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A pedagogical design for self-regulated learning in academic writing using text-based generative artificial intelligence tools: 6-P pedagogy of plan, prompt, preview, produce, peer-review, portfolio-tracking

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Abstract

The emergence and popularity of generative artificial intelligence (AI) tools, particularly text-based ones known as large language models, pose both opportunities and challenges to education. The ability of these tools to generate human-like texts based on minimal instructions causes concerns among educators about students' use of these tools for academic writing, which may constitute a breach of academic integrity. We propose a pedagogical design that models on self-regulated learning and the authoring cycle and develops students' critical thinking and self-regulation when composing academic writing using text-based generative AI tools. It contains six iterative and interactive phases. Students first plan the content and structure of the writing, then generate prompts for text-based generative AI tools. Next, students preview and verify the tools' output, followed by the fourth phase of producing the writing using the corrected output. Fifthly, peer review by fellow students may be required to polish and proofread the writing. Lastly, through portfolio-tracking, students reflect on the writing process, and formulate strategies for future usage of text-based generative AI tools for writing. This pedagogical design helps students and teachers embrace text-based generative AI while addressing the perils these tools present, and guides the development of education interventions and instruments.

Keywords: 6-P pedagogy, Academic writing, Artificial intelligence literacy, ChatGPT, Critical thinking, Pedagogical design, Self-regulated learning

Introduction

The year 2022 has seen the release of a number of generative artificial intelligence (AI) algorithms and models that are able to generate images, videos, texts and sound (Peres et al., 2023). In particular, thanks to its ability to generate diverse forms of original, human-like texts, the text-based generative AI tool ChatGPT (which stands for Chat Generative Pre-trained Transformer) has become the most popular and influential. Although the GPT family of AI models to which ChatGPT belong was initially released in 2018 (Floridi & Chiriatti, 2020), it was not until the emergence of ChatGPT, which was trained on a larger dataset than previous GPT versions and is readily accessible without requiring much technological knowledge, that society began to notice the impact of text-based generative AI on various disciplines.

The education community has pointed out numerous challenges and opportunities that text-based generative AI presents to education (Cooper, 2023; Dwivedi et al., 2023; Kasneci et al., 2023). Its effect on writing assessment is especially concerning, since text-based generative AI tools can generate original content with minimal instructions from students, who could have little to no knowledge of the subject (Kohnke et al., 2023). This leads to attempts to ban these tools (Tlili et al., 2023), or to return to traditional, in-person examination (Stahl & Eke, 2024). However, a more sustainable response may be to embrace these tools by adapting them to existing pedagogies or designing new pedagogies to incorporate them into school curricula (Milano et al., 2023). Indeed, the wise and proper use of text-based generative AI can augment students' productivity and creativity, which can be translated to real-life scenarios (Dwivedi et al., 2023). Consequently, there is a need to develop a pedagogical framework to educate students the proper use of these tools, with academic writing as the focus. The choice of academic writing naturally stems from the fact that both the input and output of the tools are texts. The framework has to centre students in the writing process, with them directing the process and text-based generative AI simply assisting them. It should be embedded with elements of the authoring cycle that informs the writing process and involves connections with the students' experiences as well as investigation through writing (Kong & Lee, 2023; Short, 2009). It will also be modelled on self-regulated learning, so students can develop the critical thinking skill necessary for using text-based generative AI tools (Milano et al., 2023), and continue self-enhancing their ability to use these tools as AI technology keeps advancing.

Literature review

Self-regulated learning

Self-regulated learning (SRL) is a concept that have been variably defined; Panadero (2017) identified at least six models of SRL. In this paper, we follow the model proposed by

Zimmerman (2002). According to this model, SRL is a type of proactive learning where leaners know their strengths and limitations, and are guided by personally-defined goals and task-oriented strategies (Zimmerman, 2002).

SRL consists of three stages: forethought, performance, and self-reflection. The forethought stage consists of the activities that students engage in and beliefs they hold before starting the learning task. Students set feasible goals of the task and plan their strategies, which require their prior knowledge and experience (Pintrich, 2004; Wolters & Brady, 2021). A number of psychological factors influence students' confidence and motivation to engage in the learning task. Major factors include self-efficacy, personal impact and interest, and the intrinsic value of the learning process (Zimmerman, 2002).

The performance stage is comprised of the processes that take place during the learning task. This is where students apply the planned strategies and monitor their progress, which Zimmerman (2002) termed self-control and self-observation respectively. As digital tools become prevalent, students have adopted and teachers have encouraged more real-time and personalised self-observation methods such as learning analytics (Araka et al., 2020) and educational data mining (Biswas et al., 2018).

As students monitor their performance of the learning task, they often record their own feedback and reflections (Chou & Zou, 2020). This record, which may be termed a portfolio or a learning journal, is the essence of the self-reflection stage of SRL (Glogger et al., 2012; Mejia-Domenzain et al., 2022). Students have to first evaluate their plan and performance in the learning task, compare it against their previous engagements with the task or the performance of fellow students. They also need to delineate the causes for successes and challenges during the learning experience to prepare for similar or identical learning tasks in the future (Zimmerman, 2002). Students then need to formulate psychological and behavioural responses to the self-evaluation. Ideally, they feel satisfied with their performance, and are not simply welcoming but motivated to future learning tasks (Mouratidis et al., 2013). Students must also address the causes they identified for the challenges, and adaptively adjust to overcome those obstacles in future learning tasks (Zhu & Mok, 2018).

A key feature of these three stages of SRL is that they are iterative and interactive (Zimmerman, 2002). This means students' thoughts and behaviours in each stage inform and influence those in the other two. For instance, the psychological and behavioural responses that students formulate in the self-reflection stage guides their planning and shapes the motivational factors in the forethought stage.

Critical thinking

Critical thinking is the ability to evaluate and judge logically and with evidence a thinking process, its outcome, or both. The objective is to make decisions and to improve the thinking process (Halpern, 1998; Kong, 2014). Although critical thinking is not a component of SRL, the two concepts are closely related, and SRL has been found to be essential in developing students' critical thinking skill (Anwar & Muti'ah, 2022). Self-regulated students proactively search for information that may enrich themselves for future learning tasks, spontaneously initiate the learning process, and constantly review their performance to perfect their strategies. These actions are also required for students to become critical thinkers (Vardi, 2015).

Critical thinking has been suggested as a fundamental skill for citizens in the age of AI and especially with the widespread use of generative AI (Crawford et al., 2023; Rampersad, 2020). Several features are necessary for critical thinkers. When approaching a topic for analysis, they should be able to use extensive relevant evidence to define the topic clearly and comprehensively. They also need to examine all existing assumptions, perspectives behind assertions, and thoroughly and systematically identify the contexts of those assumptions and assertions. When analysing and evaluating the subject, they must do so logically and again apply extensive relevant evidence. Lastly, to form their own judgment, critical thinkers have to synthesise external viewpoints with their own, and to acknowledge the limits of their decision and the complexity of the topic.

Academic writing and the authoring cycle

Throughout their study, students are asked to compose various forms of writing. While more junior-grade students write to develop their language skills and reading and writing literacy (Kim et al., 2013), older students write to learn and think (Nückles et al., 2020). Through writing, not only do students reinforce acquired knowledge, but they also improve such skills as organization and critical thinking, and enhance their motivation to further learn and write.

Generically speaking, academic writing refers to any writing for academic purposes. More specifically, Irvin (2010) described academic writing as both argumentative and analytic. Students ground their opinions in evidence and present them in a logical and organised manner not too different from a debate, albeit in a written, not oral, format. The analytic part of academic writing means students have to go beyond mere summarisation of a topic and include critical insights in the writing. Collectively, academic writing commands students to use relevant evidence to rationally examine a topic and present their viewpoints. Saqr et al. (2021) additionally emphasised the key role of self-regulation when students compose academic writing.

The authoring cycle is a pedagogical framework proposed in Short et al. (1996) initially to teach writing but later expanded to other subjects that require some form of student-centred thinking and inquiry. Short (2009) further conceptualised the elements of the authoring cycle as nine steps. Other than the first step, all components of the authoring cycle is iterative and interact with each other, emphasising the non-linearity of the writing process. Despite being designed for educators, the framework could also be student-centred and the nine elements interpreted as steps students take to approach academic writing. The first step, connection, refers to how writing's thesis relates to students' lives and experience, and functions as the starting point of the writing process. Invitation, the second element, is when students explore knowledge and perspectives around the writing's thesis, and recall their history in academic writing to apply relevant experience to the present writing. The third step, students then identify the specific issues, or tensions, that the piece of writing attempts to address. The fourth step, investigation, in the context of academic writing is the synthesis of students' knowledge and experience into a piece of writing which serve as a detailed investigation of the identified issues. During the writing process of the fifth step, students often need to search for more information and evidence. Short (2009) termed it demonstration as instructors demonstrate possible methods for investigation. After writing in the sixth step, students engage in revision of the piece of writing and also of their writing process. Examples of what students may reflect on include their approach in gathering information, their thinking process before and during writing, and potential improvement for future academic writing tasks. The remaining three elements of the authoring cycle, representation, valuation, and action, involve students sharing what they gained from the writing process and the importance and implications of their new knowledge.

Text-based generative AI

Generative AI refers to all AI algorithms that generate content (such as texts, images, videos, and sound) according to users' instructions, as opposed to object classification or pure pattern recognition (Lim et al., 2023). Specifically, text-based generative AI tools, such as ChatGPT, are AI-enabled tools whose input and output are both text-only. Traditionally, language models, which underlie all text-based generative AI tools, uses recurrent neural networks (RNNs) to calculate the probability of certain words occurring sequentially or in proximity (Luitse & Denkena, 2021). This changed with the introduction of the transformer algorithm (Bouschery et al., 2023), which automatically establish associations between each and every part of the input data. It is thus particularly suitable for training language models with a massive amount of text input data from diverse sources (Luitse & Denkena, 2021). This type of language models is termed large language models (LLMs).

Despite the improved performance and the expanded training dataset over traditional, RNN-based models, recent text-based generative AI tools still generate texts by statistically predicting the likelihood of words occurring together (Luitse & Denkena, 2021). They are, however, able to better mimic human-generated content and produce a wider range of texts, from article summarisation to original stories and essays. Nevertheless, the purely generative nature of text-based generative AI tools means they are prone to fabricating content, a phenomenon known as hallucination (Azamfirei et al., 2023; Walters & Wilder, 2023).

Academic integrity in academic writing

While it is not new that students use digital writing tools when composing academic writing, the proper use of these tools is generally not considered a breach of academic integrity. Digital writing, in general, is writing with the help of digital tools, which may be used for any step along the writing process, from researching evidence to drafting and proofreading manuscripts (National Writing Project, 2010). Academic integrity is especially relevant in digital academic writing, as students can readily access and appropriate information using digital tools. The most common type of academic integrity violation is plagiarism, where students use someone else's work as their own without proper acknowledgement. Before the advent of text-based generative AI, instructors may deploy plagiarism detection software, which compare students' writing with online texts and determine a similarity index (Hill et al., 2021). However, text-based generative AI tools are able to generate different output every time, and the content could be completely original. This makes detection very challenging and inaccurate, and leads to concern among the educators on the detection of AI-generated content (Casal & Kessler, 2023; Gao et al., 2023; Perkins, 2023; Sison et al., 2023).

Proposed pedagogical framework

The six-phase pedagogical framework proposed in this paper is grounded in Zimmerman's (2002) SRL model. The first phase, planning, matches the forethought stage of SRL, as students plan how to best convey the thesis of a piece of writing. The second to fifth phases (prompting, previewing, producing, and peer reviewing) together constitute the performance stage of SRL, where students carry out their plan and, crucially, monitor their progress of writing and learning. The last phase, portfolio-tracking, correspond to the self-reflection stage of SRL. Not only must students evaluate their writing and learning performance, they also have to think of ways to improve their performance in the future, which serve as input for planning the next academic writing task. The six phases are discussed in greater detail in the following sections.

The framework is also designed so that students can use not only text-based generative AI in academic writing but also other forms of generative AI (and AI in general) with acumen and appropriate attitudes. This is consistent with proposals in engineering and science disciplines to develop students' T-shaped competency profile (Uhlenbrook & de Jong, 2012). The broad scope for which generative AI (and AI) can be applied requires students to effectively interact with the technology in their everyday lives, which is signified by the horizontal bar of the alphabet T. The vertical bar, in contrast, represents the deep knowledge in text-based generative AI tools that students must have in order to properly use these tools to help with academic writing. This is especially vital when they formulate and modify the textual instructions for the tools, a step known as prompt-engineering (see Prompt).

Plan

The first step of academic writing, whether involving text-based generative AI tools such as ChatGPT or not, is to plan the content and structure of a piece of writing. By doing so, students can ensure that they are in control of the writing process and are using text-based generative AI as a tool. The planning phase is not too different from a problem-solving procedure (Flower et al., 1989). The writer must first build a mental representation of the writing's overarching thesis, which is usually a response to an issue, a research question, or a problem. The flow of the writing refers to its structure and what each section discusses. For example, readers need background information to effectively understand the context and pertinence of the writing, and the writer's views have to be supported by arguments and evidence.

The planning phase corresponds to the forethought stage of SRL, where students analyse the task, set goals and plan their way forward (Zimmerman, 2002), and also matches the connection, invitation, and tension steps of the authoring cycle in Short (2009). Task analysis of the forethought stage requires students to retrieve prior knowledge (Pintrich, 2004; Wolters & Brady, 2021), which, in academic writing using text-based generative AI tools, includes the underlying concepts of these tools and their strengths and limitations. The goal of academic writing is to effectively and clearly deliver the writing's thesis to respond to an issue, a research question, or a problem. The last step in the forethought stage is the selection and implementation of strategies (Wolters & Brady, 2021). While there exist multiple strategies for planning to write an academic work, research has indicated that the result of planning is more important than the specific strategies employed (Hounsell, 1989).

Prompt

All text-based generative AI tools require users to prompt them. A prompt is an instruction, question, or input that users provide to a text-based generative AI tool, and is the means by which users interact with these tools (Liu et al., 2023). In the context of academic writing with the help of text-based generative AI, the writers modify the prompts to control the output of the tools. Text-based generative AI tools may be regarded as a portal to information on which they were trained, in much the same way search engines are used (Shepherd, 2007). What these tools additionally do is to present information in a coherent and readily usable manner (Pavlik, 2023), which serves as resources for thought, discussion, and further exploration (Atlas, 2023; Su et al., 2023). Researchers have also suggested the authentic and interactive experience users have when engaging with these tools as another of their appeal (Kohnke et al., 2023).

The process of modifying the prompts to obtain the desired format and content of output is known as prompt-engineering (Reynolds & McDonell, 2021). It can be also considered the way text-based generative AI tools are commanded, since users can only interact with the tools through prompting them. Similar to search engines, where users may need to change the search keywords to obtain useful information, when using text-based generative AI tools for academic writing, students have to modify the prompts in order for the tool to generate content and information that they can adapt to produce the writing.

Preview

Output of text-based generative AI tools are known to contain mistakes, ranging from factual errors to vague answers and to bias (Floridi, 2023; van Dis et al., 2023). Indeed, although ChatGPT, one of the most popular text-based generative AI tools, passed the United States Medical Licensing Exam, it only did so marginally with a 60% accuracy (Kung et al., 2023). These tools also generate content that lacks references (Kohnke et al., 2023; Lund et al., 2023) and, when prompted to include a reference list, invent works that do not exist, a behaviour known as hallucination (Azamfirei et al., 2023; Tyson, 2023). Therefore, before writers adapt the output of text-based generative AI tools for academic writing, they have to examine and evaluate the output. This is the preview phase, where the writers verify the AI-generated draft and screen it for discrepancies. They must also search for literature to support their viewpoints and substantiate the writing's thesis, and to provide additional information, perspectives, and arguments when necessary.

Evaluating the output of text-based generative AI tools requires critical thinking from students. Instead of taking the information these tools produce at face value, the writers need to critically assess the validity of the output and ensure the information is accurate. Indeed, due to concern that the usage and reliance of text-based generative AI may reduce students' critical thinking ability (Lee, 2023), multiple studies have emphasised the need to develop students' critical thinking when interacting with these tools (Cooper, 2023; Dwivedi et al., 2023; Kasneci et al., 2023).

Produce

As a tool, text-based generative AI only provides ideas and information; the writer remains in control and direction of the writing process. After evaluating and revising the output of text-based generative AI tools, students need to actually produce the writing. They must integrate the ideas or themes in the tools' output with those from academic sources, and then incorporate them into the writing alongside their personal insights and viewpoints.

To avoid plagiarism, students are required to digest the information from various AI and non-AI sources and synthesise the information into a coherent piece of writing (Dwivedi et al., 2023). That students are the one producing the writing also emphasises that they are responsible for ensuring the credibility of the content, in accordance with the ethical principle of human autonomy in AI usage (Kaur et al., 2022). The education community agrees that there is an urgent need to develop students' awareness in and attitudes to academic integrity when using text-based generative AI tools for academic writing (Cotton et al., 2023; Dwivedi et al., 2023).

Peer review

In scholarly publishing, peer review refers to the process post-submission where researchers with considerable expertise in a specific field examine and comment on a paper (Woods et al., 2023). The process is usually anonymous, and the result is to accept, reject, or – most often – revise and improve the paper before it is published (Flynn & Goldsmith, 2013). In academic writing at school, peer review is the process where other students assess the quality of another student's writing and provide suggestions (Noroozi et al., 2023). The purpose is to polish and perfect the writing, and to ensure the content and supporting references are reasonable.

Peer review achieves this by offering feedback from multiple perspectives, so the writer can compare the original writing to various potential enhancements and improve the writing accordingly (Carless, 2022). Studies have confirmed the positive effect peer review has on students' performance and ability in academic writing (Huisman et al., 2019; Noroozi et al., 2023). In terms of using text-based generative AI tools for academic writing, peer review helps students further recognise the limitations of these tools, and informs them of more ways to appropriate and adapt the tools' output into their own writing.

The prompting, previewing, producing, and peer reviewing phases collectively make up the performance stage of SRL in our pedagogical design, where students apply the planned strategies and monitor their progress (Zimmerman, 2002). The essence of the performance stage is progress monitoring (Wolters & Brady, 2021), since students have to be aware of how they formulate prompts, evaluate the output of the text-based generative AI tools, produce the writing, and polish the writing based on comments from peers. These four phases also mirror the investigation and demonstration steps in the authoring cycle (Short, 2009) as students address the writing's thesis and search for relevant information and evidence to support it.

Portfolio-tracking

Corresponding to the SRL stage of self-reflection (Zimmerman, 2002), the final phase of our pedagogical design involves students reflecting on the process of writing with the help of text-based generative AI tools and formulating strategies for future academic writing tasks. When students compose portfolios or learning journals, they deliberate over the learning experience and suggest potential improvement, thereby engaging in self-reflection (Bavlı, 2023). As a type of reflective writing, portfolios naturally allow students to learn through reflection (Buckley et al., 2009; Mejia-Domenzain et al., 2022; Procter, 2020).

According to Zimmerman's (2002) model of SRL, the self-reflection stage consists of self-judgment and self-reaction. This matches the dual nature of our pedagogy's portfolio-tracking phase, where students have to carry out the reflection process and respond accordingly. Self-judgment includes self-evaluation and causal attribution. In terms of portfolio-tracking, self-evaluation is students' comparison of their writing with and without text-based generative AI tools, and their assessment of their ability to use these tools efficiently and appropriately. Causal attribution refers to students' reflection on any challenges during the writing process and the possible underlying reasons. For self-reaction, portfolio-tracking allows students to recognise the merits and limitations of text-based generative AI tools, so they will be well-prepared as these tools become more and more prevalent and readily available. When generating a portfolio, students also need to formulate adaptive reactions (Zimmerman, 2002), which are actions that students can do to improve their writing and their use of text-based generative AI tools in future academic writing tasks. In terms of the authoring cycle, the portfolio-tracking phase corresponds to the last four steps of revision, representation, valuation, and action (Short, 2009). In particular, students' self-reaction concerns how they perceive the value in understanding the merits and limitations of text-based generative AI tools, while their adaptive reaction is how they act given their new knowledge around these tools.

Implications for teachers and educators

One of the implications of the proposed pedagogical approach is that it demands the availability of infrastructure for students to effectively use text-based generative AI tools to help with academic writing. At the most fundamental level, students should have access to a platform where they can interact with text-based generative AI tools. Since many of these tools are freely available, this may be considered the most readily attained infrastructure. More challenging is the mental infrastructure, which is teachers' and students' attitudes towards text-based generative AI. The proposed framework implies teachers should permit the use of text-based generative AI tools, insofar as a guideline is available for students and teachers and that interactions with the tools are recorded for academic integrity purposes. Indeed, students are concerned about the lack of clear institutional policies on text-based generative AI (Chan & Hu, 2023). The framework proposed in this paper could serve as a foundation for educators and institutions to establish guidelines and best practices around text-based generative AI.

Another implication is that the framework suggests the need for teacher and student development so they may respond to the revolution that text-based generative AI tools bring to writing and education as a whole. Teacher development programmes are potentially required so they can guide students in the proper use of text-based generative AI tools on the one hand and engage students individually and collaboratively as inquirers and critical thinkers on the other hand. While there have been calls and efforts to ban these tools in schools (Kasneci et al., 2023; Tlili et al., 2023), we believe it is more realistic and constructive to educate students in the effective and proper usage of these tools. Indeed, before AI, let alone generative AI, began having widespread impact on education and the larger society, Schmid et al. (2009) have indicated the need to transcend a simple binary option of permitting or forbidding a piece of technology in education, but to explore and study how the technology may enhance (or impede) learning and how it can be incorporated into existing pedagogical designs. This is pivotal to students' ability to use text-based generative AI tools, as we believe the skills to effectively interact with these tools should be promoted to and popularised in the coming generations, who will highly likely live in the age of AI, and that everyone needs these skills to participate in the future society. The proposed pedagogical framework leverages a learning task that all students have to undertake over their study, namely academic writing, to promote students' critical thinking and self-regulation while using text-based generative AI tools. Despite an emphasis on academic writing, the framework can be generalised to other learning tasks that may involve other forms of generative AI. We believe that the self-regulation and critical thinking skills promoted by the proposed pedagogical design can even be applied when students engage with AI in general in the future.

The proposed pedagogical design also establishes a theoretical foundation for developing instruments to evaluate students' usage of and attitudes towards text-based generative AI tools, as well as their critical thinking, self-regulation, and writing process when interacting with these tools. The reflective portfolio that students compose as part of SRL may serve as a qualitative instrument and be analysed longitudinally to study the change in students' writing process and their understanding and use of text-based generative AI tools in academic writing (Wong & Trollope-Kumar, 2014). Similarly, researchers could also analyse how and why students modify the prompts they provide to text-based generative AI tools, in order to investigate how our pedagogical design may help develop their self-regulation and critical thinking. Quantitative questionnaires may be used to gauge students' critical thinking and self-regulation skills not just in academic writing with the help of text-based generative AI tools but also in everyday scenarios. Similarly, surveys could be used to assess students' perception of their ability to adopt the 6-P approach as recent research has suggested students are troubled by issues pertaining to academic integrity when using text-based generative AI tools (Chan & Hu, 2023). Validating these instruments may require educational interventions such as providing courses. However, given the student-centred nature of the 6-P approach, it may also be possible to provide a platform for students to use text-based generative AI tools for academic writing and compare their critical thinking, self-regulation, and writing process as they interact with these tools over a period.

Lastly, we acknowledge the challenges for educators to guide students and for students to self-regulate their behaviours when using text-based generative AI tools. This, however, underscores the necessity of students' and teachers' literacy in generative AI, including text-based ones and other forms of generative AI such as text-to-image and text-to-sound. Generative AI literacy, which could be considered part of AI literacy (Kong et al., 2021), encompasses the knowledge of the principles and limitations of generative AI, the skills to interact with generative AI tools effectively and ethically, and the mindset required to do so. Importantly, students and teachers need to understand the generative nature of generative AI tools, meaning there is no inherent truth or falsehood in the content these tools create, and the users have to decide whether and how to leverage the generated content. Two contrasting examples are a student writing a novel and another preparing for academic writing. While the former may exploit generative AI to obtain ideas and could be more permissive with fabricated content, the latter has to validate the content and ensure its accuracy and relevance. Generative AI literacy is especially pertinent to students' unethical use of text-based generative AI tools which includes but is not limited to plagiarism, as it is likely inevitable that students will engage in some form of behaviour unanticipated or unaddressed under the proposed pedagogical framework. While there have been a number of tools developed to detect AI-generated content (Elkhatat et al., 2023) and some successes in differentiating that from human-generated content (Desaire et al., 2023; Li et al., 2023), it remains challenging to consistently accurately perform this differentiation (Casal & Kessler, 2023; Gao et al., 2023; Perkins, 2023). To mitigate this issue, researchers have proposed the adoption or revival of in-person assessment formats alternative to academic writing (Stahl & Eke, 2024), such as oral examination and proctored written test. In addition to these suggestions, we argue generative AI literacy may be a valuable solution that encourages and motivates students to be effective and ethical generative AI users (Kohnke et al., 2023).

Conclusion and future work

We are living in a society where the capabilities and influence of AI continues expanding, and where new, more powerful AI models arise at a daily basis. The emergence and popularity of text-based generative AI tools has transformed the education landscape. It is necessary to prepare both students and teachers for the ever-advancing impact of generative AI, and to equip students with the skills and mindset to properly use text-based generative AI tools. Critical thinking is integral when interacting with text-based generative AI, as students must be able to evaluate AI-generated content and judge their accuracy. Since generative AI technology continues to develop, students need self-regulation to self-improve their ability to write with the help of text-based generative AI. Importantly, self-regulation goes beyond school education and extends into students' everyday lives, so they can keep abreast in the age of AI and be ahead of the influence of AI. The proposed pedagogical framework follows the model of SRL (Zimmerman, 2002), and centres students in the writing process so they direct the process, with text-based generative AI merely applied as helping tools. The framework allows students to develop self-regulation and critical thinking when using text-based generative AI tools for academic writing. The first phase of our pedagogical design, planning, corresponds to the forethought stage in SRL, where students draw on their own and others' previous experience to plan the content and structure of the writing. The second to fifth phases (prompt; preview; produce; and peer review) constitute the performance stage in SRL, which focuses on students' enactment of their plan and the monitoring of their writing and accompanying learning process. The sixth and last phase of our pedagogical design, portfolio-tracking, matches the self-reflection stage in SRL. This is where students reflect on and assess their performance, and formulate strategies to improve their ability to use text-based generative AI tools during future engagements with these tools.

We acknowledge that a limitation of this paper is the lack of empirical evidence as the proposed pedagogical framework has yet to be validated in a real-world setting. Thus, a university in Hong Kong has already adopted this framework as part of the General Education component for all their undergraduates. Students are encouraged to use text-based generative AI tools to help with academic writing and to follow the 6-P approach. At the end of their study, students will compose a self-reflective portfolio on their university experience, including how the 6-P approach helped them effectively and properly engage with text-based generative AI tools.

Furthermore, as discussed in the Implications for Teachers and Educators section, evaluation instruments are required to assess students' change in their self-regulation, critical thinking, and writing process after following the 6-P approach. It is also necessary to bolster students' and teachers' literacy in generative AI, ensuring that they can use generative AI tools in an effective manner and with an appropriate attitude. We believe education interventions are potentially needed so both educator and students can be prepared for a future where generative AI plays an ever more central role.

Abbreviations
AI: Artificial intelligence; LLM: Large language model; RNN: Recurrent neural network; SRL: Self-regulated learning.

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Authors' contributions
The authors are responsible for the whole manuscript.

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