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THINKING ABOUT THINKING: SHIFTING THE CONVERSATION ABOUT GENERATIVE AI

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ABSTRACT

This article proposes a conceptual shift about generative AI (genAI) in language teaching and research. There are very real concerns about potential harms from genAI, including invasion of privacy, erosion of creativity, theft of intellectual property, cheating on assignments, and degradation of the environment. However, genAI is here to stay, and educators should shift their attention to helping students and colleagues use genAI tools productively in a way that affirms our common humanity. The history of technology has already long demonstrated that devices do not invariably cause an inevitable and uniform transformation of the social world; indeed, human values and aspirations have often shaped the use of technology. GenAI is no different. Reviving the concept of metacognition, which has already been shown to help improve computer-based instruction, this paper demonstrates practical ways that English language educators can promote uses of genAI that foster critical thinking and innovation.

Keywords: computer-aided instruction, critical thinking, English language pedagogy, generative AI, metacognition

INTRODUCTION

When I was an undergraduate student in the previous century, I was hired and trained by the university peer tutoring service. One concept I took away from that training, which was based on learning theory, was the power of metacognitive thinking.

The term was then relatively new, popularized in educational contexts by John Flavell, who stated that metacognitive knowledge is “stored world knowledge that has to do with people as cognitive creatures and with their diverse cognitive tasks, goals, actions, and experiences” (1979, p.

906). In tutor training, we learned to ask questions and listen more than tell students what to do.

During my tutor training days, my professors focused on metacognition, or thinking about thinking. Whether we were helping a student with writing, mathematics, or another subject, the peer tutor's goal was to help students see problems like we do. Transferring our expertise by asking questions was key to our success. By asking where to start and what to try, we aimed to foster metacognitive awareness in students who came to us for help. Through asking questions, I learned that what was getting in the way of success was sometimes cultural, like the student from South America who did not know what a checking account was, giving him trouble with his algebra word problems. In several semesters as a peer tutor, I learned to inquire and wait for responses.

This method resulted in interesting insights from the students seeking help. Although I had my own ideas, a typical session would consist of me asking questions, then taking notes as the student spoke. Many good ideas would come from this preliminary session, and then I would talk to the student to focus on something workable. This training has served me well as a lecturer because I know to ask questions about what interests a student and then wait quietly for a response. I can confirm I have done a good job when a student comes up with something that I would never have thought of before.

REVIVING "METACOGNITION"

Generative AI tools have become quickly ubiquitous, raising a plethora of concerns, ranging from exacerbating environmental inequalities, eroding academic values, promoting cognitive atrophy (Ren & Wierman, 2024; Al-Hajaya, 2026; Kosmyna, Hauptmann, Yuan, Situ, Liao, et al., 2025, albeit the last not yet peer reviewed). As we grapple with these challenges, the insights I gleaned into metacognition seem invaluable. As a peer tutor, I was admonished in training to never take over the thinking process for a student; this has been a guiding principle for me today because we would prefer that students do not relinquish intellectual activity to a computer.

Metacognition is essential in learning contexts, but it is also a universal benefit of human culture. All literate people can benefit from metacognition because they can write out their ideas and then reflect on them. The ability to examine one's thinking is an important part of all societies that use writing: as pointed out by theorist Walter Ong (1982), written language allows people to examine and refine their own thought processes. Not all people in all contexts, however, feel empowered to use culture in that way.

I have previously discussed this failure to inculcate reflective thinking, which was clear at the start of the century when educators had the chance to engage students with computer-assisted learning on a broad scale (Leslie, 2006). The first uses of computers were in the style of electronic fill-in-the blank workbooks that did not encourage self-direction. At that time, the concept of metacognition became a popular corrective to imagine better designs of educational computer tools (e.g., Aleven & Koedinger, 2002; Graesser, McNamara, & VanLehn, 2005). In recent years, metacognition (as "critical thinking") has reemerged in pedagogies involving generative artificial intelligence (Muthmainnah & Oteir, 2022; Ng, Luo, Chan, & Chu, 2022). Admittedly, the term "critical thinking" is more often used in research about genAI, but the goals are the same: encouraging students to examine their own thinking processes.

These educators make an important point: technology does not have an inevitable and uniform impact on society; training and human ideals play an important role in how devices are used. This point has been demonstrated many times in the history of technology. Founders of the computer age, for instance, articulated metacognitive goals for their visions of computing devices that were overwhelmed by industrial and cultural norms. Consider the statements of these prominent visionaries: Norbert Wiener, the mathematician who founded the field of cybernetics; Vannevar Bush, who became U.S. President Franklin D. Roosevelt's science advisor in World War II; and J. C. R. Licklider, an administrator at the U.S. Advanced Research Projects Agency that sponsored the first widespread packet-switching network, ARPANet. Although the visions of these early thinkers were not upheld, they serve as a reminder of how computing technology should be used.

Wiener (1948) coined the term "cybernetics" from the Greek word κυβερνήτης (kybernētēs), meaning "navigator." We can imagine this as the dynamic of television's Captain Kirk, who makes decisions based on information from many sources and gives orders to the helm, often managed by Lieutenant Sulu, who independently takes care of the associated tasks. In a similar way, Wiener dreamed, the computer user could delegate management tasks to an autonomous system. In his later work, Wiener (1950) stated that he was concerned how operating machinery had relegated humanity to drudgery, wishing to "protest against this inhuman use of human beings" where humans are required to work on tasks that demand "less than a millionth" of their "brain capacity" (p. 16). Certainly, not all computer users since Wiener have had the opportunity to use their time for creative, metacognitive thinking, but this was part of the original vision for human-computer interaction.

Another visionary who had a robust plan for human-computer interaction was Bush (1945), who was not a relative of the U.S. presidents with the same surname. Bush's idea of the memex has been lauded for anticipating later developments, including the personal computer and the hypertext links used on Web pages. The memex, though, was not really the device for efficient processing of information that later scholars imagined (Leslie, 2020). It is true that memex users could input all kinds of reference materials and find documents quickly. However, they could also annotate their materials and use links between documents to examine the "scaffolding" of their thoughts (Bush, p. 108). This brooding, retracing the steps of one's thinking or even the thinking of one's predecessors, shows the metacognitive experience the memex could have given to its users. It was key to Bush's imaginary device but not found in the efficient devices it inspired.

For his part, Licklider was an academic psychologist before he became a federal administrator. In the 1960s, surrounded by large, mainframe computers, he began writing about the potential for expanding human cognition. Conducting an auto-ethnography, he estimated that 85% of his work time was "getting into a position to think … activities that were essentially clerical or mechanical: searching, calculating, plotting, transforming" (1960, p. 6). These predecessor tasks, he dreamed, could be better done by computers. He dreamed of a network of computer centers that would be like libraries, allowing for sharing and resources and information (p. 7; see also Licklider, 1965). Even though today the capability to get work done quickly and gain easy access to information are on computer users' minds, Licklider reminds us that those are not necessarily the only use of computers. Like Wiener and Bush, Licklider promoted using computers to free time for higher-order thinking.

One should not lionize Wiener, Bush, and Licklider. They were embedded in the U.S. military-industrial complex that resulted in war machines that, of course, helped defeat the Nazis in World War II but also that destroyed small villages in Southeast Asia at the same time the ARPANet was established. The goal of protecting humanity, as a result, must be nuanced. One can observe that, as members of modern bureaucratic organizations, they wished to protect the power of human creativity, but part of the benefit would go to entities devoted to war. What is more, these authors did not consider the differentials in access to computers that would follow. These limitations should provide a springboard for thought, reminding us to consider equitable uses of genAI technology.

INCULCATING METACOGNITION

Although different genAI services have various capabilities and features, they have certain commonalities that can be exploited to encourage students to reflect on their thinking process. For the purposes of this discussion, a brief overview of the way computers generate output can illustrate the opportunities and limitations of genAI tools.

1. BIAS AND METACOGNITION

One important insight is that the "chat" part of the name means that the user interface is based on a chatbot model. A user supplies a question or a request, which is known as a *prompt*, and the tool provides output. However, this should not be the end of the interaction; the output is likely to miss the user's request to a certain extent, and students need to be instructed that they should *iterate* their prompts with new information to bring the output closer to what they are looking for.

The chatbot interface has two implications. The first is that users should create an account and sign in, so the chatbot remembers the conversation and users can go back to an earlier discussion, even when they are on a different device. The second consequence is that the dynamic between iterating the prompt and evaluating the output is not only an important skill in the age of AI, but also an opportunity to think metacognitively. Any use of genAI will subtly have this impact on users, but educators can highlight this experience to encourage students to make the most of it.

Another essential insight into genAI comes from the "P" in the name ChatGPT: these services are *pretrained.* Long before any users start prompting the chatbot, engineers have created a large language model (LLM) that the tool uses to craft its responses. In order to create the LLM, engineers feed as much text into their tool as possible, currently trillions of words (Cummins, 2024). Engineers look at which words and concepts are likely to be associated in authentic texts. The output a user receives is among the most likely associated words that the LLM has analyzed. In other words, the output is aligned with what most users think. In information theory, this is known as low *perplexity*: the tool's output is acceptable to and reflects the experience of a wide range of users (Jim the AI Whisperer, 2023). For this reason, genAI will not provide information that is surprising or innovative; human creators, though, are likely to make unexpected connections. This is an educational opportunity: students can learn how genAI output is designed to be acceptable and pleasing but lacks the surprising and personal connections unique to their personalities, dreams, and histories.

Another consequence of pretraining, though, is harder to accept and counter. LLMs are trained on Web pages, social media posts, freely available books, and in some cases through arrangements with publishers. It might seem that this training is an objective way to understand how real people think, yet Internet resources like the Web do not reflect the world's population. It is not simple to measure the proportion of Web pages that are written in English, but one estimate is that 55% of documents online are in English even though only around 5% of the world's population speaks English as a main language. Chinese speakers represent 16% of the world's population, but the amount of Web pages in Chinese are less than 2% of the total (Brown, 2023). For those of us living and working in regions where English is not a native language, the output from genAI will reflect the worldview of speakers who are far away. Teaching students to recognize this bias can be a way of helping them to be innovative in their own writing.

This kind of bias has long been observed in other contexts. In corpus linguistics, researchers already know that using authentic language risks replicating the status quo or even exacerbating bias through reification of social prejudices. These lessons can be repurposed in genAI pedagogies. For instance, with sufficient training, a bias in a corpus that women are more likely to be associated with cooking or shopping can be countered (Zhao, Wang, Yatskar, Ordonez, & Chang, 2017). Researchers have gone further, developing a corpus of bias based on responses to gendered situations (Garnham, Vorthmann & Kaplanova, 2021). These methodologies can now be applied to analyses of genAI output.

Bias enters genAI output in other ways. Input from users become part of the LLM, not just their prompts but also any files they upload as part of their interaction with the chatbot. The users of genAI services are not distributed evenly; even though they do not fit neatly into a global west and north versus global east and south divide, users in Africa and Asia (with some exceptions) clearly provide the least input to genAI (Qiang, Liu, & Wang, 2024). Middle-income countries, like Brazil and India, have outstripped upper-income countries in genAI usage. This seems "promising," except that it "underscores the widening divide with low-income countries," Qiang et al. note. This phenomenon has also been long observed in other contexts. In the 1970s, concern about the negative synergy between information production and economic development was noted by researchers. Five transnational companies were shown to provide 80% of international news, meaning that developing countries were forced to learn about themselves from an outsider's privileged position (Masmoudi, 1979). Developing countries decried this "new world information order" and sought better appreciation for cultural autonomy that can lead to effective cooperation (Argumedo 1981). The fact that information passed through a bottleneck of just a few global cities raised concern and calls for support of diversity in media outlets.

Unfortunately, the growing fascination with the information superhighway – along with the belief that the Internet reduced barriers to production and access of information – "resulted in loss of interest in the issues imbalance and inequality in the flow of international information” (Tsuda, 1999, p. 451). Momentum behind addressing information equity flagged as policymakers and advocates felt that Internet-based technologies like the Web would offer easy access to a global audience.

Of course, the coming of the Web and the dot-com boom was the time when the digital divide started to be noticed, first within the U.S. and internationally six years later (National Telecommunications and Information Administration 1995; Norris 2001). Global inequality was exacerbated due to the fact that Internet users were primarily from the global north, despite the perception of platforms like Wikipedia being the “sum of all human knowledge” (Graham, Hogan, Straumann, & Medhat, 2014, p. 760). In the new century, user-influenced media like Wikipedia was seen to demonstrate gender bias because Internet users predominantly identified as male (Wagner, Garcia, Jadidi, & Strohmaier, 2015). GenAI, being trained on sources like Wikipedia, naturally replicates and even amplifies those biases.

Any classroom exercise can be used to demonstrate the inherent bias in genAI, using metacognition to imagine better responses. For instance, I am a lecturer in the Faculty of Liberal Arts. A natural question for students in their early years is what are the liberal arts and how to they prepare students for their future careers? As a classroom exercise, I have shown ChatGPT’s answer to the question, “who are the top 10 people who spoke positively about the liberal arts?” The results, shown in Figure 1, are telling. One the one hand, the people on the list are have prominently supported liberal arts education. However, with some prodding and patience, students can recognize that all the people on the list are from the U.S., and most are white, Christian, and male.

Figure 1: *Sample Classroom Slide about Bias in ChatGPT*

In my experience, I have often heard Steve Jobs cited as an individual whose technical innovations benefitted from his undergraduate experience in the liberal arts. He took a calligraphy class that led him to appreciate typography, so he included different fonts in early Apple computers (Isaacson, 2015, p. 130). This a good example of how multidisciplinary experiences can lead to innovation. However, is it the best way to motivate students in southeast Asia about the power of the liberal arts? Jobs had educational and entrepreneurial opportunities that students in my classes cannot access.

What happens, however, when we iterate the prompt with the intention of eliminating genAI bias? This activity can and should be conducted with students because the results are instructive. The prompt can ask for supporters of liberal arts in a geographical location (i.e., Asia, Southeast Asia), who are members of national or other groups (i.e., Thai, Chinese, Muslim), or even be tied to specific people (i.e., Mahidol Adulyadej, Confucius). Students can create their own prompts in small groups and then share what they see after a few minutes. This is makes metacognition a part of the course. The output I received from ChatGPT to a prompt requesting supporters from southeast Asia was, in part:

> the concept of "liberal arts education" in its Western form is relatively recent in Southeast Asia, and not always described using that exact term. However, many Southeast Asian educators, public intellectuals, and policymakers have strongly spoken in favor of *broad*, *holistic*, *interdisciplinary*, or humanities-based education (emphases added).

This needs to be unpacked for students so they can understand the depth of the bias. ChatGPT output will point out that one origin of the liberal arts is in medieval European universities. It is understandable that the query to the LLM for a phrase "the liberal arts" returns few responses before recent decades, when the term became more popular to describe an ideal educational philosophy, particularly languages that do not use terms based on the Latin phrase "artes liberalis." However, the second part of the statement, offering synonyms like "broad, holistic, interdisciplinary" to describe this pedagogy, is revealing. A sanity check quickly reveals that this kind of education is not a new phenomenon; to the contrary, specialized, skills-based education is the more recent development.

Although the first universities were in the Middle East, not in Europe, one can easily identify printed material that says otherwise. For instance, one scholar states: "The first universities grew out of the cathedral and municipal schools of the reviving cities of 12th century Europe" (Perkin, 2007, p. 161). In this context, the University of Bologna's founding in the 11th century CE is often used as a marker. However, in the 9th century CE, Fatimah al-Fihr founded a mosque and school that is today known as the University of al-Qarawiyyin in Fez, Morocco. The curriculum of her school went beyond religious studies to include topics like "medicine, economics, philosophy, law, astronomy" (Taqiyah & Sapri, 2025, p. 72). Thus, the holistic and interdisciplinary ideal we place under the rubric of the liberal arts was alive and well centuries before its supposed inception in Europe. However, due to the reliance on frequencies in LLMs, this fact and its implications are not readily apparent – and, in fact, ChatGPT balks at the idea that the liberal arts existed outside of Europe before recent times.

In this way, biases are imbricated in genAI, coming from the cultural material used for pretraining, where the worldview of the global north and west overpowers other perspectives. Like many other technologies, genAI makes existing biases transparent, even if it runs the risk of reifying and exacerbating them. In a circular fashion, though, the broad-based education offered by the liberal arts serves as a foundation for students to be effective detectors of bias related to many topics, including the liberal arts themselves. Additionally, the lessons learned from the critical examination of genAI output shift the conversation about ethical uses of the technology. Instead of, "how much genAI content is acceptable in an essay?", a different ethical consideration develops: "how can users of genAI avoid replicating the preexisting biases that come from the pretraining of LLMs?" This new conversation shifts from admonishing students toward activating their sense of justice and correcting prejudices of the social world. If nothing else, metacognition offers an additional avenue for encouraging students to be innovative in their writing.

2. LITERARY METACOGNITION

Instead of using GenAI as a shortcut to analyze literary texts, it can be used to foster critical thinking about literature – and as a way to illuminate one's own expectations about a text. The oft-cited framework originated by Benjamin Bloom is effective. In the revised taxonomy, actions like “comparing,” “differentiating,” and “generating” are the foundations of learning (Anderson & Krathwohl, 2001). GenAI output can readily be utilized as a springboard for metacognitive thinking about literature.

For example, reading literature often requires language learners to navigate cultural and historical allusions that might seem confusing distractions at first, but this thinking is worth examining and reconsidering. A poem like “Jim Crow’s Last Stand” by Langston Hughes is rife with references to historical figures and events. One might dutifully investigate each, finding out their relevance, without ever considering the bigger picture: what is the effect on the reader of a text with so many allusions? One way to do this is prompt genAI to rewrite the poem with contemporary figures. This fits in with the Bloom categories of “comparing” and “generating,” enhancing understanding through metacognition.

The output from genAI changes some of the unfamiliar names to names that a contemporary person has heard of: Malcolm Luther King, Jr., Ketanji Brown Jackson, Colin Kapernick, and the names of victims of police violence mourned by the Black Lives Matter movement. Now, one can ask, do you understand the poem better? The range of student responses might be “yes” from students who are attuned to U.S. news to “maybe” from students who have heard the names in passing on social media. The dialogue that follows between those who know and those who want to know, then, is something like the situation for Hughes’s readers in the 1940s. This allows for a deeper understanding of the dynamics of the original: students move from feeling overwhelmed by the allusions to considering how that feeling might not be so far away from the experience of contemporary, native speakers.

Independent learners who are invested in improving their language skills by reading literature might be amazed by the potential for genAI to create skills exercises. For instance, after being introduced to Hughes’s poetry in class, they might be inspired to read more on their own. However, without the careful scaffolding of a literature classroom, students might feel intimidated by the task. They will benefit from learning that genAI can be used to create the scaffolding they are accustomed to help them on their independent quest. I find it instructive to show students how they can ask genAI to create a vocabulary list at an appropriate CEFR level and provide multiple choice questions or reading prompts to aid their understanding. Those students who became English majors so that they could encounter foreign cultures then find that they have an assistant on their journey if they can utilize metacognitive strategies.

Another way that genAI can help learners focus on broader issues that complement summary and understanding is to use image generators. The setting of Hughes’s poems like “Steel Mills” or “Johannesburg Mines” might not be familiar, and some of the specialized vocabulary might distract from the larger meaning. One can use genAI, such as Adobe Firefly, to request images of these poems. As seen in Figure 2, students from an agricultural area who are not familiar with industrial plants can better imagine the poem. Copying just a few lines of the poem, a student is rewarded with a stunning image of smokestacks that “belch red fire” at the end of the day (Hughes 1995, p. 43). This image allows students to zoom out of from the minutia of vocabulary and grammar. Pausing for a moment, they can think about the setting of the poem and have the opportunity to imagine similar settings and ponder the impact of the poem. Again, students use "generating" as a bridge into comparing with their own experiences.

Another task to improve metacognition is to utilize genAI output as a representation of what many people might think. For instance, while studying a novel or story, one can ask for an illustration. Imagine we are studying *Weep Not, Child* by Ngũgĩ wa Thiong'o. At one point, a European teacher comes to teach English to a group of children in what today is known as Kenya but was then a British colony. My first effort resulted in a black teacher, which could conceivably be a person from Europe, but misses the point of text. Asking for a white teacher, though, confused the image generator, which then created an image of a multicultural group

Figure 2. *Adobe Firefly's Illustration of the Setting of a Hughes Poem*

of children like one might see in a modern classroom. Struggling with genAI is an opportunity to use "comparing" from Bloom's taxonomy. Students can compare the output with the original text to consider how Ngũgĩ captures a moment of colonial history that is outside the bounds of what ordinary users would expect.

A similar opportunity to compare the expectations most people would have about a text and the original comes when one prompts genAI to create a dialogue in the same situation as the novel. The colonial school depicted by Ngũgĩ is not an inclusive learning space, and it eventually is how the main character is wrongfully folded into a violent police investigation. One can ask genAI to create a dialogue between a student and an English teacher in Kenya and even ask for accompanying illustrations. The output is resoundingly cheerful, a mismatch with the main character's experience. One can ask, when did protagonist ever smile like this?, and the answer is that young Njoroge was only smiling in anticipation of going to school, not during the actual education. Understanding this difference between expectations and the actual words in the text is an important part of understanding literature, yet it is hard to inculcate. Using "generating" and "comparing," though, one can more easily see how the reader's expectations are not met by the text.

GenAI can help readers understand literature in obvious ways, such as creating summaries and simplifying texts to match a learner's reading level. However, this use of genAI does not promote thinking about the original text nor does it encourage readers to examine their own experiences and expectations while considering a work of literature. With some guidance, though, readers can find better ways of using genAI metacognitively to have a literary experience beyond understanding vocabulary words.

3. METACOGNITIVE PROMPTS FOR RESEARCH WRITING

Using genAI to prepare a manuscript for submission to a peer-reviewed journal is a perilous proposition. A process that uses genAI as a metacognitive tool can lead to insightful manuscripts that are likely to be sent out for peer review, but relying on genAI output is likely to result in rejection prior to publication or sanctions after a paper has been published.

The stakes are high. Even if an article makes it through peer review and is published, a journal has the right to retract it later. Retractions are highest in STEM journals, with some cases becoming notorious, like a young researcher at the University of Manchester who faced 11 retractions of papers because they seemed to use genAI output: convoluted phrases, citations to non-existent papers (also known as hallucinated citations), and questionable contributions from co-authors (Orrall, 2025). A study of the impact of a retraction on an author's career indicates that nearly half leave publishing immediately, a group that is characterized by authors who were early in their careers and had not attained many citations. Those who remain in publishing tended to build "quantitatively weaker collaboration networks" as compared to peers who did not experience retraction (Memon, Makovi, & AlShebli, 2025, p. 1142). When a paper is retracted, the journal leaves up a page stating the name(s) of authors and the reason, making the event a permanent blot.

That being said, papers that rely on genAI output may not get past the peer review stage. First, genAI use might lead to a desk rejection, especially when it is not acknowledged by an author. When a journal first receives an article, several pre-checks are likely to take place, including similarity to published works (seeking evidence of plagiarism or previous publication) and markers of genAI created text (such as hallucinated citations and phrasing that lacks human variations). Not all editors will explain the rationale behind a desk rejection, offering only boilerplate text that the manuscript is not suitable for the journal. This causes a conundrum for authors who work on a team and may not realize that the output from one of their colleagues was developed by genAI.

A second difficulty that might stop a paper from passing peer review, though, is harder to anticipate. A reason for rejection can be that a manuscript seems to lack novelty. This does not mean that the research project itself is ordinary; a complaint about the lack of novelty can sometimes be blamed on writing that does not highlight what is new about the findings. This can be a side effect of tools based on LLMs: in creating output, genAI links the words and concepts that are most likely to be associated based on the training data. The plausibility of the output is an indicator of how well genAI predicts what most people will think is acceptable. This presents a problem for research writers, though, because what everyone knows is the opposite of innovative thinking. Even if the core of the research project is original, it will be wrapped in text that obscures the originality.

As has been the consistent theme in this paper, the best way to use genAI is as a consultant that promotes metacognition. GenAI is good at telling us what everyone knows, but it falters with questions that should be answered by human intuition. For instance, the NotebookLM service from Google allows users to upload published articles and notes for to create a personalized language model. One can ask NotebookLM to identify the research gap, but this information will come from the articles themselves (in other words, what others have identified as the research gap).

Instead of using genAI to substitute for thinking, a better technique is to ask epistemological questions: what are the common methodologies and which methodologies are not represented? From there, the researcher can reflect on their own expertise and experience to identify a gap that only they can fill.

I recently experimented with GenAI to demonstrate the difference between what genAI is good at – telling us what everyone knows – and the original thinking it cannot do. While I was working on page proofs for an article that was about to be published, I asked ChatGPT for some advice. In my prompt, I introduced myself and my goal of publishing an article in a journal that is indexed in Scopus or Web of Science. Pretending that my article was not about to be published, I asked: take a look at my title and abstract and recommend suitable journals. This is not a metacognitive task, but a task based on what everyone already knows.

As one might expect, ChatGPT did an amazing job of producing output based on the most likely answer to my query, providing me with five potential journals. I was aware of the first two recommendations because they are elite venues in the history of science – and in my opinion, my article was not general enough and my research might not reach their high bar. The third recommendation was the journal which had, in fact, accepted the paper. The fourth journal had given me a desk rejection, and the fifth was an interesting choice that would have been suitable had I not already secured publication.

To check the ability of genAI to serve as a substitute for original thinking, I then asked ChatGPT to help me write an article about my topic for the third recommendation (the journal in which my research would be published). Here, the output was far from acceptable. For one thing, the output outlined five different points to make, which were more like book chapters than sections of an article. This would have been suitable for a presentation for a general audience, but it lacked the focus of a research article. More importantly, the output suggested that I follow what everyone already knew about this topic, even though my article sought to address an interpretive gap in the existing scholarship. In other words, ChatGPT suggested that I write an article about the oft-repeated claims that my article sought to debunk. I suppose this could be helpful for someone seeking to know the common thinking before seeking to interrogate it, but it would not serve as an effective basis for an innovative article. One can imagine what would have happened had I used the ChatGPT framing for my abstract, introduction, and methodology, and then moved to my innovative research findings. I do not think an editor or peer reviewer would have read through eight pages of what everyone knows to uncover my new insights. To the contrary, I expect after reading a few pages they would have said that my research lacked novelty.

Thinking about how genAI can be a metacognitive partner in research writing is much better than seeking ways to mask the use of genAI. Concomitant with the many new genAI tools has been a rise of services that purport to spot AI influence on a writing sample; one only has to conduct a Web search for “detect AI in writing” to get a list. After I did this, my social media feeds were populated by the contrary service: advertisements for tools that promised to make the use of AI output undetectable. Conversations about what percentage of AI output is acceptable in a paper are popular these days, but the situation is absurd. Creating generic text from AI and then using a tool to deregularize its grammar and vocabulary so that it evades detection is a troubling process. It is bad enough to substitute human intuition with the obvious answers that come from genAI; even worse is when authors use a tool to weaken the syntax of this already mediocre text so that its AI origins are undetectable. This is a sad prospect. Shifting the conversation to the effective and responsible use of genAI is a better alternative.

It seems like editors and editorial teams are becoming increasingly vigilant, investigating articles for potential AI early on, such as being more stringent about including DOIs for articles so they can easily check if the citations are to actual sources. However authors use tools to obfuscate their use of genAI on the sentence level, attending only to surface qualities will lead to a lack of innovation in the text. The use of common keywords will suggest to editors that the research is ordinary. Even if the editor decides to commit some of the people on the journal's limited roster of peer reviewers, the normative influence of genAI is likely to trigger a negative response. Practicing metacognitive strategies will lead to better outcomes.

4. CUSTOM AI AGENTS FOR METACOGNITIVE LEARNING

A final way to implement metacognitive strategies to assist learning is through the creation of custom AI agents. ChatGPT provides paid users of their service the opportunity to create bespoke agents. Similar to a customer service chatbot for a commercial enterprise – and with the same opportunities and frustrations – a customized GPT can be pre-loaded to support independent learning.

According to the interface design at the time of this writing, the steps to create a GPT are as follows (one can also ask ChatGPT for help with understanding what an agent is and setting one up). After signing in to a paid ChatGPT account, select a menu item like "Explore GPTs" and click the "Create" button. The next step is to select the "Configure" option. Then, fill in the options:

- Name: The title students will see
- Description: Students read this when they open the GPT
- Instructions: A prompt that tells the GPT what you want it to do (users do not see this text directly)
- Conversation starters: Up to five action buttons for users
- Knowledge: Documents about the lesson (coursebook or worksheets)

The Instructions part might be the hardest to write, and it is unlikely that one will get it right the first time. Following best practices with prompt engineering will be helpful. Figure 3 shows some ideas for the Instructions field based best practices. One may, at first, create only a basic description and then try it out: describe the objective and audience, upload a sample file, and then open the GPT and pretend to be a student. After interacting with the GPT, one will see what is going well and what needs to be improved. Errors are a chance to edit the description to make it an accurate supplement to your classroom lessons. (Please note that during my first time using the agent, I felt that it was drawing too much information from the Web, which caused it to miss the point of my lesson. So, I unchecked the "Web Search" box under Capabilities.)

When offering the GPT to students, I remind them of the limitations they already know about. For instance:

- Like any other genAI tool, there may be errors

- Feel free to challenge the agent or ask for clarification
- I am always available to discuss anything odd they see

Figure 3. *Elements of the Description of a Bespoke GPT to Support Independent Learning*

Element	***Description***	***Example***
Objective	The goal of the interaction	Ajarn Chris seeks to help students create more complex sentences without making errors
Audience	Describe your students (chatbots are familiar with CEFR levels)	Aj. Chris's students are second-year English majors in Thailand. Their English level is B1 or B2, and they are on track to reach C1
Persona	Reminders that help the GPT overcome some of its default tendencies	This GPT is designed to play the role of Aj. Chris's teaching assistant. Students will come to you to supplement their classroom lessons. You are not a lecturer, so reply with short statements (100 words) and encourage them to ask follow-up questions
Approach	The way you prefer the interaction to unfold	The approach is constructive: lead students to creating longer sentences without making errors in a supportive manner
Resources	Describe the files you have uploaded	Please take careful note of the ideas from the "Sentence Structure" file Aj. Chris uploaded. There are six paradigm sentences …
Buttons	Describe each of the conversation starters	The conversation starters are: 1. Help me understand the basics: You can …
Error correction	As you interact with the agent, add to a list to correct the errors	Please take careful note of these points from the "Sentence Structure" file: • Transitional adverbs need a comma after them (before the subject of the clause) ….

After using this tool in class, I was happy to hear back from students with their questions about the tool's output. In some cases, I was able to improve the Description field in the agent. Other questions offered me the opportunity to help students understand the finer shades of the lesson.

Creating focused learning agents with genAI can help meet students where they are. They are already using genAI to inquire about class lessons and gain assistance with their homework tasks. A custom GPT affords them a metacognitive vantage point to see the course lessons in action. A bespoke GPT allows an educator to draw a boundary between the lesson and distracting information on the Web that trains the GPT. For students who are shy about contacting their instructor, the agent has another potential role: it gives a student a reason to engage with the teacher about the course content.

CONCLUSION

Technological change is often accompanied by hyperbolic and apocalyptic thinking about its impact on society. At the end of the twentieth century, pundits and scholars wrongly predicted that the spread of the Web would wipe out local languages, forcing people to use English if they wanted to communicate (Leslie, 2025). That this prediction did not come true is only part of the point; one must also be mindful that the relationship between technology and society is more complex than a simple cause-and-effect interaction.

Humans use tools in way that reflects their ideals and aspirations. Even though technological solutions encourage users to think in certain ways, paying attention to what one wants from a tool can help to change the outcome of the encounter between human and machine. In educational contexts, promoting independent learning and metacognition are examples of the educational values that must and can be maintained while incorporating new technology like genAI. Conversations about environmental degradation, dishonesty remediation, intellectual property, and the like are valuable. Shifting the conversation to the kinds of outcomes educators value in teaching, though, is just as important.

Working with genAI tools is going to be a significant challenge for the current generation and those who follow. Without a doubt, those who can use new tools successfully will leap ahead of their peers. However, there is a different, harder-to-acknowledge challenge: work output that looks like it was made by genAI will not be trusted. Even if a student never uses genAI to get their work done, output that looks generic and fits in with what everyone expects might be classified as genAI. For this reason, educators have a responsibility to help students understand the benefits of genAI while differentiating their work from genAI output.

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