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Supporting learner agency in collaborative writing with generative AI

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Abstract

To support learner agency in LLM-powered writing environments, this research introduces a new interface that integrates two key features: an *Argument Outline* and a *Similarity Viewer*. These features were designed to enhance intentionality in writing and self-monitoring of reliance on AI-generated suggestions. Implemented in *CoAuthor*, a GPT-based writing tool, the interface was tested in an experiment with 52 university students who completed an argumentative writing task under two conditions: (1) SV group ($n = 26$) with Similarity Viewer only, and (2) SV-AO group ($n = 26$) with both Similarity Viewer and Argument Outline. Writing behaviours such as seeking, dismissing, accepting and modifying AI suggestions were analysed using statistical methods and epistemic network analysis (ENA). The average semantic similarity was calculated to measure the similarity between final texts and AI-generated content. Follow-up interviews were conducted to explore participants' perceptions of the two features. Results showed that the SV-AO group had stronger centrality in behaviours linked to independent text composition and produced final texts with lower semantic similarity. Interview data further indicated that participants viewed the Argument Outline as a useful scaffold for supporting independent writing while enabling the selective integration of AI-generated suggestions aligned with their writing goals. Overall, this study highlights the potential of interface design in optimizing the balance between learner agency and AI assistance in human–AI co-writing.

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KEYWORDS
agency, generative AI, human–AI co-writing, monitoring, semantic similarity

Practitioner notes

What is already known about this topic

- LLM-powered writing tools enhance productivity and support inclusive learning for learners struggling with writing.
- Integrating LLMs into writing environments shifts the balance between human agency and technological mediation, raising concerns about GenAI's potential to diminish learner agency.

What this paper adds

- This study introduces a new writing interface designed to support learner agency through two key features: the Argument Outline and Similarity Viewer.
- Learners using both features exhibit writing behaviours associated with knowledge transformation, fostering deeper engagement in the writing process.

Implications for practice and/or policy

- It is important to design learning environments where learners can exert control over AI and remain in the loop of decision making while still leveraging its benefits to enhance learning effectiveness.
- Integrating planning tools and AI usage monitoring can help support learners who tend to over-rely on AI-generated content.

INTRODUCTION

Generative AI (GenAI), powered by large language models (LLMs), has significant potential to address the cognitive complexities of writing by generating text aligned with user-provided prompts. GenAI-driven tools not only enhance learners' writing productivity but also foster more inclusive and efficient learning environments by offering personalized support, particularly for those who struggle with writing. However, concerns have emerged regarding GenAI's potential to diminish learner agency in the writing process (Chan & Hu, 2023; Iskender, 2023). Agency, which is the ability to act intentionally and exert control over one's environment, is central to human self-efficacy (Bandura, 1989, 2006). It positions individuals as active participants who shape their circumstances rather than passive recipients of external influences (Luo et al., 2019; Taub et al., 2020).

The integration of LLMs into writing environments, however, shifts the balance between learner agency and technological mediation. Although GenAI can alleviate cognitive load and support writing processes, such as idea generation and translation (Patac & Patac, 2025), learners often accept AI-generated suggestions without critical evaluation and favour quicker solutions over more deliberate, analytical approaches (Zhai, Wibowo, et al., 2024).

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This over-reliance on AI not only transfers greater control to AI but also risks undermining the development of essential skills, such as critical thinking, creativity and problem solving (Li et al., 2024).

In human–AI collaborative writing environments, research has largely focused on interaction mechanisms, such as prompt types and learners' perceptions of ownership and self-regulation (Luther et al., 2024). However, relatively little attention has been given to design strategies that support learner agency in co-writing with GenAI. From a human–AI interaction perspective, the weakening of learner agency in LLM-powered environments stems from the predominantly linear prompt-response design of many tools (Sharples, 2023). This structure often encourages passive adoption of AI-generated text rather than critical engagement through evaluation and revision. To address these challenges, it is crucial to develop design strategies that promote learner agency by fostering deeper interaction with AI-generated content. Rather than diminishing learners' writing abilities, these strategies should empower them to refine their cognitive and metacognitive skills while effectively leveraging GenAI tools.

Building on this foundation, the present study proposes a new interface design to support learner agency in human–AI co-writing and empirically examines its impact on the writing process. The proposed interface integrates two key features, *Argument Outline* and *Similarity Viewer*, designed to enhance learner agency within *CoAuthor*, an online writing platform powered by the GPT model (Lee et al., 2022). The Argument Outline feature, based on Toulmin's model (Toulmin, 2003), helps learners structure their ideas and arguments before engaging with GenAI. Reflecting the principle of intentionality (Bandura, 2006), it provides a structured space for learners to form intentions and plan their writing. Meanwhile, the Similarity Viewer, leveraging the RoBERTa model, tracks and visualizes the semantic similarity between AI-generated suggestions and learners' original sentences. By promoting continuous self-monitoring (Mercer, 2011), this feature enhances metacognitive awareness, helping learners assess their level of control and reliance on GenAI. In this paper, we present the design and development of these two agency-supporting features, and detail an empirical study conducted with 52 university students in Korea. This study investigates the extent to which these features influence learners' agency and writing behaviours, particularly in terms of their engagement with AI-generated suggestions.

THEORETICAL BACKGROUND

AI and learner agency

Agency refers to individuals' ability to intentionally influence their own lives and capabilities, positioning humans as active agents rather than passive recipients of external forces (Bandura, 1989). Four essential attributes of human agency are intentionality, forethought, self-reactiveness and self-reflectiveness (Bandura, 2006). Agency arises from individuals' recognition of their ability to regulate their own actions, which involves (a) engaging in metacognitive planning, strategy use and monitoring, (b) participating in decision making and (c) perceiving a sense of control over the outcomes of their actions (Frazier et al., 2021; Metcalfe & Greene, 2007). This perspective closely aligns with self-regulated learning and self-determination theories, which emphasize learners' capacity to take charge of their learning by regulating behavioural, motivational, emotional and environmental factors (Frazier et al., 2021; Ryan & Deci, 2000; Winne & Hadwin, 2008). In this sense, agency can be viewed as the potential for self-directed actions, activated through the interplay of metacognitive skills, beliefs, motivation and emotions (Mercer, 2011).

As AI with generative models has been increasingly used in learning environments, concerns have emerged regarding its potential to diminish the active engagement and

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decision-making processes critical for fostering learner agency (Zhai, Wibowo, et al., 2024). A major concern is that uncritical acceptance of AI-generated outputs may weaken learners' critical thinking, autonomous judgement and cognitive engagement. Research has shown that standardized outputs limit opportunities for effortful thinking and diminish the benefits of AI-assisted learning when metacognitive strategies, such as self-monitoring are neglected (Ahmad et al., 2023; Wen & Imamizu, 2022). Prior research also indicates that students using dialogue-based AI in writing often prioritize rapid solutions and optimization over strategic planning and monitoring, shifting their focus toward execution rather than process-oriented regulation (Contel & Cusi, 2025; Zhan & Yan, 2025). Although such behaviours may enhance short-term performance, they risk fostering 'metacognitive laziness' (Fan et al., 2024, p. 492).

As collaborative interaction with AI becomes increasingly essential for learning, it is critical to support learners in balancing cognitive and metacognitive demands while engaging AI as a strategic partner. For example, AI can initially provide strong support but gradually transfer regulatory control to learners, promoting learner agency and strategic use of AI over time (Molenaar, 2022). These discussions on learner agency and AI-assisted learning provide the foundation for designing learning environments where learners can exert control over AI and remain in the loop of decision making while still leveraging its benefits to enhance learning effectiveness.

Cognitive process in human–AI co-writing

Learner agency is a crucial concept in understanding the cognitive processes of writing. From a cognitive perspective, writing involves several stages, including planning, translating and reviewing, which are shaped by task conditions and the writer's cognitive processes (Hayes & Flower, 1980). At each stage, monitoring functions as a critical metacognitive mechanism, enabling writers to consciously regulate and adapt their writing strategies. Scholars have distinguished between two primary models of writing. The Knowledge-Telling (KT) model describes a process where writers focus on task completion without a comprehensive plan or a deep engagement with problem constraints (Bereiter & Scardamalia, 1987). Conversely, the Knowledge-Transformation (KTr) model conceptualizes writing as a sophisticated problem-solving activity characterized by iterative reflection, revision and the formulation of new sub-goals. Proficient writers typically demonstrate KTr behaviours, leveraging metacognitive strategies to construct and refine their text in alignment with the writing's purpose, audience expectations and rhetorical objectives.

Monitoring and self-awareness are critical components in cognitive models of writing, underpinning the manifestation of learner agency during the writing process (Hacker et al., 2009; Hayes & Flower, 1980). These processes involve the interplay between object-level thinking, which focuses on practical tasks such as idea generation and drafting, and meta-level thinking, which monitors and regulates these activities (Hacker et al., 2009). This interaction forms a cyclical process of planning, execution and evaluation through which writers continuously regulate their work. Throughout this cycle, learners enact agency as reflective agents, adapting their writing according to purpose, audience and rhetorical context (Hacker, 2018).

However, the integration of GenAI tools introduces new challenges to the cognitive process of writing and necessitates a re-examination of the relationship between human writers and their writing environments. For example, Cheng et al. (2024) reinterpreted Bereiter and Scardamalia's (1987) KT and KTr models within the context of AI-supported collaborative writing. They described KT as the near-direct acceptance of AI-generated sentences, whereas KTr involves reconstructing sentences to align with the writer's intentions and goals.

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Building on these redefined cognitive models of writing, recent studies have explored the collaborative writing processes between learners and AI and their effects on writing quality and learner agency. Yang et al. (2024) found that actively revising AI-generated text led to more creative and coherent writing, while minimally edited texts resulted in increased dependency on AI. Similarly, Yang et al. (2025) reported that learners who actively modified AI suggestions produced higher-quality writing characterized by greater lexical precision and textual cohesion. These findings suggest that encouraging intentional revisions of AI-generated suggestions is essential to ensure that GenAI tools function as a cognitive and creative partner rather than replacing the human writer's role in the writing process.

Agency-supporting design features in human–AI co-writing

The advancement of LLM-powered writing tools has contributed significantly to improving learners' writing productivity. However, recent research highlights the need to support learner agency throughout the writing process (Calma et al., 2022; Kasneci et al., 2023; Li et al., 2024). Studies have increasingly focused on developing features that give human writers greater control and regulation over AI-generated content.

A key design approach involves enabling writers to adjust AI outputs according to their writing plans and strategies, thereby aligning generated text with their original intentions (Fang et al., 2023). For example, Zhang et al. (2023) proposed VISAR, a system that visualizes user-provided claims and evidence in a tree structure to guide AI draft suggestions. Similarly, Chakrabarty et al. (2024) designed an interface that generates drafts based on user-inputted genre and plot elements, while Lee et al. (2024) introduced Writing Path, which creates drafts aligned with user-specified purposes, text types, styles and keywords. These tools allow learners to actively control AI outputs by establishing a writing plan in advance, thereby strengthening their sense of agency. However, because these systems often produce near-complete drafts, they can limit opportunities for learners to dynamically monitor, regulate and interact with AI during the writing process (Fan et al., 2024; Zhan & Yan, 2025). Thus, there remains a need to examine how AI usage in drafting influences learner agency and to explore interface designs that foster real-time regulation and a strategic balance between human and AI contributions.

Another emerging design feature in LLM-powered writing environments is the development of monitoring functions that promote learners' self-awareness of the writing process through analysing and visualizing learner–AI interaction data. Monitoring has been closely associated with effective self-regulation and positive learning outcomes (Son & Schwartz, 2002), and learners proficient in monitoring strategies can critically evaluate, revise or reject AI suggestions to maintain control over their writing (Cheng et al., 2024). Lee et al. (2022) developed CoAuthor, a GPT-based writing platform that records keystroke data at both event and event-block levels, providing a quantitative foundation for analysing learner–AI interactions during argumentative and creative writing tasks. Building on this, Shibani et al. (2023) introduced CoAuthorViz, a tool that visualizes sentence-level AI usage patterns, offering learners enhanced awareness of when and how they relied on AI or independently managed their writing.

However, the role of agency-supporting features within AI-assisted environments remains inconclusive and requires further investigation. For example, Darvishi et al. (2024) found no significant differences in final writing outputs between learners who used AI prompts and those who used AI prompts with self-monitoring support. They interpreted this result to suggest that the perceived usefulness of AI was so strong that monitoring interventions could not exert a meaningful influence. Their study provided only limited monitoring support during the collaborative content generation process and relied solely on learners' self-assessments

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for evaluating monitoring behaviours. To address these limitations, the present study examines the role of self-monitoring in AI-assisted co-writing by analysing learners' AI usage behaviours. In addition, our proposed feature incorporates natural language processing (NLP)-based semantic similarity data to provide a more objective and visually accessible form of monitoring support.

METHOD

Research purpose and questions

To support learner agency in LLM-powered writing environments, this research introduces a new interface that integrates two agency-supporting features: an Argument Outline and a Similarity Viewer. These features were designed to enhance learners' intentionality during the writing process and foster self-monitoring of their reliance on or control over AI-generated suggestions. The agency-supporting features were integrated into CoAuthor, a GPT-based writing tool initially developed by Lee et al. (2022). To examine the impact of the agency-supporting features, an experiment was conducted in which learners completed an argumentative writing task under two interface conditions: (1) an interface with the Similarity Viewer only and (2) an interface with both the Argument Outline and the Similarity Viewer. The study aimed to answer the following research questions:

RQ1: How do learners engage with the writing process in an LLM-powered writing environment when using agency-supporting features (ie, Argument Outline and Similarity Viewer)?
RQ2: How do agency-supporting features influence the semantic similarity between learners' writing outputs and AI-generated suggestions?
RQ3: What are learners' perceptions of agency-supporting features during their co-writing process with GenAI?

Interface design and development

This study designed an interface for human–AI co-writing based on the Writing Cognitive Process Model proposed by Hayes and Flower (1980) and Flower and Hayes (1981) (Figure 1). This model conceptualizes writing as a metacognitive process involving the dynamic interaction of planning, translating and reviewing. Our proposed interface was designed to foster learners' metacognitive regulation, specifically planning, monitoring and control, throughout each stage of the writing process. During the planning phase, the Argument Outline feature supports learners in systematically structuring their ideas and clarifying the logical flow of arguments. In the translating phase, learners generate text based on their plans and can selectively engage AI support through CoAuthor by requesting sentence suggestions when needed. This design promotes learner agency by allowing them to control AI intervention at the sentence level, maintaining a balance between AI assistance and learner-directed writing. In the reviewing phase, the Similarity Viewer provides visualizations of the semantic similarity between learner-generated and AI-suggested sentences. By offering objective indicators of learners' reliance on and divergence from AI outputs, the tool aims to enhance learners' self-awareness and monitoring.

We used the CoAuthor interface as the foundation for our system. As shown in Figure 2, the original text editing interaction was maintained in which clicking on a sentence instantly triggers the GPT model to generate five alternative suggestions displayed in a pop-up box.

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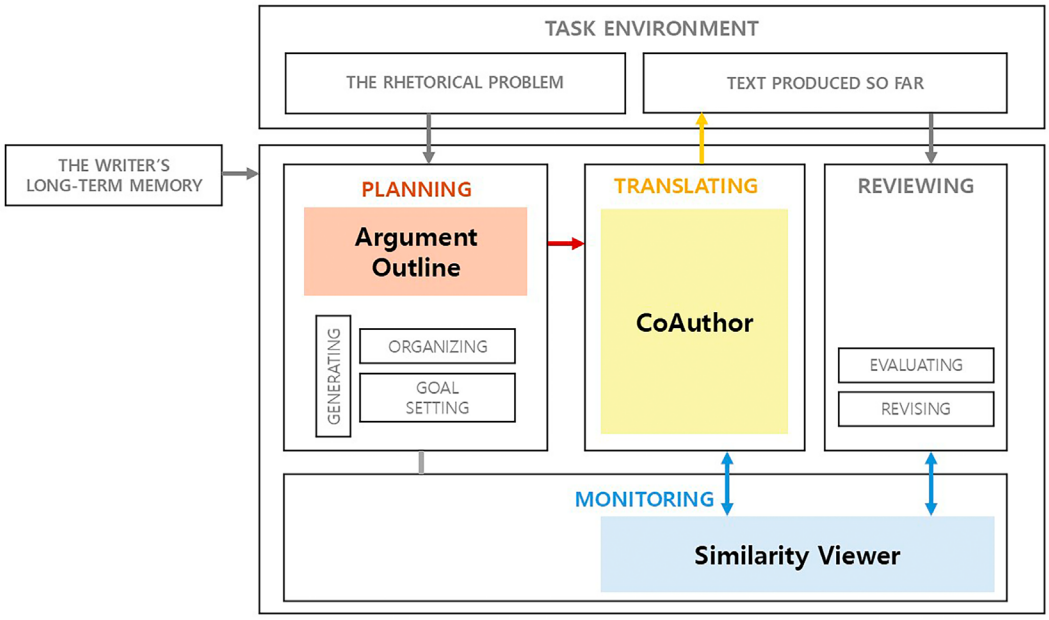


FIGURE 1 Mapping our proposed interface in the writing cognitive process.

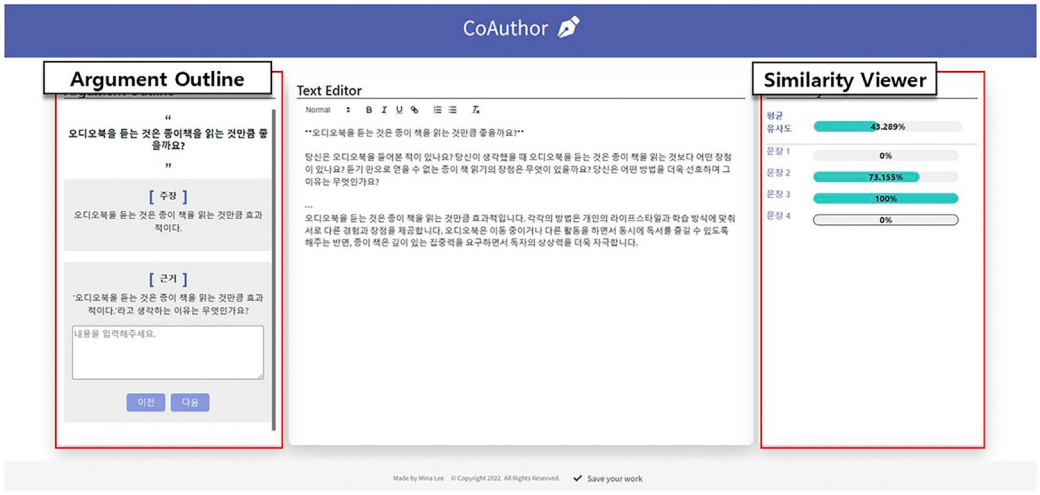


FIGURE 2 CoAuthor interface with the agency-supporting features.

This design enables users to control AI-generated suggestions at the sentence level and facilitates the calculation of semantic similarity between initial sentences and final sentences. Three key modifications were made to the original CoAuthor interface. First, the GPT-3 model used in the original system was replaced with the GPT-4o model to achieve improved performance and provide more accurate suggestions. Second, since the original CoAuthor was developed for English writing tasks, the interface was redesigned to support writing in the Korean language. Third, to enhance the accuracy and relevance of suggestions provided to learners, the parameter for decoding was adjusted to a weight of 0.75, as suggested by

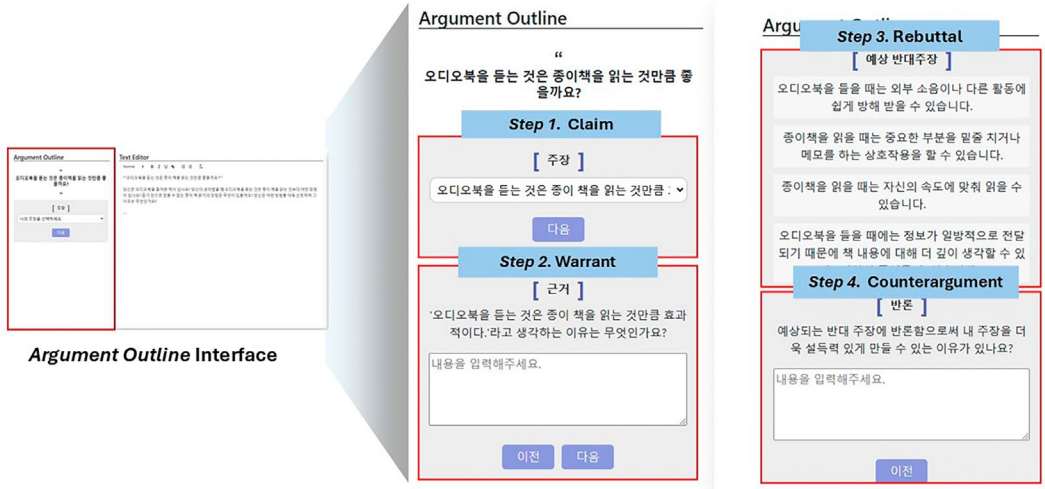
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Cheng et al. (2024). The parameter is designed to suggest sentences that naturally connect to the previously written sentence. The higher the parameter weight, the more specifically GPT reflects the context of the preceding sentence to generate a connected sentence. In the following sections, we present more details about the design of the two agency-supporting features embedded in the CoAuthor tool.

Argument outline

The Argument Outline feature was designed to support agency by helping writers plan and structure their ideas before engaging in an argumentative writing task (Figure 3). Guided by intentionality in agentic actions (Bandura, 1989, 2006), the Argument Outline provides writers with a structured space to form intentions and plan their actions. The structure of the Argument Outline was based on Toulmin's model (Toulmin, 2003), which defines an argument as comprising three core elements: claim, warrant and data. The claim represents the writer's conclusion about the issue being discussed, while the warrant provides logical connections between the claim and the supporting data. To further refine the structure of an argument, Toulmin's model introduces additional sub-elements, such as backing, rebuttal and qualifier. These elements in the Argument Outline provide writers with a framework to structure their arguments, fostering intentionality and enhancing the planning phase of the writing process.

The Argument Outline consists of three stages, as shown in Figure 3. First, writers select their claim regarding the given topic. The system provides a set of predefined claim options, allowing writers to choose the one that best aligns with their perspective. This step ensures that writers begin with a clear and structured position before developing their argument. Next, writers enter the warrant and data that support their chosen claim. In a designated text box, they can briefly outline their reasoning and provide supporting evidence based on their prior knowledge. This stage encourages writers to actively articulate logical connections between their claims and supporting data. Finally, the system presents potential rebuttals relevant to the selected claim. These rebuttals are pre-configured and dynamically adjusted to match the chosen argument. Writers can review these counterarguments and



***Argument Outline* Interface**

FIGURE 3 Argument Outline interface.

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write responses to assess the validity of their argument structure. Engaging in this process helps writers critically evaluate their reasoning and refine their position before proceeding with co-writing using GenAI.

Similarity viewer

The Similarity Viewer visualizes the semantic similarity between the sentences entered by the writer and those suggested by GPT in a bar graph (Figure 4). This visualization allows writers to monitor how closely their sentences resemble AI-generated suggestions. The primary function is to promote agency by fostering self-monitoring and awareness of writers' reliance on AI-generated text. To compute semantic similarity, we used RoBERTa (Robustly Optimized BERT Pretraining Approach) to generate sentence embeddings. RoBERTa enhances the BERT architecture by refining language representations (Liu, 2019). This method enables the model to capture not only word meanings but also their contextual roles within a sentence. We then calculated cosine similarity based on these embedded vectors.

Figure 4 illustrates how semantic similarity is visualized in the proposed interface. The Similarity Viewer presents a bar graph comparing AI-suggested sentences with user-written text in the editor. To determine sentence boundaries, the system identifies sentence-ending punctuation, such as periods, question marks or exclamation marks followed by a space. In the Similarity Viewer, a bar graph displaying 0% indicates that the writer has independently composed the sentence without any AI assistance. Conversely, a 100% similarity score signifies that the writer has directly adopted the AI-generated sentence without modifications. Each time a writer edits a suggested sentence, the

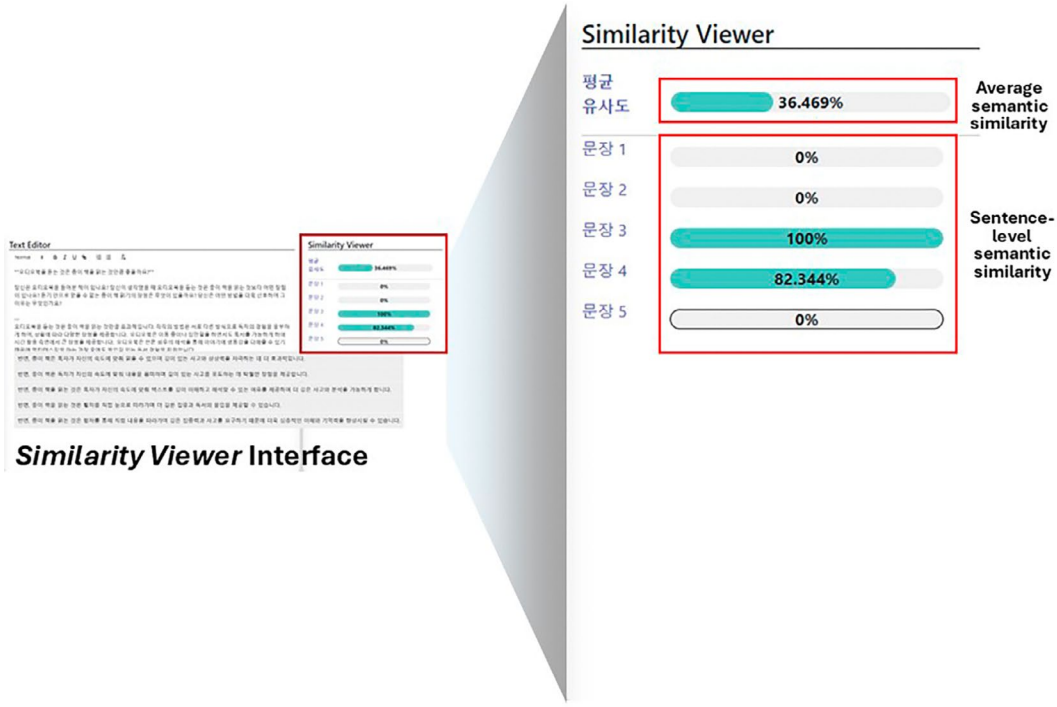


FIGURE 4 Similarity Viewer interface.

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similarity between the original output and the revised sentence is recalculated and visually represented in real-time.

Experiment design

Participants and procedure

The participants were 52 university students (28 females and 24 males) in Korea recruited through convenience sampling. Participants came from diverse academic backgrounds. The participants were randomly assigned to one of two groups: the SV group ($n = 26$), which used the interface with the Similarity Viewer only, and the SV-AO group ($n = 26$), which used the interface with both the Similarity Viewer and the Argument Outline.

The experiment procedure consisting of two writing sessions is outlined in Figure 5. In Session 1, all participants completed an argumentative writing task in the CoAuthor environment without any agency-supporting features. This session provides baseline data before entering the session with co-writing with GenAI. In Session 2, participants were assigned to different conditions based on their group. The SV group completed a writing task under the CoAuthor with the Similarity Viewer, while the SV-AO group first completed an additional 10-minute step to create an Argument Outline before starting their writing task with the Similarity Viewer. This differentiated condition enabled us to investigate the impact of the planning stage conducted by a human writer before engaging in co-writing with GenAI.

For the argumentative writing tasks, two writing prompts were selected from the CoAuthor study (Lee et al., 2022), which includes a diverse data set of writing topics from the New York Times. The writing prompts used for this study were '*Are we being bad citizens if we don't keep up with the news*?' and '*Is listening to a book just as good as reading it?*'. To mitigate any potential sequential effects of the writing tasks, a counterbalancing method was applied to randomly assign the writing prompts to each group between the two sessions. In both sessions, participants were instructed to write an essay consisting of at least 20 sentences within 30 minutes to ensure consistency in the writing task across sessions. Following Session 2, recall interviews were conducted with eight participants to explore their perceptions regarding the agency-supporting features proposed in this study.

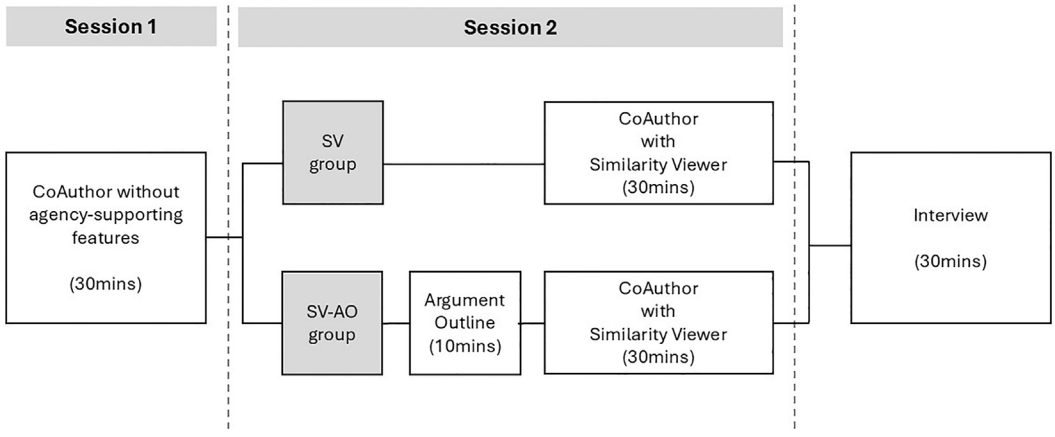


FIGURE 5 Flow of the experiment design.

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Data collection and analysis

Writing Behaviours

We recorded writing sessions using a screen recording program. These recordings were analysed using a coding framework adapted from Cheng et al. (2024). As shown in Table 1, the framework consists of five writing behaviours that generally occur during human–AI co-writing, which are composing, revising, seeking, accepting and dismissing AI-generated suggestions. Additionally, we categorized writers' modification behaviours into low modification (LM) and high modification (HM) to assess the extent of semantic changes made to AI-suggested sentences. HM indicates that writers made substantial semantic changes to AI-generated suggestions. In contrast, LM suggests minimal semantic changes, implying a higher reliance on AI-generated outputs.

The writing behaviour data collected in this study served as indicators for assessing learners' cognitive engagement and reliance on AI-generated suggestions during the writing process. Drawing on Bereiter and Scardamalia's (1987) theoretical framework of the KT and KTr models in writing composition, we interpreted learners' writing behaviours as reflections of their intentions and decisions regarding the extent of reliance on or control over AI-generated suggestions. These levels of engagement provide critical indicators of whether learners passively accept or actively evaluate AI suggestions, offering a basis for assessing learner agency.

In this study, a threshold of 0.85 was set to differentiate between HM and LM. This threshold was determined based on previous research and a pilot study involving Korean students. Cheng et al. (2024), who also employed the CoAuthor system, set a threshold of 0.80 to distinguish between HM and LM in English essay datasets. Because Cheng's study was based on English texts, additional calibration was necessary to account for semantic differences between English and Korean. Before the main experiment, we also conducted a pilot study with four Korean students and used their essay samples to refine the threshold. The analysis revealed that thresholds below 0.85 often misclassified sentences containing new information as similar, while thresholds above 0.85 risked treating structurally equivalent sentences as semantically different. Based on these findings, a threshold of 0.85 was adopted as an appropriate value to distinguish semantic similarity between HM and LM in Korean texts within our research context.

For the recorded data, we coded and calculated the frequency of each writing behaviour. To examine significant differences across sessions and groups, we applied

TABLE 1 Coding framework for writing behaviours in human–AI co-writing (adapted from Cheng et al., 2024).

Code	Behaviour	Definition
CP	Compose	Writing new sentences
RV	Revise	Revising sentences originally written by a human writer
SS	Seek suggestion	Seeking suggestions from AI
DS	Dismiss suggestion	Dismissing suggestions from AI
AS	Accept suggestion	Accepting suggestions from AI
LM	Low modification	Making minor adjustments to sentences without altering their core meaning (sentence semantic similarity >0.85)
HM	High modification	Making significant adjustments to sentence meaning (sentence semantic similarity ≤0.85)

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appropriate statistical analysis methods, including *t*-tests, ANCOVA, Mann–Whitney U-tests and Wilcoxon signed-rank tests. Statistical analyses were conducted using R Studio, with a significance level of 0.05.

Next, we employed epistemic network analysis (ENA) to explore structural differences in the patterns of coded writing behaviours between groups. ENA is a method that visualizes the relationships and connections between different concepts and behaviours in a network, making it particularly useful for identifying patterns in cognitive processes (Shaffer et al., 2016). In the ENA, a stanza represents a set of connected elements. Since our dataset was coded with seven writing behaviour categories, we set the stanza size to six, corresponding to the number of possible connections to a single node.

Average semantic similarity

To assess the extent to which participants relied on AI-generated suggestions, we calculated the average semantic similarity in the final writing output. This metric indicates the degree of semantic similarity between the final text and the AI-suggested content. A higher semantic similarity score suggests that writers adopted AI-generated sentences with minimal modification. Semantic similarity was measured using the algorithm embedded in the *Similarity Viewer*. To examine the impact of agency-supporting features, we analysed differences in average semantic similarity across the two writing sessions, evaluating whether these features influenced writers' acceptance of AI-generated suggestions.

Interviews

To investigate participants' perceptions of the proposed interface, we conducted semi-structured interviews with eight participants selected from the two groups. Based on the median value of average semantic similarity in the final writing output, four participants with high average semantic similarity and four participants with low average semantic similarity were selected from each group. The interview sessions, conducted by the authors, lasted approximately 30 minutes. To help participants recall their experiences, the first 5 minutes were devoted to reviewing a recording of their own writing session. The interviews explored participants' perceptions of the agency-supporting features and gathered suggestions for improvement. A semi-structured format was employed (Creswell, 2009), consisting of core questions with additional probes based on participants' responses. The main questions were: (a) AI-generated Suggestions: Did you find CoAuthor helpful when experiencing difficulties during writing? (b) Similarity Viewer: How did viewing the similarity monitoring influence your writing behaviours? (c) Argument Outline: When you drafted an argument outline and completed the writing task using AI, did your use of AI change?; and (d) Suggested Improvements: What additional enhancements do you recommend for the agency-supporting writing tools?

All interviews were audio-recorded and transcribed. The transcripts were analysed through open coding, with repeated readings to identify recurring themes, which were then categorized and quantified. To ensure reliability, an independent evaluator with prior coding experience, who was not involved in the study, independently coded the data. Inter-rater reliability using Cohen's Kappa yielded 0.751, indicating acceptable agreement. Discrepancies were discussed and resolved before finalizing the thematic categorization.

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RESULTS

Writing behaviours

A Mann–Whitney *U*-test was conducted on the Session 1 data to determine whether the two groups started with similar writing behaviour patterns. The results showed no statistically significant differences in any of the writing behaviour variables, indicating that both groups were comparable before interacting with the agency-supporting interfaces.

To assess how participants' writing behaviours changed with and without agency-supporting features, we compared behaviour frequency data between Session 1 and Session 2. As noted earlier, Session 1 involved using the CoAuthor tool without agency-supporting features. Regarding the length of the essay writing, both the SV and SV-AO groups showed a slight increase in average word count from Session 1 to Session 2. The SV group showed an increase from 316 to 335 words, while the SV-AO group showed an increase from 333 to 350 words. Table 2 presents the behavioural data for each session across the two groups. Overall, the results indicate an increase in the frequency of writing behaviours from Session 1 to Session 2. A paired *t*-test was conducted to determine whether these changes were statistically significant. In the SV group, significant differences were found in LM ($t = -2.68$, $p = 0.01$) and HM ($t = -2.19$, $p = 0.04$). For the SV-AO group, we applied the non-parametric Wilcoxon signed-rank test due to the violation of the normality assumption. The analysis revealed a significant difference in HM ($z = -3.70$, $p = 0.02$), while no significant differences were observed in other behavioural codes.

Next, we analysed the behavioural data from Session 2 to determine whether providing an Argument Outline, in addition to the Similarity Viewer, influenced writing behaviours. ANCOVA was conducted, using Session 1 data as a covariate to control for potential baseline differences between the groups. As shown in Table 3, the ANCOVA results indicated no significant differences between the SV and SV-AO groups. This suggests that the inclusion of the Argument Outline did not lead to significantly different writing behaviours in terms of frequency when participants completed the writing task with GenAI in Session 2.

Epistemic network analysis results

In ENA networks, nodes represent codes while edges indicate the co-occurrence of two codes, with edge thickness reflecting the relative frequency of their co-occurrence. First, we

TABLE 2 Differences in writing behaviours between Session 1 and Session 2.

	SV group ($n = 26$)				SV-AO group ($n = 26$)			
	Session 1	Session 2			Session 1	Session 2		
	M (*SD*)	*M* (*SD*)	*t*	*p*	*M* (*SD*)	*M* (*SD*)	*z*	*p*
CP	9.31 (4.26)	10.65 (3.97)	−2.00	0.06	8.77 (4.84)	8.81 (4.89)	−1.14	0.91
RV	4.27 (3.11)	3.38 (2.64)	1.39	0.18	4.31 (2.65)	3.54 (2.44)	−0.011	0.05
SS	11.46 (8.65)	13.50 (7.56)	−1.37	0.18	11.69 (9.17)	12.23 (8.83)	−0.65	0.75
DS	5.81 (5.58)	6.35 (4.60)	−0.63	0.53	5.50 (4.97)	5.54 (5.22)	−0.61	0.98
AS	5.69 (4.25)	7.00 (4.06)	−1.43	0.17	6.35 (5.49)	6.73 (4.94)	−1.02	0.95
LM	3.23 (3.05)	5.15 (3.67)	−2.68*	0.01	3.65 (4.17)	5.00 (4.79)	−1.83	0.46
HM	1.42 (1.84)	2.69 (2.98)	−2.19*	0.04	0.85 (1.41)	1.73 (2.74)	−3.70*	0.02

*$p < 0.05$.

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TABLE 3 Differences between SV Group and SV-AO Group in Session 2.

Code	Group	*M*	*SD*	Adjusted mean	Std. error	*F*	η^2
Compose	SV	10.65	3.97	10.50	0.71	2.32	0.05
	SV-AO	8.81	4.89	8.96	0.71		
Revise	SV	3.38	2.64	3.39	0.43	0.05	<0.01
	SV-AO	3.54	2.44	3.53	0.43		
Seek suggestion	SV	13.50	7.56	13.6	1.28	0.60	0.01
	SV-AO	12.23	8.83	12.2	1.28		
Dismiss suggestion	SV	6.35	4.60	6.27	0.82	0.32	0.01
	SV-AO	5.54	5.22	5.62	0.82		
Accept suggestion	SV	7.00	4.06	7.12	0.82	0.19	<0.01
	SV-AO	6.73	4.94	6.61	0.82		
Low modification	SV	5.15	3.67	5.22	0.81	0.07	<0.01
	SV-AO	5.00	4.79	4.93	0.81		
High modification	SV	2.69	2.98	2.44	0.49	0.42	0.01
	SV-AO	1.73	2.74	1.98	0.49		

conducted ENA on the Session 2 data to examine structural differences associated with the use of different agency-supporting features. The left panel of Figure 6 presents a comparison plot of the two groups where the SV group is represented in purple and the SV-AO group in green. In ENA, a comparison plot visualizes two or more groups (or sessions) simultaneously on a single screen to facilitate pattern comparison. By overlaying the networks, it enables an intuitive examination of differences in connections between the same nodes. Overall, the SV group exhibited strong co-occurrences in writing behaviours, such as seeking suggestions (SS), accepting suggestions (AS), LM and HM. In contrast, the SV-AO group showed strong co-occurrences among behaviours like revising (RV), composing (CP), SS and dismissing suggestions (DS), indicating more critical evaluation and independent management of AI suggestions.

The differences between the SV and SV-AO groups in Session 2 were further supported by the *t*-test results presented in Table 4. In ENA, the *X*-axis represents the primary dimension capturing major patterns in the connections between coded data, while the *Y*-axis reflects additional, orthogonal differences in these patterns (Shaffer et al., 2016). In this study, the *X*-axis captured connections in coded writing behaviours. The *t*-test ($t = 2.13$, $p = 0.04$) revealed a statistically significant difference along the *X*-axis, indicating that the two groups exhibited structurally distinct patterns within the ENA projection space. No significant difference was observed along the *Y*-axis.

Additionally, we analysed the differences in writing behaviour patterns between Session 1 and Session 2 for both groups. For the SV group (see Figure 7), the ENA network in Session 1 (red) showed the strongest connection in DS-HM and SS-DS, with links associated with HM. In contrast, the ENA network in Session 2 (blue) exhibited strong connections between RV and LM, with overall high connections observed in links associated with LM.

For the SV-AO group (see Figure 8), the ENA network in Session 1 (red) displayed strong connections in SS-CP, AS-CP, SS-RV and AS-RV. In Session 2 (blue), the network showed strengthened connections in RV-LM and RV-HM. Overall, the SV-AO group in Session 1 exhibited a high co-occurrence tendency for behaviours, such as SS, AS and LM, reflecting a greater reliance on AI suggestions. However, in Session 2, there was a noticeable shift

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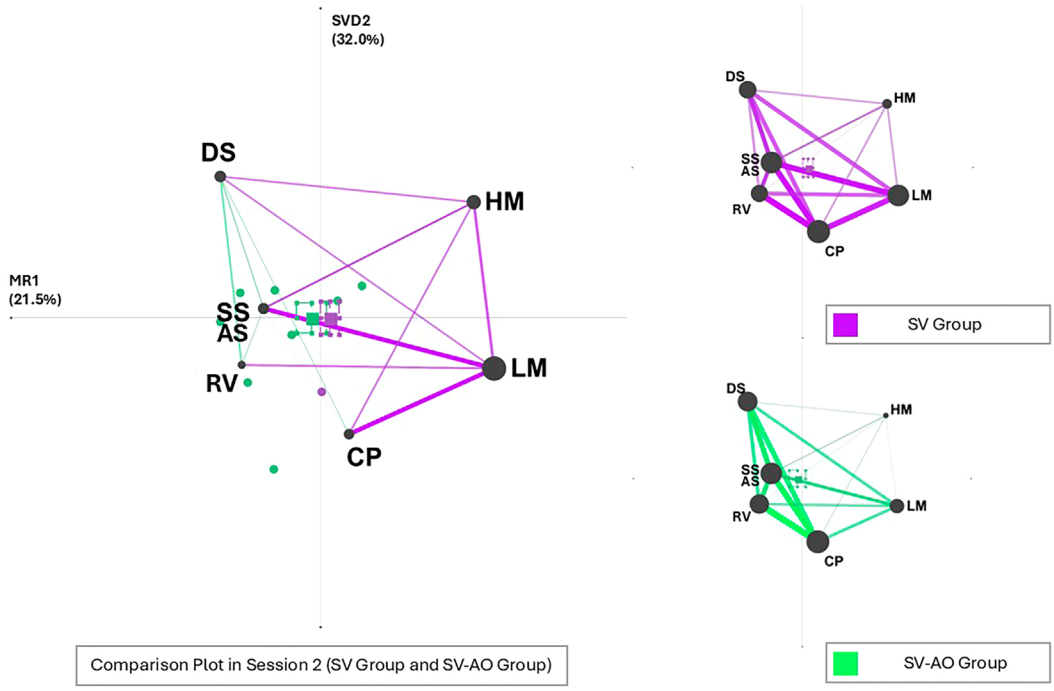


FIGURE 6 ENA plots of writing behaviours between the two groups in Session 2.

TABLE 4 Comparison of ENA networks between the two groups.

	X-axis					*Y*-axis				
	M	***SD***	***t***	***p***	***d***	***M***	***SD***	***t***	***p***	***d***
SV	0.06	0.14	2.13*	0.04	0.59	0.00	0.26	0.00	1.00	0.00
SV-AO	−0.06	0.24				0.00	0.24			

*$p < 0.05$.

toward co-occurrences involving revision behaviours like RV, HM and LM, indicating increased engagement in independent writing and modification.

The differences between Sessions 1 and 2 for both groups were further supported by the *t*-test results presented in Table 5. The SV group showed a statistically significant difference along the *X*-axis ($t = -2.07$, $p = 0.04$), which captures differences in network connections reflecting changes in writing behaviours across sessions. Similarly, the SV-AO group exhibited a significant difference along the *X*-axis ($t = -2.26$, $p = 0.03$), indicating that the structure of writing behaviour patterns changed significantly following the introduction of agency-supporting features. In contrast, no significant differences were observed along the *Y*-axis for either group.

Average semantic similarity

In the semantic similarity analysis, the proportion of AI-suggested sentences used in the final output was compared between the two experimental groups. Before conducting the semantic similarity analysis, we removed extreme values that violated the normality assumption. As a

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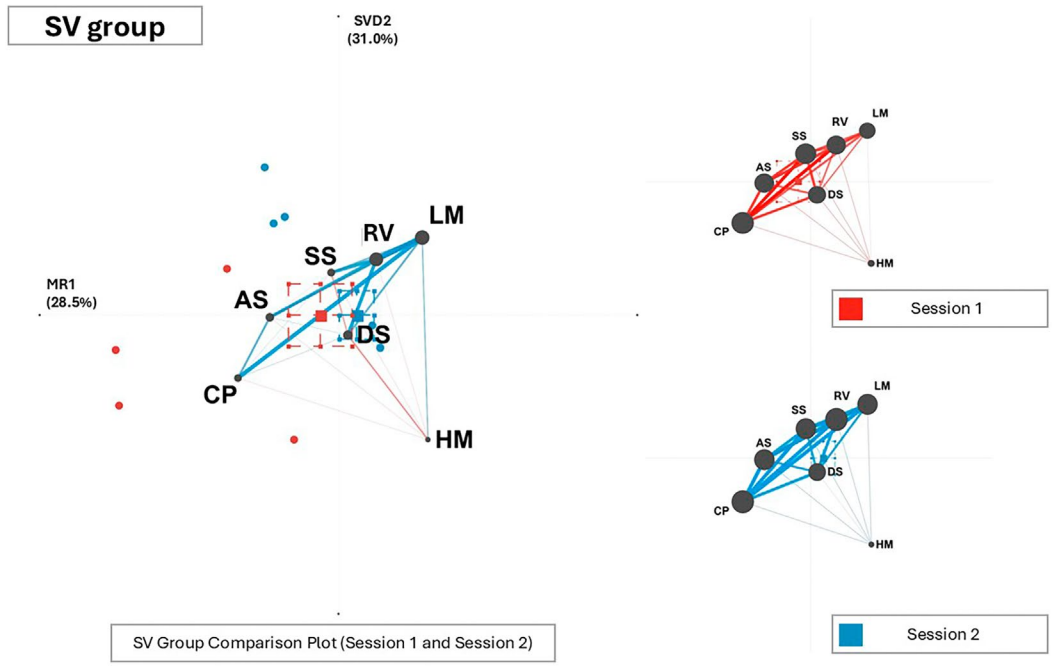


FIGURE 7 ENA plots of writing behaviours between Session 1 and Session 2 (SV group).

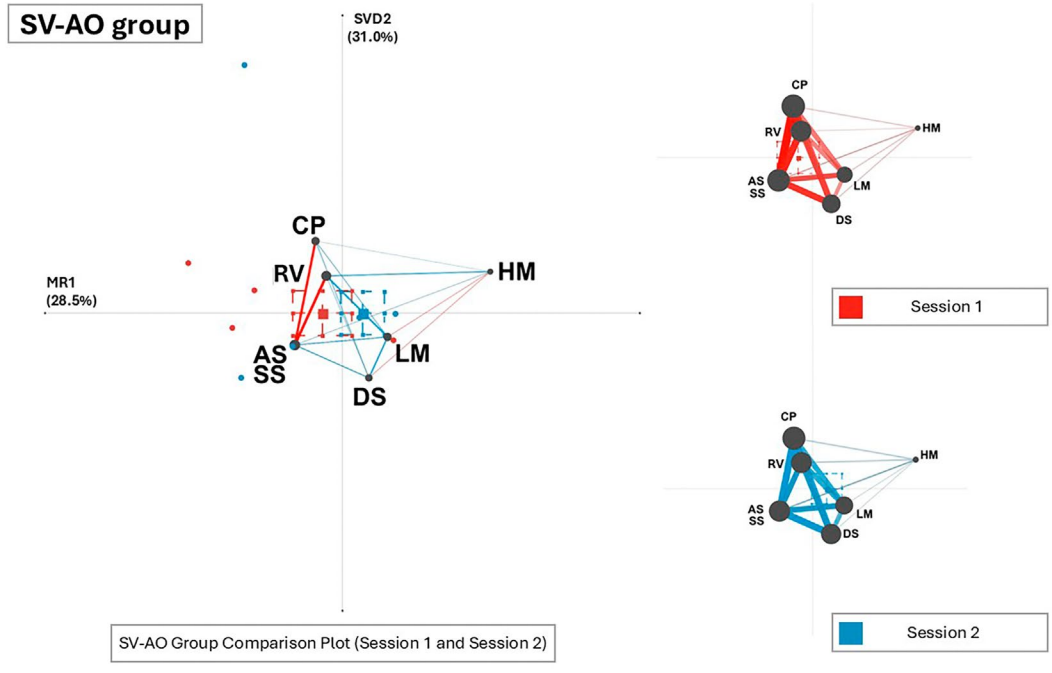


FIGURE 8 ENA plots of writing behaviours between Session 1 and Session 2 (SV-AO group).

result, the final dataset included 25 participants in the SV group and 23 in the SV-AO group. The *t*-test results showed no significant difference between the groups ($t = -1.14$, $p = 0.26$) in Session 1, confirming that they did not differ significantly before Session 2.

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TABLE 5 Comparison of ENA networks between Session 1 and Session 2 across groups.

		X-axis					*Y*-axis				
		M	***SD***	***t***	***p***	***d***	***M***	***SD***	***t***	***p***	***d***
SV	Session 1	−0.06	0.25	−2.07*	0.04	0.57	0.00	0.25	0.00	1.00	0.00
	Session 2	0.06	0.14				0.00	0.19			
SV-AO	Session 1	−0.08	0.30	−2.26*	0.03	0.63	0.00	0.23	0.00	1.00	0.00
	Session 2	0.08	0.22				0.00	0.23			

*$p < 0.05$.

TABLE 6 Differences in average sentence similarity in Session 1 and Session 2.

	Session 1	Session 2		
Group	***M* (*SD*)**	***M* (*SD*)**	***t***	***p***
SV	18.13 (12.06)	25.20 (15.25)	−2.31*	0.03
SV-AO	19.58 (16.68)	14.63 (11.55)	1.82	0.42

*$p < 0.05$.

Next, we examined whether participants' average semantic similarity changed significantly after using the agency-supporting features by comparing data from Session 1 to Session 2. As shown in Table 6, the SV group exhibited an increasing trend, from $M = 18.13$ ($SD = 12.06$) in Session 1 to $M = 25.20$ ($SD = 15.25$) in Session 2. A *t*-test revealed that this difference was statistically significant ($t = -2.31$, $p = 0.03$). In contrast, the SV-AO group showed a decreasing trend, from M = 19.58 (SD = 16.68) in Session 1 to $M = 14.53$ ($SD = 11.55$) in Session 2. However, the *t*-test results indicated that this difference was not statistically significant ($t = 0.82$, $p = 0.42$).

Next, ANCOVA using Session 1 data as a covariate was conducted to examine differences in average semantic similarity between the two groups in Session 2, where participants received agency-supporting features. As shown in Table 7, the ANCOVA results revealed a statistically significant difference in average semantic similarity ($F = 5.48$, $p = 0.02$, $\eta^2 = 0.11$). The SV group had a mean semantic similarity of $M = 25.20$ ($SD = 25.40$), whereas the SV-AO group had a lower mean of $M = 14.53$ ($SD = 11.55$). These results indicate that participants in the SV-AO group, who utilized the Argument Outline, exhibited significantly lower semantic similarity compared with those in the SV group who only used the Similarity Viewer.

Interviews

We extracted and categorized themes from interviews with eight participants across the two experimental groups who used the CoAuthor interface with agency-supporting features. Among them, four participants from the SV-AO group were interviewed specifically about their experiences with the Argument Outline. Table 8 presents the key themes identified from the interview data with frequency data. The themes are organized into four major categories: (a) AI-generated suggestions, (b) Similarity Viewer, (c) Argument Outline and (d) suggested areas for improvement.

Participants most frequently reported using AI-generated suggestions to overcome difficulties in generating ideas or providing supporting arguments. They also found CoAuthor useful for refining expressions, particularly in enhancing clarity, coherence and lexical variety. These features helped learners explore alternative phrasings and diversify argument

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TABLE 7 ANCOVA of average sentence similarity between the groups in Session 2.

Group	*N*	*M* (*SD*)	Adjusted mean	Std. error	*F*	η^2
SV	25	25.20 (15.25)	25.40	2.64	5.48*	0.11
SV-AO	23	14.53 (11.55)	16.50	2.75		

*$p < 0.05$.

TABLE 8 Perception of CoAuthor interface with the agency-supporting features.

	Themes	Frequency	%
AI-generated suggestions	Generating ideas and supporting arguments	5	41.67
	Enhancing clarity, coherence and lexical variety	3	25.00
	Reiterating or summarizing existing content	2	16.67
	Requiring independent revision and rewriting	2	16.67
	Total	12	100
Similarity viewer	Prompting sentence revision and reorganization	6	33.34
	Encouraging intentional monitoring of GenAI usage behaviours	5	27.78
	Risk of overemphasis on average semantic similarity	4	22.22
	Psychological discomfort	3	16.67
	Total	18	100
Argument outline	Evaluating AI-generated sentences based on logical structures	3	27.27
	Facilitating cognitive expansion	2	18.18
	Limited effectiveness due to pre-existing writing habits and varied motivation	2	18.18
	Restricted argument structure	2	18.18
	Total	11	100
Suggested areas for improvement	Visual cues to indicate overreliance on AI	4	57.14
	Customizable interface for the Argument Outline	2	28.57
	Chatbot-style interface with AI agents	1	14.29
	Total	7	100

presentation. However, negative perceptions emerged when AI suggestions merely repeated or summarized existing content, leaving participants to revise or rewrite sentences independently. Such dissatisfaction was most consistently reported by learners in the low-similarity group. As one participant noted:

> When I couldn't think of what to write next, it was really helpful that the system provided multiple suggestions. However, there were times when none of the suggestions fit what I wanted to say, so I ended up rewriting the sentence myself. Overall, I felt there were both strengths and limitations to the tool.
>
> (SV-AO group, Interviewee #2, Low Semantic Similarity)

The Similarity Viewer was most often used to prompt revision and reorganization of sentences flagged with high similarity scores. Participants also emphasized that monitoring similarity scores encouraged more deliberate regulation of their AI use. For example, one participant stated,

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> I relied more on AI as I progressed in my writing, especially near the end. But seeing high similarity scores like 100% or 80% often led me to delete and rewrite those sentences.
>
> (SV group, Interviewee #2, High Semantic Similarity)

At the same time, some limitations were identified. Some participants focused too heavily on average similarity scores rather than sentence-level detail, sometimes retaining highly similar content if deemed useful. Others likened the tool to a plagiarism detector and described experiencing psychological discomfort when confronted with high similarity values.

Learners who used the Argument Outline frequently evaluated AI-generated sentences against their planned logical structures. Many reported that having a predefined outline reduced reliance on AI and promoted deeper thinking. However, its benefits were uneven. Some participants reported no change in writing habits, while others criticized the rigid structure for limiting creative expression. As one participant explained:

> The fixed format of the argument structure made it difficult to develop my writing more freely, which was disappointing.
>
> (SV-AO group, Interviewee #3, Low Semantic Similarity)

Participants recommended several enhancements to strengthen the agency-supporting features. The most frequent was adding stronger visual alerts and colour-coded cues to the Similarity Viewer. Others suggested allowing customization of the Argument Outline so learners could adapt it to their own styles, as well as introducing a chatbot-style interface to support dialogic interaction with AI agents for generating more diverse outlines.

DISCUSSION

This study aimed to design agency-supporting features (Argument Outline and Similarity Viewer) and to examine their impact on writing behaviours in the human–AI co-writing process. A total of 52 participants were assigned to either the SV group, which used the Similarity Viewer only, or the SV-AO group, which had access to both the Argument Outline and Similarity Viewer. In this section, we revisit the research questions and discuss key findings.

The first research question investigated learners' writing behaviours when using agency-supporting features in the CoAuthor tool. While statistical analysis revealed no significant differences in the frequency of overall writing behaviours between the two groups, the ENA networks, which visualize connections among coded data, provided deeper insights. The SV-AO group demonstrated stronger centrality in behaviours associated with independently composing text with less reliance on AI-generated suggestions. This suggests that intentional planning, such as developing an outline, may encourage more independent writing. However, despite this potential benefit, there were no significant differences between the groups in the frequency of modification behaviours, such as LM and HM.

The differences in modification behaviours were more evident between Session 1 (which used the original CoAuthor tool without agency-supporting features) and Session 2. The SV group exhibited an increase in LM, with a stronger emphasis on LM-SS and LM-AS, indicating a high frequency of seeking and accepting AI suggestions. In contrast, the SV-AO group demonstrated an increase in HM and a stronger focus on HM, RV and LM, behaviours associated with more comprehensive text editing. These findings suggest that providing the semantic similarity viewer alone may not be sufficient to fully promote writing behaviours linked to knowledge transformation in composition, such as critically evaluating AI suggestions and effectively integrating them into argumentative writing. In the cognitive writing process,

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planning and reviewing are considered critical stages that require high levels of cognitive engagement (Kellogg, 1987). In this context, the SV group, which lacked a structured planning interface (Argument Outline), was likely to have engaged in lower levels of cognitive processing compared with the SV-AO group. This aligns with Limpo and Alves's (2018) findings, indicating that the absence of planning contexts can reduce cognitive engagement in writing. This implies that just as planning is vital in non-AI writing environments, it remains equally significant in human–AI co-writing settings.

The second research question explored whether agency-supporting features influenced the semantic similarity between learners' writing outputs and AI-generated suggestions. Average semantic similarity reflects the proportion of AI-generated text incorporated by learners and serves as an indicator of their engagement with AI suggestions. Prior research has raised concerns about learners' potential over-reliance on AI suggestions (Cummings et al., 2024; Stojanov et al., 2024). The Similarity Viewer was designed to help writers monitor their integration of AI suggestions, thereby mitigating over-reliance. Unexpectedly, the SV group demonstrated a significant increase in average semantic similarity from Session 1 to Session 2. Instead of promoting greater modification behaviours, the Similarity Viewer may have reinforced tendencies to accept AI-generated text with minimal or no modification.

We speculate that this outcome may be linked to the way participants interpreted the visual similarity indicators. Rather than encouraging substantial revisions, the feature may have subtly influenced participants to accept AI-generated content as long as the overall similarity remained within an acceptable range. During the interview after the experiment, some participants reported that they were more concerned about the overall similarity rather than sentence-level similarity. In addition, we argued that an increase in semantic similarity does not necessarily indicate over-reliance, provided that learners actively set and regulate their boundaries for acceptable levels of similarity. In the SV group, the average semantic similarity was approximately 25%. This suggests that while some AI suggestions were incorporated, the final outputs remained sufficiently distinct from the AI-generated text. Some interview participants reported setting their thresholds for acceptable levels of overall semantic similarity. In such cases, learners did not accept AI outputs uncritically. Rather, their integration decisions likely involved analytical thinking based on self-established goals or quality standards (Zhai, Nyaaba, et al., 2024).

Overall, the SV-AO group demonstrated lower average semantic similarity compared with the SV group. This suggests that the argument structuring activity strengthened learners' independent writing behaviours and reduced their reliance on AI-generated suggestions. Semantic similarity serves as an implicit indicator of the degree of dependence on AI outputs (Stojanov et al., 2024). Thus, the lower semantic similarity observed in the SV-AO group indicates a relatively lower level of AI reliance. Structured planning activities likely encouraged learners to prioritize accuracy and coherence in line with their writing goals, thereby promoting more critical evaluation of AI suggestions (Yang et al., 2024). This interpretation is further supported by interview data where many participants reported using the feature to assess whether AI-generated sentences aligned with their logical flow of thought. These findings, however, contrast with those of Dhillon et al. (2024), who reported that receiving sentence-level suggestions could disrupt the writing flow by alternating between human- and AI-generated text. In the present study, the use of the Argument Outline helped learners predefine their writing goals and rhetorical structures. Ultimately, the sentence-level suggestion approach, when supported by structured planning, appears to clarify the boundary between human- and AI-generated text.

The third research question explored the impact of agency-supporting features through participant interviews. While the Similarity Viewer was useful for monitoring and adjusting AI acceptance levels, participants identified certain limitations and areas for improvement. Particularly, when the average similarity score was low, it did not sufficiently prompt sentence-level revisions. This suggests that displaying similarity scores at the overall text

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level may be inadequate for encouraging more granular revision behaviours, emphasizing the need to adjust the design to facilitate sentence-level revision and review by users. Participants also recognized the Argument Outline as a valuable tool for evaluating and refining AI-generated content within a logical framework. However, learners with advanced writing skills perceived the fixed-structure outline as less beneficial. These findings highlight the need for adaptive support mechanisms (eg, Butterfuss et al., 2022; Su et al., 2023) that can accommodate different levels of writing proficiency and individual writing styles.

Another key finding is that learners' perceptions of the Similarity Viewer varied according to their value alignment. Interview data revealed that some participants adopted AI-generated suggestions without substantial revision when those suggestions aligned with their intended writing goals. This suggests that learners may interpret high semantic similarity as a form of legitimate co-authorship, depending on how they perceive their collaborative relationship with GenAI. Such interpretations are shaped by multiple factors, such as the perceived level of AI assistance and the complexity of the writing task (Formosa et al., 2025). Given that these factors influence learners' sense of authorship, average semantic similarity scores should not be interpreted as direct indicators of writers' agency. That is, optimal agency in human–AI collaborative writing is not defined by a higher proportion of human input, but rather by the learner's intentional selection, adaptation and regulation of AI-generated suggestions in alignment with personal writing goals and intentions.

Although this study did not directly measure the long-term effects of the agency-supporting features, interview findings suggest their potential to foster sustained learner agency. Interview participants in both SV and SV-AO groups viewed the agency-supporting features as facilitating intentional engagement rather than passive interaction. This aligns with Emirbayer and Mische's (1998) structure–agency perspective, which conceptualizes agency as temporally embedded engagement through which individuals reproduce or transform existing structures by interacting with environmental conditions across past, present and future contexts. In this view, agency emerges through the selective reactivation of an individual's accumulated patterns of thought and actions. The Similarity Viewer and Argument Outline fostered iterative engagement, enabling learners to continually monitor their interactions with GenAI and strategically align them with their writing goals. This process encouraged learners to progressively reconfigure their collaboration with GenAI, suggesting the potential that such tools may support not only immediate writing performance but also the development of more autonomous writing practices over time. Further, previous research has highlighted the lack of structured engagement in GenAI-supported writing environments and emphasized the need for scaffolds that promote critical reflection and strategic decision making (Lee et al., 2025). The agency-supporting features introduced in this study respond to that need by providing alternative modes of engagement through which learners can exercise optimal agency, actively selecting, adapting and regulating AI-generated suggestions in line with their intentions. Importantly, these experiences may extend beyond task completion to support learners in internalizing writing strategies through intentional interaction.

LIMITATIONS AND AREAS FOR FUTURE RESEARCH

Some limitations of this study should be acknowledged. First, the sampling method did not account for variations in participants' writing proficiency and prior academic experiences, which may have influenced their writing behaviours. Future research should consider learners' writing levels and cognitive–affective characteristics to better understand their impact on human–AI co-writing processes, as well as the cultural and linguistic variations. Second, as this study focused on learners in a Korean educational context, we acknowledge that writing practices differ across cultures and languages, which limits the generalizability of the findings. Future

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studies should explore the applicability of agency-supporting features in other cultural and linguistic settings. Third, this study focused specifically on argumentative writing tasks, limiting the generalizability of the findings to other writing genres. Given that the CoAuthor tool used in this study also includes prompts for creative writing, future research should explore how agency-supporting features function in creative and other writing genres. Fourth, although the AI suggestion accuracy was enhanced by setting the parameter for decoding to a weight of 0.75 based on the previous research (Cheng et al., 2024), further research is needed to validate the effectiveness of the proposed agency-supporting design across different system settings. Examining variations based on parameter adjustments could provide deeper insights into optimizing AI-generated suggestions in human–AI co-writing environments. Finally, this study underscores the need to examine the long-term effects of agency-supporting features through the collection and analysis of quantitative data. While our discussion of long-term implications was informed by participant interviews, it should be further substantiated with empirical evidence. We recommend future longitudinal studies involving diverse writing tasks and learner profiles to investigate how these features influence the development of learners' writing skills over time.

Overall, the findings of this study suggest that, in GenAI-supported collaborative writing environments, fostering learner agency is more effectively achieved through design strategies that help learners clarify their writing goals and strategically engage with AI suggestions rather than through simply visualizing the extent of AI reliance via similarity scores. In authentic educational settings, learners' acceptance and revision behaviours in response to AI suggestions are fluid and shaped by situational factors, including task importance, cognitive difficulty and time constraints (Gado et al., 2022; Liu et al., 2024). As a result, learners' perceptions of 'optimal agency' in GenAI interactions may vary across contexts. These findings highlight the importance of providing learners with explicit decision-making criteria and strategic thinking frameworks that support the selective and adaptive use of AI suggestions, rather than focusing solely on delineating authorship boundaries between humans and machines (Yusuf et al., 2024). Supporting learners in this way enables them to critically integrate GenAI outputs in alignment with their personal goals and values, promoting more intentional use of AI in writing. Accordingly, GenAI-integrated writing tools should incorporate pedagogical scaffolds that assist learners in articulating and refining their ideas and intentions as a core design principle for building human-centred writing environments that position AI as a collaborative partner rather than a dominant agent.

CONCLUSION

This study makes several key contributions to the current understanding of learner agency in human–AI co-writing environments. First, this study introduces a new interface specifically designed to promote learner agency during human–AI co-writing, ensuring that learners actively engage with AI without compromising their autonomy. Second, the design fosters cognitive engagement by encouraging learners to independently develop and refine their ideas, rather than passively accepting AI-generated suggestions. This approach supports active co-creation, emphasizing the learner's role as an active participant in the writing process. Finally, through the empirical analysis of learner behaviours and interaction patterns within the proposed interface, the study provides valuable insights for future design directions in human–AI co-writing environments, particularly in supporting learner agency. Beyond the design proposed in this study, future research should explore personalized support tailored to learners with varying writing proficiency levels. Adaptive interface approaches can be developed to accommodate different levels of AI reliance among learners. Building on these insights, future AI-powered co-writing tools not only enhance writing efficiency but also strengthen learners' overall writing skills and critical engagement with AI-generated content.

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CONFLICT OF INTEREST STATEMENT

There are no ethical issues or conflicts of interest emanating from this study.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

We obtained ethics approval for this research project from the Institutional Review Board (IRB) of Ewha Womans University. All participants were thoroughly briefed on the study's objectives, data collection procedures and the anonymization of their information. Both verbal and written informed consent were obtained prior to their participation.

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