming outputs without questioning, exhibited weaker academic performance than those who held a resourceful or reflective approach by engaging with GenAI proactively, refining and verifying GenAI outputs. The researchers concluded that the frequency and depth of learners' interactions with GenAI were associated with students' perception on GenAI, as well as learning possibilities and outcomes.

Researchers have conceptualized characteristics of GenAI usage patterns in view of goal orientations and have argued that GenAI usage with different goal orientations have implications for learning possibilities. According to [17], performance-goal orientation and learning-goal orientation may lead to differential learning behaviors, cognitive engagement, and resilience in face of challenges. Adopting this theoretical perspective, [18] categorized ChatGPT prompts into 3 categories based on purposes of interaction - Asking, Doing and Expressing. They argued that Asking prompts were driven by learning orientation and Doing prompts were driven by performance orientation. Similarly, [19] conceptualized two types of GenAI prompt: 1) Performance-oriented AI prompt, which concerns interacting with GenAI to optimize learning process, get better grades and achieve desirable learning performance; and 2) Learning-oriented AI prompt, which concerns interacting with GenAI to understand learning content, analyze results and achieve learning goals. This study adopts this conceptualization and explores the potential of using learning analytics dashboards to boost learning-oriented AI prompts.

2.3. Learning Analytics Dashboard and GenAI

Learning analytics dashboards (LADs) involve "visualiz[ing] results of educational data mining in a useful way" (p. 145) [20]. In the field of writing education, previous studies have demonstrated the effects of real-time analytics on students' writing learning experience by providing process-oriented feedback [21] and timely interventions [22] that enhance metacognitive awareness. However, recent reviews have also highlighted limitations of recent LAD research. [23] discovered that out of 38 LAD studies, only a few demonstrated meaningful effects on students' academic outcomes with self-regulated learning (SRL), and most studies are only designed for one-off interventions. Additionally, [24] commented that most LADs only focus on descriptive analytics, with limited prescriptive analytics

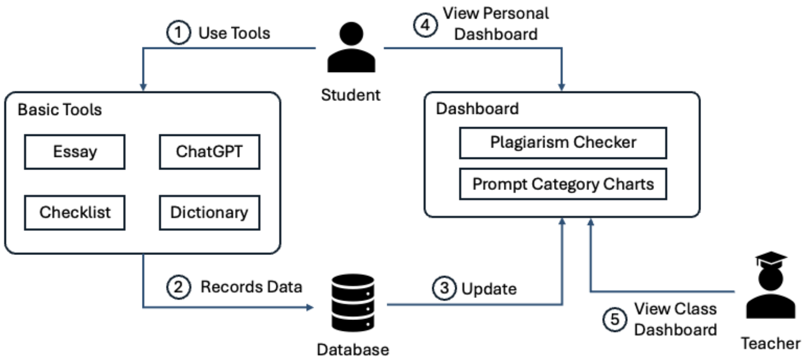

Figure 1: The workflow of the GenAI-empowered system with learning analytics

and no automated recommendations or instructions that can support long-term personalized learning with early intervention.

Researchers have further explored the synergy of GenAI and LADs and demonstrated that GenAI can be used to empower LADs [10]. For instance, [9] illustrated possibilities of integrating GenAI models with LAD designs by automatically visualizing data with LLMs. Moreover, researchers have explored the integration of GenAI chatbot with LADs to enhance learners' abilities to interpret and utilize information from LADs [25]. Yet, few studies have explored whether LADs can result in students' optimization of their GenAI usage patterns, especially in writing education.

3. Research Questions

To address the research gaps, this study aims to 1) explore the extent to which GenAI can be used to empower LAD through automated classifying student prompts; and 2) to examine the use of LADs in supporting writing education with GenAI. This study developed a LAD that goes beyond descriptive analytics to recognize behavioral patterns and prompt use and translate them into actionable feedback. The study aims to explore the feasibility of developing LADs that can help students assess and change their GenAI usage patterns.

RQ1: How reliable is GenAI on coding students' AI prompts to inform the LAD?

RQ2: What are the relationships between LAD views and students' GenAI usage patterns?

4. Method

4.1. Design of LAD

In this research, we extend from FLoRA [26], which is a Moodle-based, GenAI empowered platform for writing education. The FLoRA platform includes a range of functions to scaffold students in the writing process, such as a planning tool that guides students in planning their essays and reminds students of the plan from time to time (Li et al, 2025). In this study, we configured the FLoRA platform to include the following functions: 1) an essay writing box, 2) a ChatGPT tool, 3) a checklist tool that lists grammatical errors, and 4) a dictionary tool. To monitor and visualize students' ChatGPT usage, we developed a series of LAD tools on top of FLoRA. The integrated system is named GAILA, standing for GenAI and Learning Analytics. The workflow of the LAD-empowered system is shown in Figure 1. The LADs include 1) Use Time charts, 2) Plagiarism checker, and 3) Prompt Category charts.

4.1.1. Plagiarism Checker

To address the concerns of originality in student writing, we implemented a plagiarism checker that compares students' essays with their received ChatGPT responses and highlights overlapping text

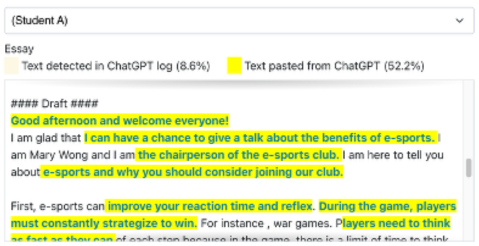

Figure 2: Example of plagiarism detector interface

Table 1
Code definition for natures of prompts

Nature	Definition
Performance-oriented prompts	Prompts are more inclined towards asking AI to do the tasks for them: show more reliance on AI to directly provide answers or complete tasks for the students, with limited efforts from the user to engage in active learning.
Learning-oriented prompts	Prompts are more inclined towards asking AI for guidance to improve understanding – elicit AI's suggestions that students can select from or elicit AI's feedback, advice and explanations that can guide students to learn.

segments. Considering that ChatGPT responses may repeat phrases given in the writing topic or written by the students, we have designed two levels of inspection. A writing segment is classified as suspicious if it is found in ChatGPT responses and is classified as highly suspicious if the trace logs showed that the text is also pasted onto the essay box. The former is highlighted in light yellow, and the latter in bright yellow. Figure 2 shows an example of the displayed detection result. To avoid detection of pasting common vocabulary and phrases during essay edits, we filtered out segments with fewer than 30 characters (i.e., about 6 English words). We then calculate the percentage in length of suspected segments to the whole essay to allow quick detection of high AI usage.

Teachers and students can view the detection results. Teachers can view all students' results and percentages, potentially supporting feedback discussions between teachers and students on responsible AI use. Students can also view their own detection and percentages, which encourages them to lower the percentage by paraphrasing or reformulating ideas from LLMs.

4.1.2. Prompt Category Charts

With reference to [18] and [19], the GenAI prompts recorded from students were classified into a coding scheme illustrating key writing processes. Students' prompts were coded into 2 categories based on goal orientations: performance-oriented prompts and learning-oriented prompts (Table 1). With reference to [27] and [28], students may seek help from GenAI on the following aspects of the writing process: content (content idea; structure help; content revision) and language (language help; rhetoric help; error correction). Student prompts were also coded based on these aspects (Table 2). The definitions of codes are shown in Tables 1 and 2.

The prompt categories are then shown to teachers and students in visualizations. Figure 3 shows the teacher's interface for prompt categories. First, the bar chart lists the 6 aspects of writing (Table 2) and shows the counts of performance-oriented and learning-oriented prompts in blue and red respectively. In another tab, the proportion of different types of prompts is visualized in two separate pie charts for clearer reference. Then, teachers can choose to drill down to individual students' actual prompt history for more detailed observation/inspection.

Figure 4 shows the prompt category interface for students. Students can switch between charts for perform-oriented prompts and learning-oriented prompts using the tabs at the top. Their category

Table 2
Code definition for aspects of prompts

Aspect (general)	Aspect (specific)	Definition
Content/Idea	Content idea	Seek idea inspirations or other help related to the drafting of the content of the essay
	Structure help	Help to generate a written product by structuring or organizing the pieces of ideas provided by the learners or ask for tips/advice to learners on how to do so
	Revision	Make revisions on learners' written products concerning the ideas/-content and structures of the contents or provide tips on how to revise existent written products in terms of ideas/content and/or structures
Language	Language help	Help with the recall/retrieval/selection of word- or sentence structure to convey/express intended meaning
	Rhetoric help	The use of rhetoric devices and strategies to enhance the persuasive and emotional impact of communication. This includes guidance on word choice, rhetoric devices, tone and style, persuasive techniques, and conciseness to strengthen the overall effectiveness of the message.
	Error correction	Identify or correct language errors at word or sentence structure level

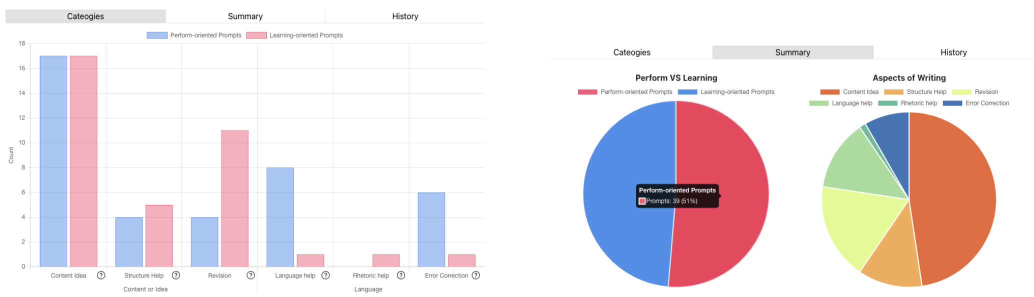

Figure 3: Prompt category chart interface for teachers, including bar chart for each category (left) and pie charts for overall distribution (right)

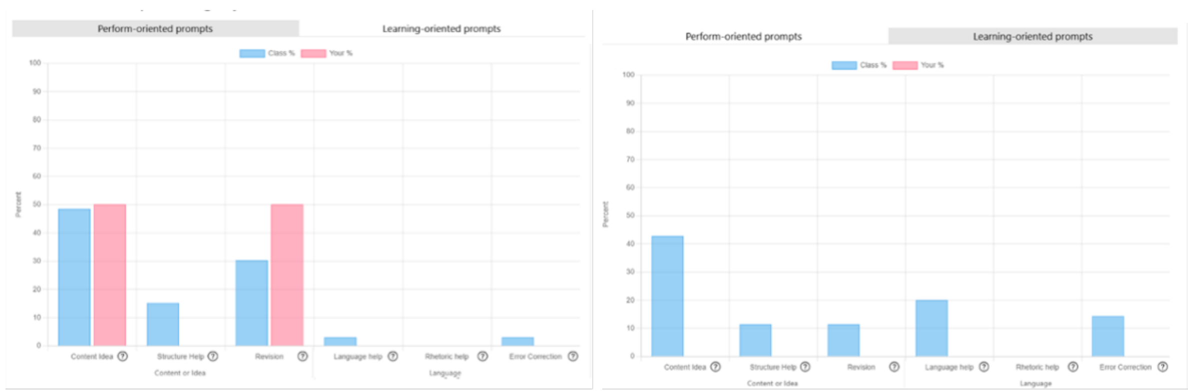

Figure 4: Prompt category chart interface for students, including bar charts for performance-oriented prompts (left) and learning-oriented prompts (right).

distributions are shown in blue, while the class's overall distribution is shown in red. Highlighting this comparison allows quick review of one's own prompt categories and comparisons with the class, hence promoting self-regulation.

4.2. Research Context

The platform was deployed at a secondary school English class in Hong Kong during the Spring 2025 semester. The students were learning English as a second language with low-intermediate proficiency level. A total of 46 students (20 female, 26 male) at Grade 9 aged 14-16 agreed to participate in the study. The students were given an essay topic and instructed to follow a suggested workflow with three stages, outlining, drafting, and revising. The essay was assigned as homework. Students completed the essay outside the classroom within a duration of three weeks, one week for each of the three writing stages in the workflow. We then collected log data as the students used the system, including keystrokes and mouse clicks on the system, and ChatGPT prompts and responses. Based on these logs, we calculated metrics that provide preliminary indications of how students engaged with each LAD component.

4.3. Data Analysis

To answer RQ1, we calculated the reliability of the automatic coding of students' prompts by ChatGPT based on the coding schema shown in Tables 1 and 2. We deployed the few-shot prompting strategy by providing 5 random examples of each code in the coding prompt. We also provided the essay topic as the context to filter out irrelevant student prompts. The reliability of ChatGPT automatic coding is demonstrated in [29] with reports on strong correspondence between ChatGPT and human coding. We also re-verified this method by asking two graduate students in education to independently code the prompts without looking at ChatGPT's results. Since the nature of prompts (Table 1) and aspect of prompts (Table 2) are independent, and aspect of prompts are subdivided into hierarchical codes, the coders were instructed to first decide on the nature of prompts (Code 1), then the general aspect of prompts (Code 2), and lastly the specific aspect of prompts (Code 3). Agreement between the two human coders was measured with Cohen's kappa score, and discrepancies were resolved through discussion. Using human coding as the ground truth, the correspondence between human coding and ChatGPT coding is measured with both Cohen's kappa score and F1 score.

To answer RQ2, we analyzed how often each student viewed the visualization tools and their behaviors before and after viewing the visualization tools. This includes 1) examining if students' detected plagiarism percentage changed before and after viewing the plagiarism detector, and 2) calculating students' ratio of learning-oriented prompts to the total number of prompts before and after viewing the prompt category charts. For the plagiarism detector, we also examined if final plagiarism percentages of those who viewed the detector differ from those who did not. Similarly, for the prompt category charts, we compared the final ratio of learning-oriented prompts of students who viewed the charts and those who did not.

5. Results and discussion

5.1. Reliability of Prompt Categorization

Figure 5 shows the result of consistency between two human coders, and between human and ChatGPT-4o in Cohen's kappa metric. For human coding, all scores exceed 0.8, indicating a strong agreement between them. We then filter the human-agreed codes and compare them with ChatGPT codes. For human coding versus ChatGPT coding, all scores exceed 0.65 with Code 2 exceeding 0.8, showing a high reliability of using the ChatGPT-4o model in automated categorization.

Figure 6 shows the results of the F1 score calculation between human-agreed codes and ChatGPT codes. The first two columns are codes on "nature of prompts" (Code 1). The next two columns are codes on "aspect of prompts (general)" (Code 2). The next 6 columns are codes on "aspect of prompts (specific)" (Code 3). As illustrated in the figure, the accuracy for codes for "nature of prompts" is consistent, while accuracy fluctuates for "aspect of prompts", with lower F1 scores on "Structure help" and "Rhetoric help". The overall macro-average of F1 measures across all eight categories is 0.757, indicating ChatGPT could reliably code students' GenAI prompts automatically.

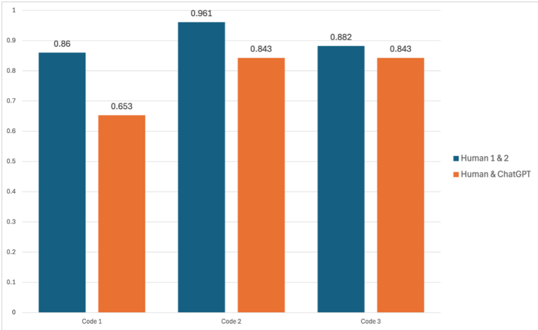

Figure 5: Cohen's kappa score between 2 humans, and between human and ChatGPT

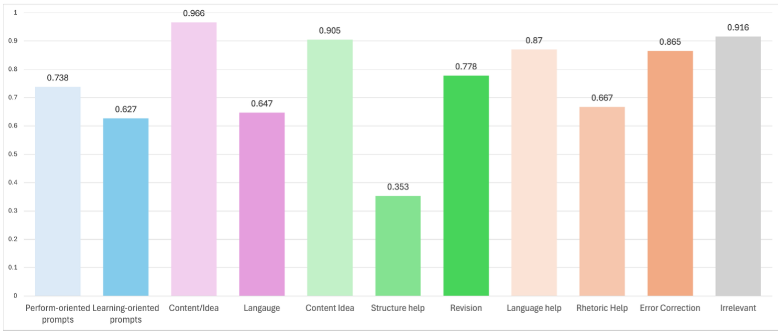

Figure 6: F1 score of ChatGPT coding

5.2. Behavioral Changes of Students

5.2.1. Plagiarism Percentages

We first compared the final plagiarism percentages of students who viewed the plagiarism checker ("viewers") and those who did not ("non-viewers"). Table 3 shows the results of the analysis. We also ran an independent-samples t-test between the two groups. The results are $t(46) = 0.66$, two-tailed $p = 0.514$, and Cohen's $d = 0.2$. The 95% confidence interval for the mean difference is [-0.029, 0.058], indicating uncertainty in the estimated effect. However, the maximum percentage of non-viewers is substantially higher. Among the viewers, 3 students revised their essay after viewing, of which 2 of them reduced their plagiarism percentage to 0% at the end.

Table 3
Final plagiarism percentages of students' essay

	Viewed plagiarism checker	**Never viewed plagiarism checker**
# of students	16	32
Mean %	4.33%	2.91%
S.D.	6.68%	7.29%
Max %	22.29%	38.98%
Min %	0%	0%

5.2.2. Prompt Category Distribution

As one of the main goals of the prompt category is to promote learning-oriented prompts, we compared the ratio of learning-oriented prompts of students who viewed the category charts ("viewers") and those who did not ("non-viewers"). Table 4 shows the results of the analysis. The independent-samples t-test results for the two groups are $t(25) = -1.13$, two-tailed $p = 0.27$, and Cohen's $d = -0.44$. The 95%

confidence interval for the mean difference is [-0.59, 0.17], indicating uncertainty in the effect. It is somewhat unexpected that non-viewers had a higher mean ratio of learning-oriented prompts. This might be related to the voluntary nature of the LAD usage, which warrants further study in future research.

Table 4
Ratio of learning-oriented prompts

	Viewed category charts	**Never viewed category charts**
# of students who used the ChatGPT tool	15	12
Mean ratio of learning-oriented prompts	0.284	0.493
S.D.	0.444	0.515
Max ratio	1	1
Min ratio	0	0

We also investigated the change in learning-oriented prompt ratio of viewers. Among the 15 students who prompted ChatGPT tool and viewed the prompt category charts, eight had an increase in ratio of learning-oriented prompts after viewing the prompt category charts.

6. Conclusion, Limitations and future work

This study found that GenAI can automatically code students' AI prompts in terms of their goal orientations (performance-oriented and learning-oriented) with high kappa values and F1 scores. It can also code students' AI prompts in terms of the aspects of writing support students sought from GenAI with generally good performance. The findings concur with previous research findings on using GenAI for automatic classification [29, 30]. The findings support researchers' arguments of using GenAI to empower learning analytics [10] and concur with previous research findings on using GenAI for automatic classification [29, 30]. The findings hence confirmed the potential of using GenAI to empower LADs in the GenAI-enhanced writing context. However, as classification performance can vary across categories and granularity of coding schemes, it is necessary to re-valid classification performances on different coding schemes and/or in new contexts.

This study also explored the potential of GenAI-empowered adaptive LADs in changing students' use of the tools on GenAI-supported writing platform, in reducing their likelihood of copying directly from ChatGPT, and in increasing students' use of ChatGPT for learning-oriented purposes. The findings have both positive and negative implications. On one hand, after viewing the LADs, some students did adjust their behaviors, namely modifying their writings to reduce or eliminate content with suspected plagiarism, and increasing learning-oriented prompts. These findings suggest that GenAI-empowered LADs might be a possible solution to the often-observed overreliance issue and reduced level of thinking in using GenAI for writing [1, 2]. On the other hand, the fact that only about one third of the students have used the LAD is alerting, suggesting the importance of adding mechanisms to draw students' attention to the LAD.

In conclusion, the study found that GenAI can be used to empower LADs by automatically classifying student data, particularly students' AI prompts in this study. The results also show that GenAI-empowered LADs have the potential to change students' GenAI usage patterns during writing education. This study is exploratory in nature. The plagiarism detector did not take into consideration possible content copied from outside the platform, and thus the results might have been underestimated. Further analysis can leverage keystroke data for more accurate detection. This study is based on one writing task, and the short duration of intervention restrains it from shedding light on the long-term effect of LADs on students' interaction with GenAI. Future research may explore how students' responsiveness to LADs might change over time. Moreover, this study was conducted with a group of secondary school students on an out-of-class writing assignment. Future research may explore the issue with different student populations and learning contexts.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools when preparing the manuscript.

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