WIP: *Engineering Class Students' Epistemic Cognition When Interacting With Generative AI*

Rosanna Yuen-Yan Chan
Dept. of Information Engineering
The Chinese University of Hong Kong
Shatin, N.T., Hong Kong SAR
yychan@ie.cuhk.edu.hk

Cecilia Ka Yuk Chan
Teaching and Learning Innovation Centre
The University of Hong Kong
Pokfulam, H.K., Hong Kong SAR
ckchan@hku.hk

Morris Siu-Yung Jong
Dept. of Curriculum and Instruction
The Chinese University of Hong Kong
Shatin, N.T., Hong Kong SAR
mjong@cuhk.edu.hk

Zihao Hu
Department of Information Engineering
The Chinese University of Hong Kong
Shatin, N.T., Hong Kong, China
hz021@ie.cuhk.edu.hk

Yuming Zhang
Department of Information Engineering
The Chinese University of Hong Kong
Shatin, N.T., Hong Kong, China
zy219@ie.cuhk.edu.hk

***Abstract*—This work in progress belongs to the innovative practice category. Nowadays, generative AI (also known as GenAI) can produce novel data samples that closely resemble authentic datasets. The advent of large language models (LLMs), in particular, has caused a huge interest in utilizing GenAI within and beyond the realm of higher education. However, little about engineering students' views and behaviours related to knowing and knowledge when using GenAI, such as ChatGPT, is known. In this WIP, we have engaged a class of N = 37 engineering students taking a postgraduate course titled "Social Media Analytics". They were required to write essays related to their course learning in the form of blog posts. They were required to use LLM tools, such as ChatGPT, to assist their writing processes. Their GenAI usage was guided by the cognitive-agent approach, Search Tree, Analyze and Repair, and Selection (STARS), while STARS was proposed by Kirk *et al.* in AAAI 2024 to extend and complement prompt engineering. In addition, the participants were invited to fill in the Epistemic Cognition Inventory (ECI) questionnaire to associate five aspects of epistemic cognition (EC) with their writing experience. It is confirmed in our results that students' EC, i.e., their beliefs related to knowledge and knowing, significantly predict their prompting engagement and academic performance. However, students' academic performance is found to be significantly and negatively associated with their preference for GenAI usage. Here, we have uncovered engineering students' EC when interacting with generative AI, an area where little has been known so far. Our findings also suggest that proper use of GenAI prompting might promote engineering students' EC and, therefore, engineering learning.**

I. Introduction

Generative AI (GenAI) and large language models (LLM), in particular, have attracted wide attention in higher education, including engineering education [1]. It has brought disruptive changes in all aspects of engineering teaching and learning. GenAI was received with both excitement and conservation. Besides, a number of novel pedagogies have been explored for using GenAI as a tool to enhance engineering students' learning (e.g., [2], [3]) especially on non-technical skills [4]. However, research on students' epistemic beliefs in GenAI, especially within educational contexts, is still developing.

GenAI refers to advanced artificial intelligence systems capable of creating new content, such as text, images, and music, that mimics human-like creativity. The launch of ChatGPT by OpenAI in November 2022 has caught wide attention and diverse reactions across higher education institutions regarding its impact on students' learning. GenAI powerfully produces new texts (and program codes) content based on pre-trained transformer architecture and machine learning algorithms. Meanwhile, most engineering undergraduate students experience a lack of confidence in writing and, in general, dislike writing assignments [4]. the availability of GenAI may be tempting for students to use its tools to replace their creativity.

A. Motivation and Related Works

The engineering education community is urged to investigate students' beliefs and behaviours associated with GenAI usage and how GenAI can be constructively applied to promote engineering learning. Here we are motivated to investigate students' EC when they are interacting with GenAI during course assignment completion. EC refers to an individual's understanding and awareness of knowledge and knowing [5].

A few existing works shed light on engineering students' perspectives about adopting GenAI into their studies. For example, students recognised that GenAI has the potential to improve their academic performance and enhance their understanding [6]. Another study shows that ChatGPT usage in computer programming lessons promotes students' programming self-efficacy and learning motivation [7]. Besides, a survey was performed on computer engineering undergraduates taking an embedded systems course. Results show that the students were impressed and optimistic about ChatGPT. However, researchers also admitted that the role of human knowledge in GenAI interaction is not yet understood and called for more empirical research to understand students' beliefs behind their prompts and reactions to ChatGPT's responses [8].

In this WIP, we associate engineering students' EC and academic performance with their GenAI attitude and usage. We ask the following research questions:

- (RQ1) Are there any differences in engineering students' EC and academic performance based on their preference for GenAI usage?
- (RQ2) What can we know about the relation between engineering students' EC and their engagement with GenAI during writing assignment composition?
- (RQ3) How can engineering students constructively employ GenAI in their learning?

In order to ensure that our participating students responded according to their GenAI experience, they were asked to perform a writing assignment with the help of ChatGPT and were required to submit their prompt engineering logs.

II. Background

A. Epistemic Cognition and Social Epistemic Cognition

According to Kitchener, an individual is engaged in EC when he or she reflects on knowledge-related matters such as the limits of their knowledge as well as the certainty and criteria of knowing, while EC is a high-level cognition above metacognition (cognition about cognition or self-reflection) [9]. A higher cognition level can enclose that at a lower level. However, the reverse is not true. Chinn *et al.* further identified five dimensions under their EC framework [5], which include: (1) **epistemic aims** that concerns the aims an individual adopts when conducting epistemic cognitive processes. (2) **Structure of knowledge** which refers to an individual's ontological beliefs such as the forms and representation of knowledge. (3) **Justification, source, and epistemic stance** that concerns the epistemic attitudes of an individual when facing a piece of information. (4) **Epistemic virtues** corresponds to the intellectual virtues such as courage and carefulness that an individual can exhibit. (5) **Process and reliability** concerns activities such as data analyses and research inquiries that one may conduct to achieve the epistemic aims and the process reliability.

B. Search Tree, Analyze and Repair, and Selection (STARS)

STARS is a cognitive-agent approach for prompt engineering with large language models (LLMs) that includes the search tree (ST), analyze and repair (AR), and selection (S) components [10]. It addresses the limitations of LLMs and enables a user to acquire situation-specific knowledge that aligns with his or her language abilities, environment, and preferences. In particular, the **search tree** generates a large space of responses from the LLM or GenAI. In the **analyze and repair** step, the user is promoted to analyze and evaluate each of the returned responses for potential issues such as ungrounded references. The user is also encouraged to try repairing problematic responses by purposefully re-prompting the LLM. Finally, the user can query the LLM structurally for a preferred response and *select* the final contents.

III. Methods

The overall method in this study is summarised in Figure 1. Further details are provided below.

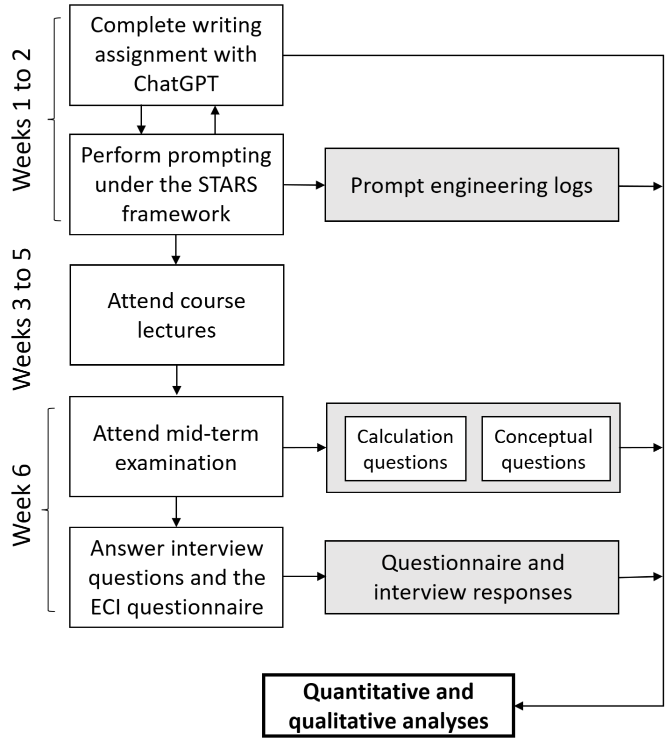

Fig. 1. Research method in this study.

A. Participants

Participants in this study were 37 postgraduate students taking an engineering course titled *Social Media Analytics* offered in Spring 2024.

B. Context

The course gives an overview of social media and online social networks and studies how different tools in information science can be used to analyze social media content. This course also involves both calculation and conceptual knowledge related to social media analysis.

C. Design and Measures

The study is done by a one-way design with one between-subject factor (GenAI usage preference in the writing assignment) as the independent variable. The ECI questionnaire [11], which contained 32 six-point Likert-scale response items grouped under five categories, was used to probe into participants' epistemic beliefs. Due to space limitations, readers can refer to (p.3293) for the contents of individual questionnaire items. The students participated in a mid-term examination, which yielded objective data measuring their academic performance in terms of calculation and conceptual questions, respectively. Students' prompt engineering logs were analysed and coded (STARS prompting). Students' preference of whether they would use GenAI to complete the writing assignment if the course teacher does not require it (GenAI Preference), and their qualitative feedback about the ChatGPT usage experience were also collected.

D. Task and Procedures

The main task performed by the participants was to complete an essay writing assignment with the help of ChatGPT and perform prompting according to the STARS prompt engineering framework. The writing task aimed to engage participants in using ChatGPT along with STARS prompting. While the topic of the essay is related to the course content. Specifically, participants were required to undergo prompting by following the *search tree*, *analyze and repair*, and *selection* procedures specified by the STARS framework. To ensure that ChatGPT had been used during the activity, the participants must submit the prompt engineering logs for verification. The summary of activities involved in our study is provided in Figure 1. The blocks on the left-hand side are activities taken by the participating students, while those on the right-hand side are empirical data output from each step. These data were collected and processed for further statistical analyses.

IV. RESULTS

A. Descriptive Statistics

Descriptive statistics, as well as the reliability analysis and confirmatory factor analysis (CFA), of our questionnaire responses are given in Table 1.

TABLE I
DESCRIPTIVE STATISTICS, CRONBACH'S ALPHA VALUES, AND FACTOR LOADINGS FOR THE EC SCALES.

Scale	**Mean (SD)**	**Factor loading**	**Cronbach's** α
Epistemic Aims (6 items)	5.03 (0.99)	.83	.92
Structure of Knowledge (6 items)	5.18 (0.73)	.83	.83
Justification (7 items)	4.90 (0.86)	.77	.83
Epistemic Virtues (7 items)	5.05 (0.92)	.70	.92
Processes and Reliability (6 items)	5.01 (0.73)	.59	.72

Overall Cronbach's α = .96. CFA indexes: χ^2/df = 1.363, CFI = .986, RMR = .024, SRMR = .035.

B. Analysis of Variance (ANOVA)

ANOVA was performed on the participants' academic performance scores, STARS prompting scores, their ECI questionnaire responses, and their binary yes-no response to GenAI usage preference (GenAI Preference). Significant main effects for the between-subject factor (prefer to use vs. not prefer to use GenAI in the writing assignment) were obtained in the academic performance score (calculation questions) and also EC associated with reliability and processes (item 28). In particular, those who preferred not to use GenAI performed significantly better ($M = 11.67, SD = 0.56$) in the calculation-type question than those who preferred using GenAI ($M = 10.23, SD = 1.97$) and the difference is significant ($F(1, 36) = 4.55, p < .05$).

Besides, a significant main effect of GenAI usage preference on participants' responses to item 28 (*A knowledge source is credible if it has been reviewed by many people.*), $F(1, 36) = 8.28, p < .01$. In particular, those who preferred not using GenAI for writing assignments ($M = 4.79, SD = 1.07$) differed significantly from those who preferred using it ($M = 3.33, SD = 1.94$), $F(1, 36) = 4.40, p < .05$. As indicated by the STARS prompt assessment scores, no significant difference in the level of STARS prompting was found between the group who preferred ($M = 4.07, SD = 0.82$) and the group who not preferred ($M = 4.11, SD = 0.65$) using GenAI ($F(1, 36) = 0.02, p > .05$).

TABLE II
DESCRIPTIVE STATISTICS ACROSS PARTICIPANTS' PREFERENCE OF GENAI USAGE AND ANOVA RESULTS

Scale (Group)	**n**	**Mean (SD)**	***F-value***	***p-value***
Academic Performance				
Calculation Questions (Yes)	28	10.23 (1.97)	4.55	.040
Calculation Questions (No)	9	11.67 (0.56)		
Conceptual Questions (Yes)	28	14.18 (4.09)	3.02	.091
Conceptual Questions (No)	9	16.61 (1.45)		
GenAI Interaction				
STARS prompting (Yes)	28	4.07 (0.82)	0.02	.900
STARS prompting (No)	9	4.11 (0.65)		
EC				
Process & Reliability (Yes)	28	3.33 (1.94)	8.28	.007
Process & Reliability (No)	9	4.79 (1.07)		

Remarks. N = 37. 'Yes' group participants opt to use GenAI even if it is not required.

C. Structure Equation Modelling and Mediation Analysis

We constructed a structural equation model (SEM) to examine the relationships between various variables in our study (Figure 2 on the next page). The model fit evaluation revealed a good fit to the data, as indicated by the chi-square test ($\chi^2/df = 1.054$), Comparative Fit Index (CFI = 0.982), Incremental Fit Index (IFI = .984), Tucker-Lewis Index (TLI = 0.973), Root Mean Square Error of Approximation (RMSEA = 0.039), and Standardized Root Mean Square Residual (SRMR = 0.079). All of the five EC components have positive and significant factor loading. It is shown that EC has a significant positive effect on STARS prompting ($\beta = .45, p < .05$) and also academic performance ($\beta = .49, p < .05$). Besides, academic performance has a significant negative effect on the preference for GenAI usage in the assignments ($\beta = -.54, p < .05$). While other relations were not significant.

We performed various mediation tests to study any mediation effects between variables. Our results showed a significant mediation effect of STARS prompting on the calculation questions (Q1) performance through EC (Goodman's z = 1.98, $p < 0.05$). This indicates that EC partially explains the effect of STARS prompting on students' calculation questions performance. No other mediation effects were found.

D. Students' Feedback

Students who preferred to use GenAI in the writing assignment affirmed that GenAI is useful to their writing for diverse

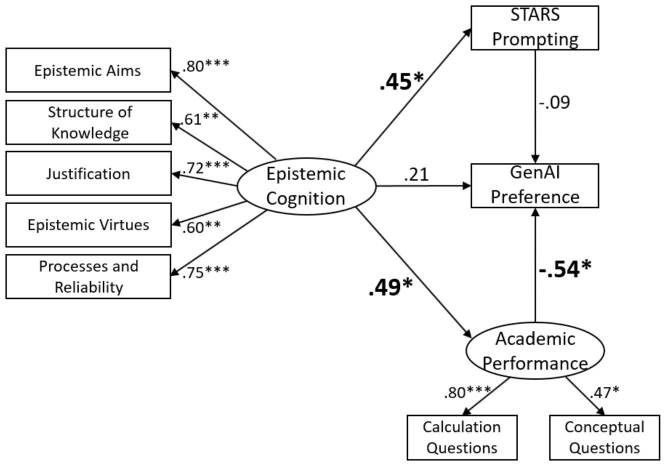

Fig. 2. Structure equation model (SEM) analysis on EC, GenAI usage, and academic performance. Model fit indexes: χ^2/df = 1.054, CFI = 0,982, IFI = 0.984, TLI = 0.973, RMSEA = 0.039, SRMR = 0.079.

reasons. They said:

> *Using ChatGPT can help me to gather information. With the help of ChatGPT, I can generate better content than what I wrote. So I can have more confidence.* (Student A)

> *ChatGPT can help me construct an initial structure and potential answer in a very short period of time.* (Student B)

> *With the help of LLMs, it is much more efficient to find the information I need. Those outputs can serve as references for me to write a more comprehensive essay and express my own thoughts.* (Student C)

A few who preferred not to use GenAI in the writing assignment gave their own views and sentiments on writing without GenAI. They said:

> *When I write, I want to influence others or create an image of my personal identity. I always think about "How to become different".* (Student D)

> *I want to make sure that the content I write is consistent with what I really think of, rather than using LLM to generate something that cannot express my ideas well. If I write all the content by myself, I can feel a sense of confidence building and a sense of credibility.* (Student E)

V. Discussion

A. EC and Academic Performance by GenAI Preference

To answer RQ1, the results of the ANOVA analysis provided significant evidence of differences between students' views on processes and reliability, and calculation questions when grouped by their preference of GenAI usage. For processes and reliability, a statistically significant difference was observed between the 'Yes' and 'No' groups (F(1, 36) = 8.28, $p < 0.01$). Specifically, participants in the 'No' group exhibited higher mean scores on processes and reliability compared to those in the 'Yes' group. A significant difference was also observed in the performance of calculation questions (F(1, 36) = 4.55, $p < 0.05$). These findings show that those who prefer not to use GenAI are high achievers in calculation and have a more sophisticated view of processes and reliability.

B. Students' EC, GenAI Usage, and Academic Performance

To answer RQ2, our SEM revealed a few significant regression weights within the model. Specifically, a significant positive regression weight was found from EC to STARS prompting (β = .45, $p < 0.05$), indicating a direct influence of students' EC on the interaction with GenAI under the STARS prompting framework. Additionally, a significant positive regression weight was observed from EC to academic performance (β = .35, $p < 0.05$), confirming that EC has a direct impact on students' academic performance in the current study. Furthermore, a significant negative regression weight was found from academic performance to GenAI preference (β = -.54, $p < 0.05$), indicating that academic performance plays a crucial role in shaping students' GenAI usage preference.

C. GenAI and Students' Learning

The findings from students' feedback, together with our statistical analyses, provide insights for answering RQ3. Students expressed that they could use ChatGPT to gather information, generate initial content, efficiently structure their work, and utilize the outputs as references to enhance their own writing. However, there were negative views on ChatGPT usage, such as the lack of personality and sense of credibility, that hindered students' ChatGPT adoption. Besides, SEM results show a strongly negative direct effect of academic performance on GenAI usage preference, indicating that high-performing students were more reluctant to use GenAI to do their assignments. Nevertheless, a significant positive direct effect of EC on STARS prompting was shown, while EC mediated the effect of STARS on academic performance, too. EC is about how individuals perceive, interpret, or make sense of information [5], which in turn influences their attitudes, behaviours, or outcomes related to GenAI prompting. Perhaps engineering educators should let (high-performing) students know about the positive relationship between EC and STARS and encourage the students to perform STARS prompting along with their GenAI usage.

VI. Conclusion

In this WIP, we studied the relationship between engineering students' EC and their interaction with GenAI under the STARS prompting framework. The statistical indexes show that our questionnaire items have high reliability and validity. We have found a number of significant statistical relations in EC, GenAI interaction, and students' academic performance. Students' qualitative feedback regarding using or not using GenAI for writing assignments was also obtained. Our findings can shed light on the constructive usage of GenAI in engineering teaching and learning, in particular, in promoting students' EC through guided prompting such as the STARS.

References

[1] C. K. Y. Chan and T. Colloton, *Generative AI in Higher Education: The ChatGPT Effect*, 1st ed. Routledge, 2024.

[2] K. Yelamarthi, R. Dandu, M. Rao, V. P. Yanambaka, and S. Mahajan, "Exploring the potential of generative ai in shaping engineering education: Opportunities and challenges," *Journal of Engineering Education Transformations*, vol. 37, January 2024.

[3] J. Qadir, "Engineering education in the era of chatgpt: Promise and pitfalls of generative ai for education," in *2023 IEEE Global Engineering Education Conference (EDUCON)*, 2023, pp. 1–9.

[4] B. E. Seabrook, "Using generative ai as an active learning tool to refine professional engineering skills," in *2024 ASEE Southeastern Section Conference*, Marth 2024, pp. 10.18 260/1–2–45 579.

[5] C. A. Chinn, L. A. Buckland, and A. Samarapungavan, "Expanding the dimensions of epistemic cognition: Arguments from philosophy and psychology," *Educational Psychologist*, vol. 46, no. 3, pp. 141–167, 2011.

[6] M. Bernabei, S. Colabianchi, A. Falegnami, and F. Costantino, "Students' use of large language models in engineering education: A case study on technology acceptance, perceptions, efficacy, and detection chances," *Computers and Education: Artificial Intelligence*, vol. 5, p. 100172, 2023.

[7] Y. Ramazan and F. G. K. Yilmaz, "The effect of generative artificial intelligence (ai)-based tool use on students' computational thinking skills, programming self-efficacy and motivation," *Computers and Education: Artificial Intelligence*, vol. 4, p. 100147, 2023.

[8] A. Shoufan, "Exploring students' perceptions of chatgpt: Thematic analysis and follow-up survey," *IEEE Access*, vol. 11, pp. 38 805–38 818, 2023.

[9] K. S. Kitchener, "Cognition, metacognition, and epistemic cognition," *Human Development*, vol. 26, no. 4, pp. 222–232, 1983.

[10] J. R. Kirk, R. E. Wray, P. Lindes, and J. E. Laird, "Improving knowledge extraction from llms for task learning through agent analysis," in *Proceedings of the 38th Annual AAAI Conference on Artificial Intelligence (AAAI 2024)*, Vancouver, Canada, February 2024, pp. 20–27.

[11] R. Y.-Y. Chan, S. Li, and D. Hui, "Social epistemic cognition in online interactions," in *CHI '14: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, April 2014, pp. 3289–3298.