

## **From cognitive outsourcing to reallocation: A 3P analysis of student–generative AI engagement in unsupervised assessments**

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The emergence of generative artificial intelligence (GenAI) poses profound challenges to unsupervised assessments in higher education. Yet little is known about how students use GenAI in after-class assessments, and which patterns of use are associated with cognitive disengagement or deeper learning. This study employed Biggs' presage-process-product model to examine these processes in authentic assessment contexts. Using a qualitative methodology, we analysed 38 undergraduate students from Japan and China, examining their GenAI usage intentions, dialogue patterns and integration with other learning activities. Our findings show that student engagement with GenAI is not uniform but can be conceptualised as a spectrum bounded by cognitive outsourcing and cognitive reallocation. This spectrum adapts the classic surface and deep approaches to learning in GenAI-supported contexts. We also identified an efficiency paradox as a prevalent misalignment; whereby well-intentioned students default to passive processes and experience cognitive laziness and overreliance. The study operationalised and contextualised the 3P model in GenAI-supported assessment by articulating how presage factors shape distinct process patterns and perceived outcomes. It argues that interventions must move beyond technical skills to foster academic GenAI literacy and dialogue competence to provide explicit guidance that supports a shift from cognitive outsourcing towards more reflective, reallocation-oriented use.

*Implications for practice or policy:*

- Educators should help students reconceptualise GenAI as a cognitive partner for exploring ideas, rather than just an upgraded search engine for retrieving answers.
- Guidance must move beyond technical skills to explicitly teach the metacognitive strategies and dialogue competence required to manage human-GenAI collaboration.
- Instructors must provide explicit, pedagogical guidance beyond prohibitions, helping students explore effective and ethical GenAI use within specific assessment contexts, shifting them away from outsourcing and towards reallocation.

*Keywords:* generative AI, 3P model, cognitive engagement, higher education, assessment, qualitative study

## **Introduction**

The emergence of generative artificial intelligence (GenAI) has introduced a profound challenge to learning and assessment (Kofinas et al., 2025; Miao et al., 2024; Xia et al., 2024). GenAI can interpret natural language prompts and produce coherent, contextually appropriate and seemingly complete outputs within seconds (Dang et al., 2025). As a result, students may adopt performance-oriented use, thereby bypassing key cognitive processes for deep learning such as information retrieval, critical analysis and original synthesis. They may also adopt GenAI ideas uncritically, misattribute them or submit them without sufficient evaluation (Corbin et al., 2026; Walton et al., 2025). In such cases, student engagement in learning may shift from active construction of knowledge to passive verification of GenAI-generated content. The necessary intellectual activities can thus be outsourced to GenAI, leading to metacognitive laziness (Fan et al., 2025). Furthermore, recent empirical evidence from Kofinas et al. (2025) has demonstrated that educators cannot reliably detect GenAI use in authentic assessments, compromising academic integrity.

However, metacognitive laziness and academic integrity concerns (e.g., Gonsalves, 2024) are merely outcomes. The prerequisite for these outcomes is the process of how students use GenAI tools. To date, a large body of research, often through experiments (e.g., Li et al., 2025) or surveys (e.g., Chan & Hu, 2023; Haq et al., 2025), has revealed the potential impact of GenAI on learning outcomes. Yet, we still lack a detailed, qualitative discussion of the patterns of student engagement in GenAI use and learning. Just as student approaches to learning vary among individuals (Marton & Säljö, 1976), student approach to using GenAI in learning will not be uniform, especially during unsupervised assessment. This approach is likely influenced by presage factors, such as student GenAI literacy and external requirements they perceived, and leads to different outcomes. Therefore, when discussing GenAI's impact on student learning, a more comprehensive and nuanced investigation is needed.

To systematically deconstruct this black box, this study adopted Biggs' (1993a) renowned presage-process-product (3P) model as its core analytical framework. This model provides a holistic, systemic perspective that links student- and context-based factors (presage) to their in-task behaviours (process) and learning outcomes (product). We argue that the way students use GenAI constitutes a new, unstudied approach, and we utilised the 3P framework to explore these approaches within the authentic, unsupervised context of after-class assessments. Accordingly, this study is guided by the following research questions (RQS):

- RQ1: How are students' key presage factors – GenAI literacy and perceived assessment guidelines – characterised in the context of unsupervised assessments?
- RQ2: How do students enact their learning processes when using GenAI for unsupervised assessments?
- RQ3: How do students perceive the learning outcomes that result from their engagement with GenAI?

## **Literature review**

### **The 3P model in learning research**

The 3P model was initially proposed by Dunkin and Biddle (1974) and was later adapted by Biggs (1993a), who argued it was highly useful for understanding the student approach to learning. In this model, learning is conceptualised not as a single event but as a dynamic, interconnected system. The model posits three distinct stages: presage, process and product.

The presage stage includes all factors existing prior to a learning task. Research (e.g., Prosser & Trigwell, 1999; Ramsden, 1992) has divided presage factors into two categories: student-centric and contextual. Student-centric factors include personal attributes like prior knowledge, motivation and conceptions of learning (Entwistle, 2009; Marton & Säljö, 1976). Contextual factors represent the student's perceived learning environment, including the curriculum, assessment methods and perceived teaching quality (Ramsden, 1987).

The process stage is the core of the theory; it refers to the how of learning – the cognitive and metacognitive strategies students employ during the task. Research in this area has identified two primary approaches: a deep approach, with the intention to understand meaning; and a surface approach, with the intention to reproduce information (Biggs, 1993b; Entwistle, 1981). The model hypothesises that presage factors (e.g., prior knowledge and perceived assessment demands) strongly influence which learning process a student adopts (Richardson, 1994; Richardson & King, 1998).

Finally, the product stage encompasses learning outcomes. These are not limited to quantitative measures (like grades) but, more importantly, include the qualitative nature of the learning itself (Biggs, 1993b; Kember et al., 2020). A deep process, for example, is hypothesised to yield a high-quality product (e.g., deep understanding, knowledge transfer), while a surface process yields a poor-quality product (e.g., fragmented knowledge). This systemic linkage is a foundational framework for understanding quality in higher education and is the basis of Biggs's (1996) constructive alignment.

The emergence of GenAI introduces a powerful variable that disrupts this entire system. GenAI simultaneously impacts student presage (demanding new literacies), alters the process (enabling new interaction patterns and cognitive outsourcing) and leads to novel products (from plagiarism to enhanced reflection). Despite this disruption, a holistic theoretical framework has been largely absent from the empirical study of GenAI in education.

### **GenAI's impact on student learning from a 3P perspective**

#### *Presage: Student perceptions and attitudes*

Since the debut of widely accessible GenAI tools such as ChatGPT (OpenAI, 2022), an initial phase of research focused on student perceptions and acceptance. Studies have shown that students have high awareness, favourable attitude, and strong intentions to adopt GenAI (Chan & Hu, 2023; Delcker et al., 2024). Attitudes are shaped by performance expectancy, while trust strengthens these links (Haq et al., 2025). Students primarily value GenAI for efficiency, information search and paraphrasing (Chan & Hu, 2023; Yusuf et al., 2024). While awareness is high, opinions on cheating are split (Yusuf et al., 2024). Recurrent concerns include inaccuracy, bias, over-reliance and erosion of critical thinking. Notably, personal development concern is the strongest inhibitor of adoption (Chan & Hu, 2023; Haq et al., 2025).

#### *Product: Efficiency vs cognitive outsourcing*

Beyond student perceptions, a large body of research has applied GenAI in various learning scenarios to explore its impact on learning outcomes. Studies converge on several positive effects: GenAI streamlines brainstorming and revision, improving efficiency and output quality in second language writing (Zou & Huang, 2024); and it enhances programming learning through personalised feedback and clear explanations (Yan et al., 2024). Comparative designs show GenAI- and human-provided feedback can yield comparable learning outcomes (Escalante et al., 2023; Le et al., 2025) and that GenAI instructor self-disclosure can increase student attachment and interest (Zhang et al., 2024).

Counterbalancing these benefits, the literature has consistently flagged risks: overreliance, learning loss, threats to academic integrity and hindered independent problem-solving or laziness (Yilmaz & Karaoglan Yilmaz, 2023; Zou & Huang, 2024). Most notably, Fan et al. (2025), in a randomised experiment, argued that GenAI's primary negative mechanism is metacognitive laziness, whereby learners outsource monitoring and evaluation. They found that while GenAI raised short-term writing scores, it did not improve knowledge acquisition or transfer. This offloading may produce immediate performance gains at

the expense of sustained learning. Thus, researchers have called for investigating students' cognitive and metacognitive abilities, not just efficiency (e.g., Xu et al., 2025; Yan, Pammer-Schindler et al., 2025).

#### *Process: How GenAI is woven into learning activities*

Compared to the extensive research on presage (attitudes) and product (outcomes) factors, studies focusing on the process factor are still limited. In recent studies, however, student learning behaviours have become important data for discussion. For instance, Fan et al. (2025) used process mining on student trace data (clicks, scrolls) to visualise the metacognitive laziness loop. Yang et al. (2025) analysed student chat logs along dimensions of prompt number, depth of knowledge, prompt relevance and originality to derive two process patterns (strategic inquirers vs exploratory inquirers), finding these patterns predicted final performance. Cheng et al. (2025) and Dang et al. (2025) also conducted quantitative analyses of student dialogues. Kim et al. (2025) coded student writing behaviours to create an epistemic network analysis. These studies provide a more visual understanding of the student learning process with GenAI. However, they did not delve deeply into how this learning process connects to the presage and product factors, and they were often conducted under supervision.

## **Study and method**

### **Research goals**

As we discussed earlier, most studies use quantitative experiments and surveys to study students' metacognitive laziness, these methods are effective at evaluating the products of learning (e.g., task performance) but are less suited to capturing the nuanced process of learning (Yan, Nakajima, & Sawada, 2025).

Furthermore, even process-oriented methods like learning analytics (e.g., Dang et al., 2025) have tended to examine GenAI use in isolation, failing to capture its integration with the complex, offline ecosystem of foundational academic tasks like reading, independent drafting and critical reflection. In other words, these may not be able to fully reflect the students' views on their intentions, interaction patterns and integration approach when using GenAI in completing their assessment. Accordingly, we need more deep qualitative research to understand how students interact with GenAI for completing their assessment. This study investigated how productive GenAI usage can foster cognitive and metacognitive development in higher education, focusing on students' intentions and dialogue patterns to shift from identifying problems to finding practical solutions.

### **Research context**

Our investigation is situated within the specific context of unsupervised, autonomous assessments. Assessment is a cornerstone of university education, serving as a critical medium for fostering autonomous learning and evaluating academic performance (Biggs, 1996; Biggs et al., 2022). The tasks we focus on were argumentative, essay-type assessments (e.g., Wingate, 2012). These are a common form of authentic assessment in higher education (Bembenuddy, 2011).

This context is crucial because these tasks are specifically designed to cultivate advanced competencies. Students are expected to engage in self-directed inquiry, locate scholarly sources, synthesise diverse perspectives and cultivate advanced academic literacies (Lea & Street, 1998). Most importantly, these tasks require students to develop and exercise their self-regulation skills (Cooper et al., 2006; Ramdass & Zimmerman, 2011).

### **Operationalising the 3P framework**

To systematically analyse student engagement in this context, the 3P model was operationalised as follows (Figure 1). The presage stage encompassed students' attitudes towards and understanding of GenAI use in learning, as well as their perceptions of instructor attitudes and guidance. The process stage captured students' use intentions, dialogue patterns with GenAI and the extent to which they integrated

these interactions with other learning activities (e.g., independent reading). The product stage refers to students' self-perceived learning outcomes resulting from GenAI use.

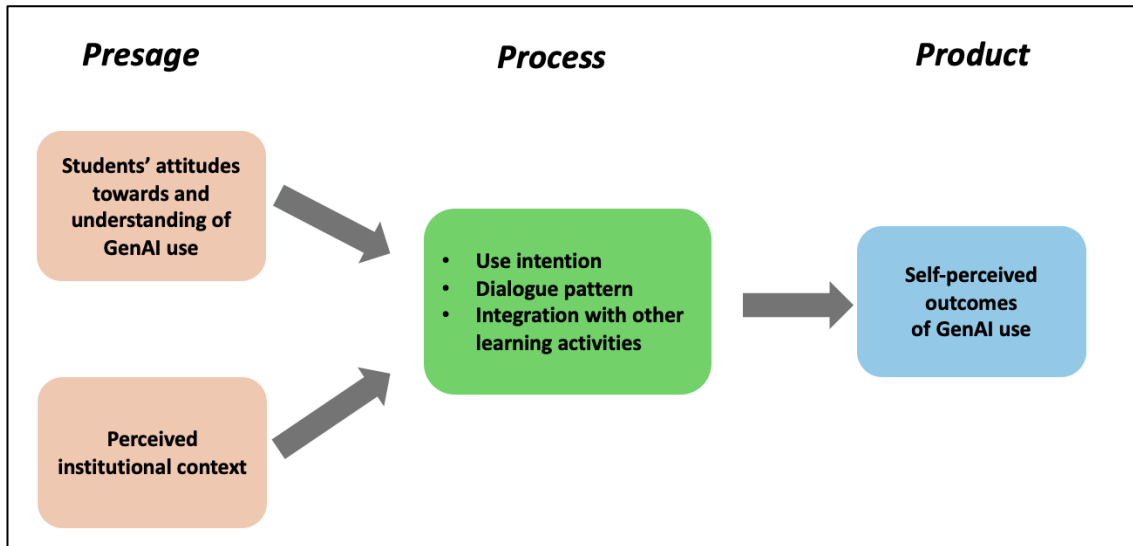


Figure 1. Interview design based on 3P model

## Participants

Participants were recruited voluntarily through personal introductions and student networks. None of the participants were enrolled in courses we taught at the time of data collection, and no supervisory or evaluative relationship existed between us and the participants. The sample comprised 38 undergraduate students (19 from Japan and 19 from China), consisting of 24 males and 14 females. They were first- to fourth-year students representing diverse disciplines such as engineering, science, literature, education, law, medicine, foreign languages and economics. To ensure anonymity, participants are identified as Student 1–38 (S1–S38), and specific majors were not disclosed.

## Data collection and analysis

In this study, interview transcripts and GenAI dialogue data were the primary data sources. The study protocol was reviewed and approved by the research ethics committee of our institutions, and all participants provided informed consent prior to data collection.

We employed in-depth, semi-structured qualitative interviews to collect participants' views on using GenAI in completing assessment. Each interview lasted between 30 and 60 minutes. During the interviews, students were asked to open the GenAI chat histories on their own devices and explain each step. This screen-assisted elicitation helped them recall concrete prompts, system responses and subsequent revisions. The interview protocol is available in the Supplementary Material section. After the interviews, participants also submitted their GenAI dialogue data, which comprised 125 interaction rounds in total.

Following Braun and Clarke's (2006) guidelines, we conducted a hybrid thematic analysis that combined deductive and inductive procedures. All interviews were audio- or video-recorded and transcribed verbatim. Excerpts originally in Japanese or Chinese were translated into English, and we subsequently reviewed and verified all translations to ensure accuracy and fidelity to the original meanings. Biggs' (1993a) 3P model provided overarching analytical categories (presage, process, product), which informed five sensitising themes: intentions, interaction patterns, integration, self-evaluated outcomes and presage factors. Within these categories, we carried out bottom-up open coding to identify emergent subthemes, grouping related codes and iteratively refining them.

The first author conducted initial open coding on a subset of the interview transcripts to identify recurrent patterns related to students' presage factors, use intentions, interaction processes and perceived outcomes. Based on this preliminary analysis and the 3P model, the first author and the second author collaboratively developed a coding framework specifying codes, definitions, and typical examples. Using this shared framework, the same two authors then independently coded all interview transcripts. Intercoder agreement for the top-level categories was high (Cohen's  $\kappa = 0.91$ ), and discrepancies were resolved through discussion.

For the GenAI dialogue data, the first author independently coded all student–GenAI interaction rounds contained in the dialogue logs, applying the established framework and inductively generating additional subcodes where necessary. The remaining co-authors acted as auditors, reviewing the codebook, coded samples and thematic map to ensure coherence and theoretical alignment across both interview and dialogue data.

## **Results**

### **Key presage factors (RQ1)**

#### *Students' attitudes towards and understanding of GenAI use in learning*

All student interviewees reported a lack of confidence in their ability to use GenAI effectively. Many assumed that GenAI generates answers by compiling all information on the Internet. They recognised "hallucinations", leading them to conclude its content cannot be fully trusted. Some had seen tips about prompt creation but did not actively engage in prompt design themselves.

However, significant variations were observed in students' perceptions of GenAI's role in completing assessments. Most students held narrow perceptions of GenAI's role in learning. Many regarded it merely as an upgraded version of Google or as a translation tool, valued mainly for performing familiar functions more efficiently. During interviews, when asked whether they knew they could use GenAI to discuss academic papers interactively, several students responded, "I didn't know" or "I never thought of using it that way".

In contrast, a few students demonstrated a more active, exploratory approach, developing a collaborative relationship with GenAI. For example, Student 19 stated that in addition to being a tool, GenAI also served as a "partner" or "friend", one they could "consult with and complete work together".

It's not about being 'friendly' in a casual sense. I consult it for opinions, but I don't accept them uncritically. It's like if I'm doing research and ask a friend for their opinion ... I wouldn't just copy everything they said. I listen, then make my own judgement before writing. It's like a friend who knows a lot about certain things. (S19)

#### *Perceived assessment guidelines*

Most students reported that their instructors allowed the use of GenAI tools for assessments but explicitly prohibited directly copying and pasting GenAI-generated text. For example, Student 10 noted, "Some teachers say that using GenAI merely as a reference, just to get an idea, is acceptable, but copying entire outputs is not".

Several students also mentioned that some instructors cautioned that while GenAI could be used for information gathering, its outputs required careful verification due to potential inaccuracies, and that students were still expected to complete the core writing tasks themselves. However, students unanimously reported receiving little concrete guidance on how GenAI should be used appropriately or where the ethical boundary between acceptable assistance and academic misconduct lies.

## **Learning processes when using GenAI for unsupervised assessments (RQ2)**

### *Usage intentions*

In completing their assessments, students often used GenAI tools with multiple intentions rather than a single, fixed purpose. For example, one student might use GenAI to assist with writing, while at other times relying on it to understand academic concepts or research methods. Our analyses showed that students' intentions for using GenAI can be broadly categorised into three groups – outsourcing tool, learning assistant and cognitive partner – as summarised in Table 1.

The first group, Outsourcing Tool ( $n = 16$ ), was primarily motivated by the desire to complete assignments quickly, especially those perceived as uninteresting. Typical uses included adjusting text length or delegating parts of the writing task.

The second and most common category, Learning Assistant ( $n = 31$ ), involved using GenAI for functional learning support. Students in this group used it for generating ideas, searching for background knowledge, clarifying formatting and revising their writing. Many students noted that before GenAI, they used the Internet for help, but GenAI provided more direct answers. They reported that the emergence of GenAI had increased the frequency of their inquiries. Despite most students regarding GenAI as a useful learning assistant, their usage intention appeared to align more with treating GenAI as an answer-providing tool rather than a reflective learning partner.

The final and least common group, Cognitive Partner ( $n = 8$ ), represented the most sophisticated use. These students interacted with GenAI to deepen their understanding and enhance their skills. Their intentions included discussing complex content from academic papers, inquiring about analytical methods or seeking alternative perspectives on their completed work to refine their arguments.

Table 1  
 Categorisation of student intentions for using GenAI

Group	Primary use case	Specific intention	Participants (ID)	n	Condensed representative examples
1	Outsourcing tool (n = 16)	Modifying length (expanding or shortening)	S5, S1, S2, S10	4	"I asked the GenAI to shorten my text to 200 characters." (S5)
		Full ghostwriting	S20, S22, S23, S21, S28, S24, S26, S8	8	"It's basically asking me to make things up ... so I asked GenAI to write it." (S21)
		Partial ghostwriting	S38, S36, S6, S4	4	"I feel like I can't write that way myself, so I asked GenAI to write it." (S38)
2	Learning assistant (n = 31)	Getting ideas	S3, S14, S16, S17, S6, S13, S25	7	"If there's something I really can't figure out, I ask ... how I should think about it." (S17)
		Content-related prompts	S27, S36, S28, S31, S15	5	"I asked it to find whether the literature mentioned any difficulties ... that was the focus I was searching for." (S27)
		Inquiring about writing structure or style	S2, S16	2	"I'd ask something like, 'I want to write this kind of discussion – what would be a good approach?'" (S2)
		Related knowledge seeking or checking	S37, S1, S7, S11, S12, S17, S21	7	"I used it to gather information ... or to look up background knowledge." (S12)
		Inquiring about format & expression	S3, S11	2	"I wanted to use [a specific] expression ... so I asked how to write it properly." (S3)
		Finding reference materials	S35, S36, S4, S18, S15	5	"When reading a paper, I use GenAI to check what it's talking about." (S35)
3	Cognitive partner (n = 8)	Checking & revising assignments	S34, S28, S2, S3, S21	5	"I submitted my self-written report ... and asked it to improve the expressions." (S2)
		Discussing questions from readings	S29, S24, S8	3	"I asked it about the difference between [concepts] ... and it even helped me trace the explanation back to official standards." (S8)
		Exploring ideas	S38, S35, S36, S18, S21	5	"I start by giving GenAI broad ideas and ask it to find a specific angle ... It's like co-creating." (S36)

### Dialogue patterns

Our analyses on GenAI dialogue logs identified two recurring patterns: single-turn, passive question and answer (Q&A), and sustained dialogue.

Single-turn, passive Q&A: This was the dominant pattern, especially in Groups 1 and 2. A total of 76.32% of students ( $n = 29$ ) relied on it. The hallmark is a straightforward, ask–get answer–stop interaction (Figure 2), much like using a search engine; students act as passive information gatherers.



Figure 2. Screenshot of a GenAI chat provided by S2

Particularly, in their attempts at getting ideas (Figure 3), students often pasted the assessment title directly into the dialogue box without clearly specifying their needs in the prompt. When dissatisfied with the output, they typically resubmitted the same prompt instead of explaining what was unsatisfactory or how they wanted the response to change.



Figure 3. Screenshot of a GenAI chat provided by S28

Sustained dialogue: In contrast, sustained dialogue involves longer, more natural back-and-forth exchanges. Students ask follow-up questions based on the GenAI's responses and integrate their own reasoning into the conversation. This pattern was rare overall (23.68%,  $n = 9$ ) and appeared mainly among Cognitive Partner users (Group 3).

Student 18 provided a typical case, and his dialogue flow can be categorised into six steps. Figure 4 illustrates each step along with the specific GenAI prompts he used. First, he asked GenAI, "Please propose an appropriate topic for the assessment and present a plan for how to write it." – a prompt that began not by requesting an answer but by clarifying the assessment requirements. Next, he asked GenAI to propose potential topics and an overall plan, using it as a brainstorming partner to map the intellectual terrain. Only after establishing a clear direction did he request provisional drafts of key sections, treating

them as scaffolds rather than final products. Crucially, he then entered a critical-dialogue phase to clarify theoretical assumptions and, finally, asked GenAI to suggest search keywords for his own independent literature review. An excerpt from Student 18’s GenAI conversation is shown in the Supplementary Material section.

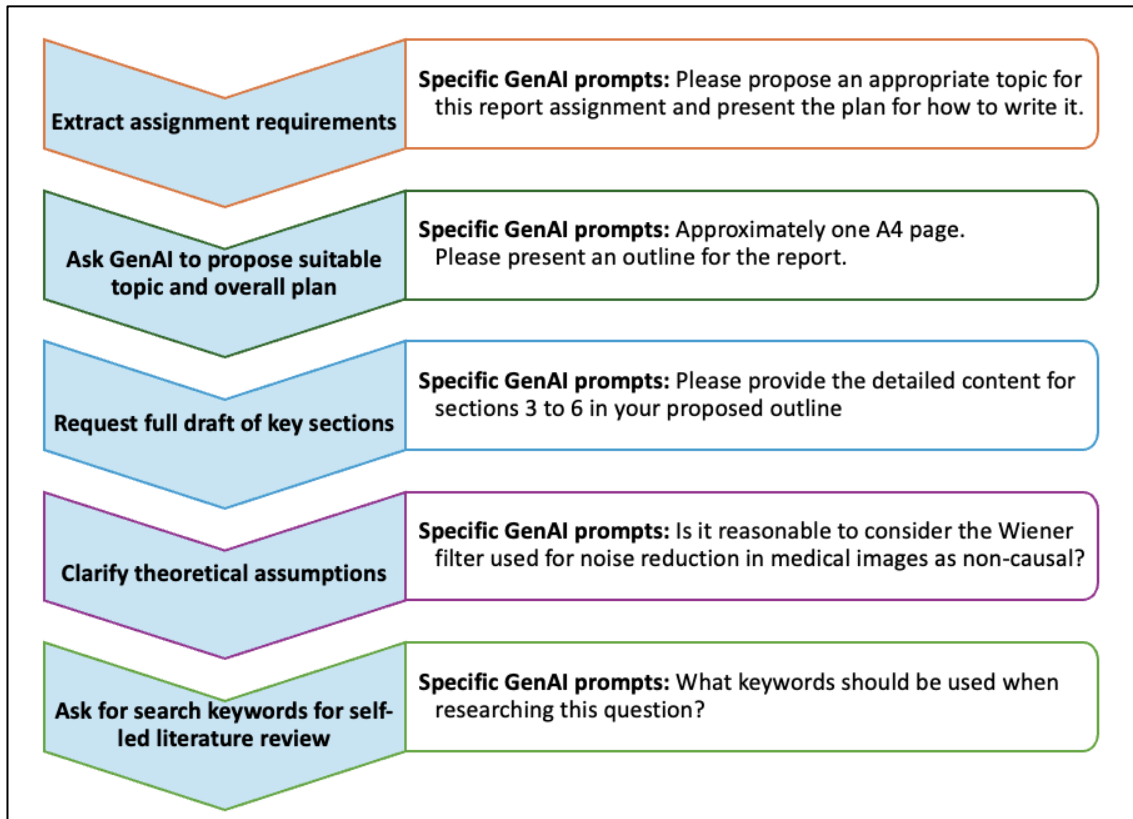


Figure 4. Student–GenAI interaction flow for S18

*Integration with other learning activities*

Our analysis revealed two distinct models of how students integrated GenAI with other learning activities (such as revisiting course materials, locating primary academic sources and producing independent written work): a fragmented model and an integrated model.

The fragmented model: Most students (78.94%,  $n = 30$ ) used GenAI either before starting an assessment (to request ideas, writing patterns or background knowledge) or after finishing a draft (to polish language or adjust length). In these cases, GenAI use was largely separated from other learning activities; students first thought and wrote independently, then turned to GenAI at the beginning or end of the process to supplement rather than to co-construct.

The integrated model: Far fewer students (21.06%,  $n = 8$ ) alternated between independent work and GenAI interaction throughout the assessment. Among those who did (primarily Group 3), Student 19 offered a prime example. Figure 5 illustrates his workflow: the green blocks represent his independent study, while the pink ones represent his interactions with GenAI.

He first analysed the assessment prompt independently, selected a personally meaningful angle, searched for relevant literature and drafted an initial version. He then consulted GenAI about parts he did not understand, asked it to generate outlines and content aligned with his own ideas and issued iterative revision directives after evaluating GenAI’s outputs. Finally, he searched for additional literature and data to refine his work, used GenAI to improve grammar and expression and concluded with his own edits and reflection. This workflow is iterative rather than linear, representing a symbiotic dialogue between

independent work and GenAI-assisted tasks. The Supplementary Material section presents the statements and prompts extracted from Student 19's interaction logs.

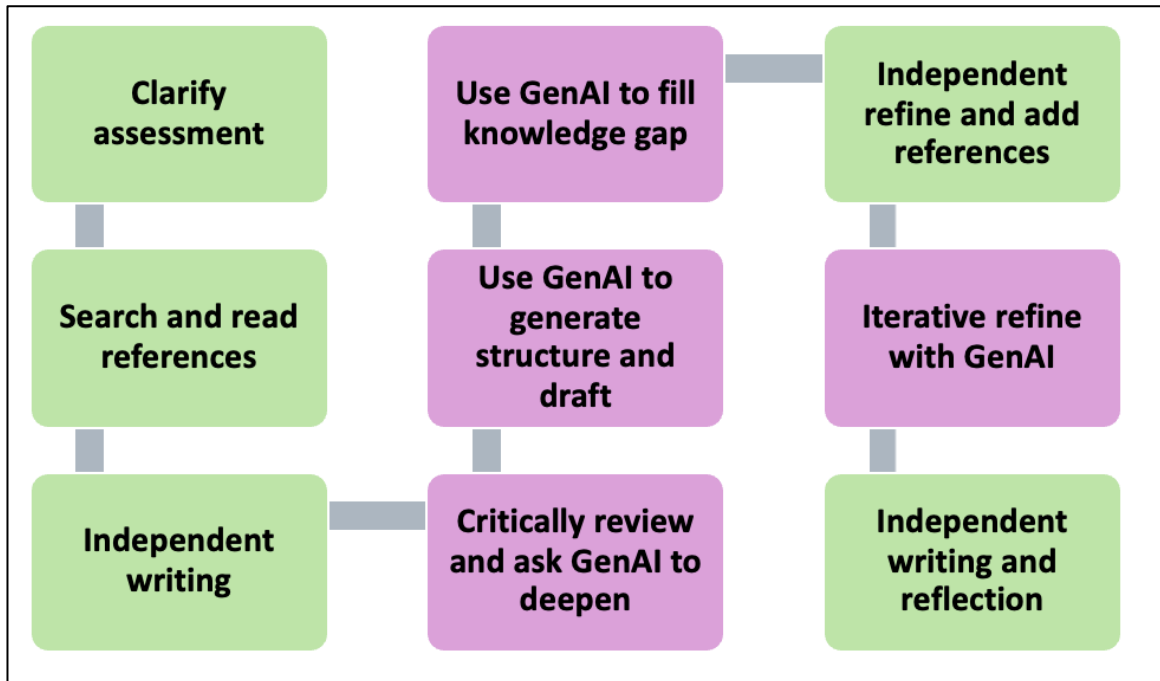


Figure 5. Student 19's workflow in assessment completion

### Perceived learning outcomes (RQ3)

#### *Academic cheating and cognitive offload*

When students' usage intentions fell into Group 1 (Outsourcing Tool), many perceived their behaviour as academic cheating. They felt that using GenAI in this way meant delegating their own learning responsibilities to the technology. In other words, the task sequence became: the teacher assigns the work → the student passes it to GenAI → the GenAI generates the answer → the student merely checks for major errors and submits it back to the teacher. This process was articulated by Student 26, who reflected on their lack of cognitive engagement:

I copied and pasted the AI-generated answer paragraph by paragraph just to fix the formatting. I glanced over the content during that process, but I didn't really stop to think about it, make any revisions or question whether it was well written. I just ... didn't. It wasn't a process of thinking – it completely replaced my brain. (S26)

#### *The efficiency paradox*

In Group 2 (Learning Assistant), some students stated that GenAI use can help improve the overall performance, because they revised the expression and collected more information in a short time. On the other hand, many students described this impact of GenAI as an efficiency paradox. While GenAI offered convenience, that ease was accompanied by a perceived decline in cognitive effort. This convenience came with concerns about overreliance and a growing sense of mental complacency.

Students' greatest concern was that GenAI's constant availability for precise answers could foster a habit of not thinking, simply because they can ask the GenAI. They reflected that before GenAI, web searches did not provide immediate, perfect answers, compelling them to think for themselves.

As Student 6 explained, once efficiency becomes the priority, the "shortest path" is to depend on GenAI for quick answers – a habit he admitted is problematic. Similarly, S12 observed, "Because you can get so much information in an instant, the speed at which you forget it is also very fast".

Student 16 compared her workflow before and after GenAI, expressing concern about her decreased cognitive engagement:

Before GenAI, when I wanted information or to quote passages for a report, I would go to the library and search through many relevant books. From those, I would find parts that seemed usable and cite them. As I looked through various books, I decided for myself, "This information is useful" and "This isn't", so I could tell on my own whether my report turned out well. But when I ask ChatGPT, I'm not the one judging whether it's truly the best; it's what ChatGPT told me, so I didn't do the selecting and discarding myself. That leaves me wondering, "Is this really okay?" (S16)

Her reflection illustrates how GenAI's efficiency can diminish active decision-making and reduce opportunities for critical engagement, even though it facilitates faster assessment completion.

### *Cognitive reallocation*

By contrast, a smaller subset of more advanced users (primarily Group 3) did not share these concerns. They reported that GenAI did not necessarily reduce their total working time but rather reallocated where their cognitive effort was invested. Student 18 described this shift succinctly:

The amount of effort hasn't changed much, but the focus has. Before, a lot of resources were spent on the "searching" part ... With GenAI, that burden is reduced, so I can now focus on checking the overall quality and creating a more well-balanced report. (S18)

Recognising that effortless retrieval could lead to shallow understanding, Student 19 developed a metacognitive strategy. After each GenAI session, he wrote short reflection notes to consolidate his understanding and ensure that quick access did not replace genuine learning:

It's based on my own experience. Before, I used to look things up on Google and search around a lot. But now I can just ask GenAI and get an answer instantly. Because I no longer put much effort into gathering information, the information doesn't really stick in my mind. I can understand it in the moment, but it fades quickly. So I need to write it down at least once. (S19)

## **Discussion**

By applying the 3P model, this study conceptualised student GenAI engagement as a spectrum bounded by cognitive outsourcing and cognitive reallocation, linking presage factors to qualitatively different processes and perceived outcomes.

### **Empirical implications**

Our findings highlight the foundational role of presage factors in shaping how students work with GenAI. Two types of deficiencies were particularly salient. First, many students had limited perceptions of how GenAI could be used for learning. When GenAI was primarily conceptualised as an upgraded search engine or translation tool, students' usage intentions were largely constrained to the learning assistant category rather than the cognitive partner category. This narrow conceptualisation, combined with a lack of specific prompting skills, also helps explain the dominance of the single-turn, passive Q&A dialogue pattern. Second, contextual presage factors, especially ambiguous instructor guidance, created an institutional vacuum. Instructors strongly prohibited plagiarism but rarely provided constructive guidance on how to use GenAI productively, encouraging a default to low-effort fragmented models and performance-oriented outsourcing rather than deeper, integrated use.

One major pattern we identified was a surface approach to learning built around cognitive outsourcing. The traditional surface approach, characterised by an intention to reproduce information, appeared here in a new form: instead of rote memorisation, core cognitive tasks were delegated to the technology. This approach was defined by the outsourcing tool intention, which reflects a performance-oriented rather than mastery-oriented goal (Pintrich, 2000). Students abandoned cognitive agency from the outset, often reporting a self-perceived sense of academic cheating, echoing concerns in prior research (e.g., Cotton et al., 2023). This intention was enacted through single-turn, passive Q&A dialogue and a fragmented model of integration, disconnected from independent thinking, a pattern also noted by Yang et al. (2025).

In contrast, a small group of students displayed a deeper form of engagement that we describe as cognitive reallocation. This approach aligns with the traditional goal of understanding meaning, but the process is fundamentally collaborative. It begins with a cognitive partner intention: a relatively rare but critical mastery-oriented goal focused on deepening understanding rather than merely completing the task. This intention was actualised through two key process features: the sustained dialogue pattern and an integrated model of study. In this model, students did not simply ask for answers; instead, they actively managed GenAI to scaffold their own thinking, sometimes enabling GenAI to play a role similar to Vygotsky's (1978) *more knowledgeable other* (MKO).

This distinction between outsourcing and reallocation maps onto Lodge and Loble's (2026) conceptual framework of cognitive offloading, which differentiates between detrimental offloading, in which learners bypass schema construction by delegating intrinsic cognitive work to GenAI, and beneficial offloading, in which GenAI manages extraneous load while the learner retains cognitive agency over higher-order tasks. This framework helps illuminate a third, intermediate pattern identified in our data.

Our analysis further suggests that many students were caught in what we call an efficiency paradox. These students adopted the learning assistant intention and articulated mastery-oriented goals, yet their actual processes remained surface like. Consistent with the findings of Delcker et al. (2024), they lacked both a cognitive partner conceptualisation of GenAI and the skills needed to manage collaboration with the tool, defaulting to single-turn passive Q&A. This misalignment led directly to negative learning effects such as cognitive laziness and over-reliance (Abbas et al., 2024; Fan et al., 2025), undermining the intrinsic cognitive load necessary for building schemas even as GenAI reduces extraneous load (Hong et al., 2025; Lodge & Loble, 2026). This group can be understood as having engaged in detrimental offloading not by intention, but by default: without the presage conditions necessary to retain cognitive agency, well-intentioned use collapsed into passive outsourcing. Pedagogically, this group is especially important: they are at high risk of defaulting to a surface approach despite not holding purely performance-oriented goals.

Taken together, these patterns suggest that student engagement with GenAI can be conceptualised as a spectrum ranging from cognitive outsourcing to cognitive reallocation. Most students clustered towards the outsourcing end or remained in the misaligned middle ground of the efficiency paradox, while only a minority consistently enacted reallocation-oriented pattern. This spectrum adapts the classic surface-versus-deep distinction and foregrounds the role of presage conditions in determining where students fall along it.

### Theoretical contributions

This study has several implications for theories of student learning and GenAI-supported education. First, our findings operationalise and contextualise Biggs' (1993a) 3P model in a GenAI-supported assessment context, demonstrating how presage factors shape qualitatively distinct process patterns that yield different perceived outcomes. We propose a conceptual distinction between a surface approach based on cognitive outsourcing, in which students delegate core cognitive work to the tool, and a deep approach characterised by cognitive reallocation, in which GenAI supports rather than replaces student thinking. This outsourcing–reallocation spectrum resonates with Lodge and Loble's (2026) distinction between detrimental and beneficial offloading. Our findings provide process-level evidence for this distinction in unsupervised higher education assessment, showing that where a student falls along this spectrum is determined not by the tool itself but by the presage conditions they bring to the task.

Second, the findings contribute to ongoing efforts to theorise GenAI's pedagogical role. The data suggest that GenAI's function is not fixed: under outsourcing-oriented, surface processes, it operates as a convenient information tool, whereas under sustained, reflective dialogue, it can play a role similar to a Vygotskian (1978) MKO, providing prompts, explanations and alternative perspectives within the learner's zone of proximal development. We do not claim that GenAI is inherently an MKO, but our results indicate that it can take on MKO-like functions when learners have sufficient GenAI literacy to structure the interaction. This perspective supports recent calls to move from viewing GenAI as a static tool towards understanding it as a potential co-regulator in human-GenAI collaboration (Yan, Nakajima, & Sawada, 2025).

## Practical implications

### *Shaping presage: Building the conditions for productive engagement*

The most consequential leverage point lies in the presage conditions students bring to assessment. Educators can address students' narrow GenAI conceptualisations by making exemplary human-GenAI dialogue visible in classroom settings, demonstrating what sustained, iterative interaction looks like and why it produces different cognitive outcomes than passive Q&A. This goes beyond technical GenAI literacy to helping students develop a more productive epistemic relationship with the tool (Chiu et al., 2024; Ouyang & Jiao, 2021). On the second dimension, educators should move from general prohibitions towards task-specific guidance, articulating which cognitive tasks students must retain ownership of and which forms of GenAI assistance are appropriate for each assessment. As Nikolic et al. (2024) noted, facilitating open classroom conversations about GenAI use can foster shared norms and more intentional engagement, preserving the intrinsic cognitive work assessment is designed to cultivate.

### *Designing for process: From fragmented use to integrated engagement*

Our findings suggest that dialogue pattern alone does not determine learning quality; equally important is whether students integrate GenAI within a broader independent learning workflow. Students who enacted cognitive reallocation alternated between GenAI consultation and independent activities such as reading primary sources and drafting their own arguments, treating GenAI as one node in a larger cognitive process rather than a substitute for it (Walton et al., 2025). Assessment design can encourage this integration by requiring intermediate artefacts, such as reflections on how GenAI was used alongside other learning activities, making the broader workflow visible and incentivising deliberate engagement. Assessments that make reasoning an explicit object of evaluation further discourage outsourcing by shifting students' perceived goal from producing a polished text to demonstrating their own thinking (Xu et al., 2025).

### *Reconsidering product: What counts as learning in a GenAI-supported context*

Students who enacted cognitive reallocation reported that their cognitive effort had not diminished but shifted away from low-level retrieval and towards critical evaluation and reflective consolidation. This raises concerns about whether traditional assessments measuring surface output quality can adequately capture genuine learning when GenAI is involved (Lodge & Loble, 2026; Yan, Pammer-Schindler et al., 2025). Assessment practices that attend to the process behind the product are better positioned to reward genuine cognitive engagement (Walton et al., 2025). More broadly, the challenge GenAI poses is not merely one of academic integrity (Gonsalves, 2024; Kofinas et al., 2025), but an invitation to reconsider what meaningful learning looks like and how it can be evidenced in higher education.

## Conclusion, limitations and future research

This study investigated students' GenAI usage intentions, dialogue patterns and integration during unsupervised assessments. Our findings reveal that student engagement is not uniform but exists on a spectrum bounded by cognitive outsourcing at one end and cognitive reallocation at the other.

Our results indicate that student intentions can be categorised as cognitive outsourcing, learning assistant and cognitive partner. The learning assistant intention was the most prevalent. However, when this intention is combined with a single-turn, passive Q&A dialogue pattern, students tend to seek direct answers. This readily leads to an efficiency paradox, a scenario where apparent efficiency is achieved at the expense of deep cognitive engagement. Conversely, a minority of students treated GenAI as a cognitive partner. They were more likely to adopt sustained dialogue interactions and integrate GenAI use with independent learning activities (i.e., the integrated model). This mode facilitated cognitive reallocation: students did not reduce their overall cognitive effort but rather shifted cognitive resources from low-level information searching to high-level quality checking and critical reflection. This integrative approach helps students maintain academic agency while leveraging technology, building a more effective human-GenAI collaboration in self-directed learning.

This study has two major limitations, which also point to directions for future research. First, the study's findings are based on a qualitative sample of 38 undergraduates. The qualitative design is, by its nature, intended to be theory building (Leung, 2015). It aims to identify and conceptualise phenomena rather than to produce statistically generalisable claims (Agius, 2013). Future research should employ large-scale quantitative methods to test the generalisability of our proposed framework. Second, while our sample was intentionally scoped to East Asian educational contexts, further validation is required to determine the generalisability of these findings across more diverse cultural and pedagogical settings.

## Author contributions

**Wanxin Yan:** Conceptualisation, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review and editing, Funding acquisition; **Yiran Cui:** Data curation, Investigation, Formal analysis, Writing – review and editing, Funding acquisition; **Thomas K. F. Chiu:** Supervision, Validation, Writing – review and editing; **Taira Nakajima:** Validation, Writing – review and editing; **Hideki Kozima:** Validation, Writing – review and editing.

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## Supplementary material

### Interview protocol

#### 1. Background information

- Please indicate your age and gender.
- Please indicate your year of study and your major.
- Please describe the main content of your major in an easy-to-understand way.

#### 2. Knowledge and perceptions of GenAI

- What specific GenAI tools have you used?
- How do you perceive GenAI (e.g., ChatGPT)? For example, do you view it as “convenient,” “risky,” “uncertain,” or something else?
- Through what channels did you learn about GenAI and how to use it? For example, through social media or online articles, friends or senior students, or university courses.
- To what extent can you explain your knowledge of GenAI—its basic principles and how it works?
- Do you have any knowledge or skills for using GenAI effectively, such as creating effective prompts?

#### 3. Use of GenAI in assessment completion

- Could you describe how you use GenAI when completing essay-type assignments?
- What is your main purpose or intention when using GenAI?
- How do you actually interact with GenAI? Please walk us through your conversation logs with GenAI. (If the student’s explanation is unclear, follow-up questions may be asked, such as “Why did you ask this question?”)
- Have you ever considered using GenAI as an exploratory partner in your studies or research activities?
- How do you perceive the role of GenAI in completing assignments?
- When using GenAI, what aspects have you found particularly helpful? Please provide specific examples.
- When you receive an answer from GenAI, how do you verify it and integrate it into your work? For example, do you copy it directly, rewrite it in your own words, or cross-check it with other sources?
- Besides using GenAI, what other learning activities do you engage in?
- Do you think using GenAI has changed your study methods or attitudes toward learning? If so, how?
- Do you have any concerns about becoming overly dependent on GenAI? For example, reduced independent thinking or uncertainty about the accuracy of information.
- Do you regard the use of GenAI for reports or homework as cheating or ethically problematic? Under what conditions do you consider its use legitimate?

#### 4. Institutional context

- Has your university or any of your courses provided guidelines on GenAI use? If so, were they clear and acceptable to you?
- How do your instructors perceive the use of GenAI in completing assignments? Is it prohibited?
- How do your instructors explain safe and appropriate use of GenAI in assignments?

**Conversation log between S18 and GenAI**

Line	Interaction round	Speaker	Utterance
1	1	S18	Select one specific industrial product that utilizes the Wiener filter and write a one-page report (A4 size, including figures and tables) on its application...
			Please propose an appropriate topic for this report assignment and present the plan for how to write it.
2	1	GenAI	Proposed Topic: "Application of the Wiener Filter in Medical Image Processing" Writing Plan: It is recommended to structure the report as follows: 1... 2... 3... 4... 5... 6...
3	2	S18	Approximately one A4 page. Please present an outline for the report.
4	2	GenAI	The report will be structured as follows and will fit within one A4 page: 1... 2... 3... 4... 5... 6...
5	3	S18	Please provide the specific text for sections 3 to 6.
6	3	GenAI	3. Overview of the overall technique... A CT scan is a technology that acquires the attenuation data of X-rays passing through the human body as projection data, and reconstructs tomographic images based on that data...
7	4	S18	Is it reasonable to consider the Wiener filter used for noise reduction in medical images as non-causal?
8	4	GenAI	Yes, it is reasonable to consider the Wiener filter used for noise reduction in medical images as non-causal. The reasons are as follows...
9	5	S18	When using a Wiener filter for noise reduction in medical images, what information—required to determine the transfer function—cannot be obtained from the measured signal alone, and how is it assumed?
10	5	GenAI	When applying a Wiener filter for noise reduction in medical images, the following information is required...
11	6	S18	What keywords should be used when researching this question?
12	6	GenAI	When researching this topic, it is effective to combine the following keywords. Each focuses on related concepts or practical applications: 1. For basic concepts of Wiener filters...

**Extracted statements and prompts from S19's GenAI interaction**

S19's workflow	S19's statements	S19's prompts
Clarify assessment	"My teacher assigned us a report on whether not attending school is 'right or wrong.' After thinking about it, I became especially interested in the question of whether skipping school is illegal."	
Search and read references	"If I rely only on my own thinking, my ideas tend to stay shallow... so I usually search online and read some sources to deepen my understanding."	
Independent writing	"I still start by writing the core parts on my own...GenAI isn't very good at generating original ideas, especially at the brainstorming stage. When I generate ideas myself, they tend to be more personal and not just the common arguments."	
Use GenAI to fill knowledge gap		"Is attending school really the basic rule?" / "If it's not against the law, why do some people still say the increase in non-attending students is a problem?"
Use GenAI to generate structure and draft		"From a legal perspective, write a well-structured and in-depth discussion about whether school non-attendance is a bad thing."
Critically review and ask GenAI to deepen		"Discuss whether not attending school is bad from three different viewpoints." / "Your explanation from the perspective of social adaptation is too shallow." / "If it's not illegal, why is school non-attendance viewed as something bad?"
Independent refine and add references	"Sometimes GenAI doesn't provide enough information... so I supplement it by searching and adding information myself."	
Interactive refine with GenAI		"Please revise this to make it easier to understand." / "Point out the problems in text 2." / "Make it easier to read."
Independent writing and reflection	"After GenAI generated the text, I revised it myself once, then sent it back to GenAI for further revision. It didn't end in just one round—after that, I removed unnatural Japanese expressions, rewrote some sentences myself, and asked GenAI to check it again. I repeated this cycle several times."	