K–12 Pre-service Teachers' Perspectives on AI Models and Computational Thinking: The Insights from an Interpretative Research Inquiry

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ABSTRACT

Computational thinking (CT) has emerged as a pivotal component of K–12 education for fostering problem-solving skills among the next generation of learners. However, CT integration remains an arduous challenge for K–12 teachers due to their limited preparation, prior knowledge, and relevant expertise in CT. To respond to this challenge in Hong Kong, we designed and implemented an introductory CT course employing plugged and unplugged CT approaches alongside AI technology to prepare pre-service teachers. To inform the design of our future course iterations, we conducted an interpretative research inquiry within the course to explore how these teacher trainees learn CT through different teaching and learning activities. Our data analysis accentuated the emergence of three core themes, encompassing numerous subthemes within our data. The three core themes are delineated as themes of (1) CT Knowledge, (2) CT Perspectives, and (3) Potential Barriers. This paper disseminates part of our findings on the trainees' CT Perspectives *only*: It delves into their post-course perspectives on AI models and CT, seeking to elucidate the pedagogical implications of integrating AI models and CT into K–12 education. These perspectives provide new insights into teaching and learning CT through prompt engineering, which could emerge as a novel approach to democratizing CT education and could be the conduit to bridge the divide between CT and general education.

KEYWORDS

AI models, computational thinking, K–12 education, pre-service teachers, perspectives

1. INTRODUCTION

The cultivation of computational thinking (CT) in K–12 education has been consistently emphasized, yet it remains a formidable challenge, primarily attributed to the limited knowledge, training, and preparedness of teachers in designing and implementing appropriate teaching and learning (T&L) activities within their specific K–12 contexts (Kong et al., 2020; Ung et al., 2022). Concurrently, with AI technology becoming ubiquitous, a growing corpus of research focuses on integrating AI with traditional CT tools. These studies typically aim to acquaint K–12 students with AI and its sub-domains via leveraging CT tools such as autonomous and programmable educational robotics, block-based programming, and specifically designed games (e.g., Park & Shin, 2022; Priya et al., 2022). Regardless, a research gap persists in exploring such integrations from a teacher's perspective, owing to its nascent nature, particularly in the context of T&L of CT.

The rapid proliferation of AI models (e.g., large-scale pre-trained and large language models) is being extensively debated in higher education settings (Michel-Villarreal et al., 2023; Xia & Li, 2022; Yilmaz & Karaoglan Yilmaz, 2023). However, these models' full potential and implications remain predominantly unexplored within K–12 education and teacher education. The study under consideration, therefore, endeavored to contribute to bridging this burgeoning research gap. It explored how CT T&L activities, employing both plugged (i.e., with computers, programming, or digital) and unplugged (i.e., without computers, programming, or non-digital) approaches alongside AI technology, influenced pre-service teacher trainees' perspectives on applying AI models for their prospective T&L to cultivating CT in K–12 education.

2. METHODS

2.1. Research Participants & Context

The research inquiry was conducted in a unique introductory CT course at the undergraduate level at a prominent university in Hong Kong. This course was a free elective for undergraduate students across the participating institution who aspired to become K–12 teachers. The course cohort comprised twenty-eight students, including twenty-five pre-service teachers and three part-time in-service teachers. The in-service teachers did not participate in the research. Altogether, fifteen (n=15) pre-service teachers participated in the inquiry; the sampling criteria are described in the next section. The pre-service teachers, who were undergraduate students, came from several faculties and departments within the institution. As a result, the cohort showcased a significant diversity in terms of educational backgrounds and disciplinary expertise, including applied artificial intelligence, computer science, mechanical engineering, information management, quantitative finance, economics, chemistry, biological sciences, molecular biology, biotechnology, education, social sciences, and education psychology.

The course was designed and implemented with T&L activities to facilitate CT knowledge construction, which was identified based on the past foundation of research. Firstly, this encompassed the theoretical and conceptual aspects of CT (Kong et al., 2020; Rich et al., 2021; Shute et al., 2017), with learning content including introductions to CT practices (e.g., decomposition, pattern recognition, abstraction, algorithm design, debugging), formal logic, technology integration, the history of computing and algorithms, and pedagogical approaches such scaffolding, active learning, and constructionism. The trainees were engaged through various passive and active T&L activities, such as lectures, individual Q&A sessions, group discussions, and interactive demonstrations.

Secondly, the course entailed T&L activities purposefully addressing the technical and applied aspects of CT (Angeli, 2022; Tedre et al., 2021; Ung et al., 2022), with learning content including CT concepts and constructs (e.g., initialization, functions, variables, conditionals, iteration, and arrays), learning of these concepts and constructs using unplugged platforms such as LEGO patterns, and applications of these concepts and constructs with plugged platforms using block-based programming languages (e.g., *Blockly* and *Snap!*). The trainees utilized *Blockly* to program Micro-Bits to develop peripheral devices and DIY (Do-It-Yourself) projects. More importantly, they designed and interacted with rudimentary chatbots leveraging AI models (e.g., ChatGPT, GPT-3, Cohere, DALLE-2, and Stable Diffusion) using Snap! (see Figure 1).

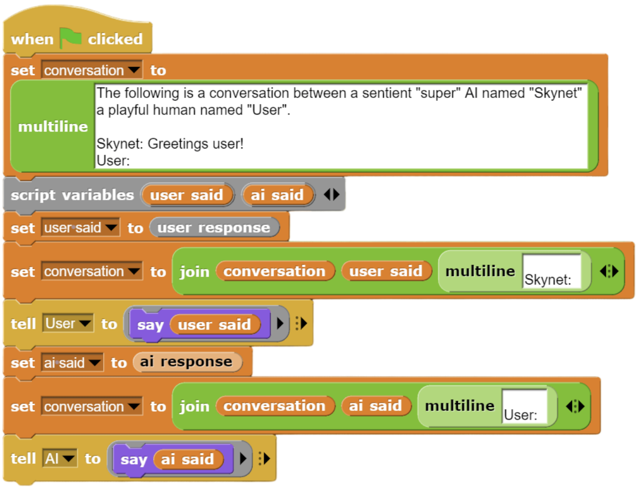

Figure 1. A Rudimentary AI Chatbot Powered by GPT-3 Model and Developed Using *Snap!*

Lastly, the course engaged the trainees in collaboratively developing learning designs for their preferred K–12 context: kindergarten, primary, or secondary (Tucker-Raymond et al., 2021). This involved designing intended learning outcomes based on the revised Bloom's Taxonomy (Krathwohl, 2002) and developing age-appropriate T&L activities with the CT tools they had previously practiced.

2.2. Data Collection & Analysis

We conducted an interpretative research inquiry exploring the pre-service teacher trainees' learning experiences of CT during the course (Merriam & Tisdell, 2015b). The trainees were sampled purposively with the following criteria: (i) Undergraduate students who aspire to be K–12 teachers, (ii) have no formal teaching experience, (iii) participated in all the T&L activities, (iv) completed all their weekly reflections, and (v) consented to participate in the study. Fifteen trainees met the criteria and were engaged in the data collection. We used multiple qualitative data sources for triangulation and generating a *think* description (see Figure 2). This included (a) Participant Observations (e.g., field notes, photographs, video records, and learning artifacts), (b) Participant Reflections (e.g., reflections, personal insights, and comments), and (c) Participant Interviews (e.g., response to semi-structured interview questions). Concurrently, we engaged in the inductive content analysis following a two-phase iterative coding process (Merriam & Tisdell, 2015a). During this, two coders worked independently and reported an inter-coder agreement greater than 89% afterward. The data analysis accentuated the emergence of three core themes, encompassing numerous subthemes within our data. The three core themes are delineated as themes of (1) CT Knowledge, (2) CT Perspectives, and (3) Potential Barriers (see Figure 2). Nevertheless, this paper disseminates part of our findings on the trainees' CT Perspectives *only*: It delves into their post-course perspectives on AI models and CT, seeking to elucidate the pedagogical implications of integrating AI models and CT into K–12 education, respectively.

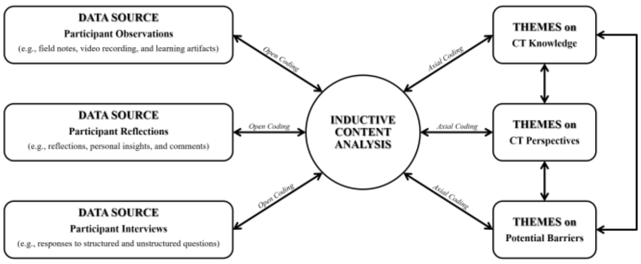

Figure 2. Iterative Process of Data Collection & Analysis.

3. FINDINGS

This section presents part of our findings on the pre-service teacher trainees' CT Perspectives. The inductive content analysis revealed that only *ten* of the fifteen participating trainees extensively evidenced meaningful perspectives on AI models and CT; Table 1 provides these trainees' background information. Subsequently, four major themes emerged within their perspectives based on the axial coding (Merriam & Tisdell, 2015a): (i) Embrace AI Models to Enhance T&L; (ii) Perceive AI Models as Computational Thinkers; (iii) Employ CT for Effective Prompting of AI Models; (iv) Recognize the Challenges of Adopting AI Models. These themes are discussed along with the qualitative evidence seriatim.

Table 1. Background Information of the Trainees.

Name	Gender	Major	Study Year
Bennett	Male	BEng in Mechanical Engineering	Year 3
Beckett	Male	BSc in Information Management	Year 4 (Final Year)
Blaine	Male	BSc in Chemistry and BEd	Year 4 (Final Year)
Carter	Male	BSc in Quantitative Finance	Year 2
Nolan	Male	BEng in Computer Science	Year 2
Jasper	Male	BASc in Applied AI	Year 2
Ethan	Male	BEng in Computer Science	Year 2
Orion	Female	BEng in Computer Science	Year 2
Graham	Male	BSc in Biological Sciences	Year 1
Mateo	Male	BSocSc in Education Psychology and BEd	Year 5 (Final Year)

3.1. Embrace AI Models to Enhance T&L

Firstly, the trainees generally perceived AI models to have the capacity to enhance the T&L experience of K–12 students and beyond. These models can facilitate idea generation, provide students with new insights, and enable them to solve problems independently (Bywater et al., 2019; Holstein & Aleven, 2022; Kim et al., 2022). They can catalyze creativity, nudging students towards curiosity and inspiring them to think outside the box. For instance, Mr. Bennett, a Bachelor of Engineering (BEng) in mechanical engineering student, remarked,

These days, students are born into an AI generation. They're surrounded by AI, and it's [an] essential and very useful tool for them to tackle problems in the world for their future. So as a teacher, we must use [or] apply AI in our education, in our teaching. The role is vital. For example, we have to teach our students to get used to AI chat systems and AI language models. These are very useful tools for generating ideas in education.

Similarly, Mr. Beckett, a student of a Bachelor of Science (BSc) in information management, said,

Talking about AI, I think it can certainly help people do things, learn things, or manage things. Integrating these tools into education seems like a great opportunity. Education is about teaching, and AI tools also serve a similar purpose—to help someone find the right way.

Another trainee, Mr. Blaine, studying BSc in chemistry and Bachelor of Education (BEd), expressed,

Well, in my learning, it's a good way that I can learn with AI supplementing me with some very insightful ideas, perhaps some of the insights such as commonly mentioned [insights] or common sense that AI provides me. And also, it may give ideas that I've already thought of. But yes, I don't know why they always bring me some new insights.

3.2. Perceive AI Models as Computational Thinkers

Secondly, some trainees perceived AI models as capable of employing CT when tackling complex problems. These models can systematically approach an overarching, complex problem by breaking it down into smaller, more manageable parts (Kojima et al., 2023; Wei et al., 2022). Thus, they can give an impression of employing CT practices, notably decomposition and abstraction. They can simplify and analyze intricate problems methodically, akin to human reasoning (Huang & Chang, 2023; Qiao et al., 2023). For instance, Mr. Carter, pursuing a Bachelor of Science (BSc) in quantitative finance, observed,

Like you ask ChatGPT, "I have this math problem, how do I solve it?" It's going to break that problem up for you in an easier manner and try to make you understand it. So, it's also using its own sort of CT mindset, you could say, in order to solve the problem that you give it.

Mr. Nolan, a BEng in computer science student, noted, "But if you're talking specifically about AI models, since they're programmed and they are running on CT themselves, in a sense…"

3.3. Employ CT for Effective Prompting of AI Models

Thirdly, the trainees overwhelmingly perceived CT as critical for effectively prompting AI models, which entails instructing and interacting with the models (Arora et al., 2022; X. Liu et al., 2023). They recognized that strategic formulation of prompts (i.e., prompt engineering) could drastically improve the quality of AI-generated outputs. This can lead to more accurate and contextually relevant outputs, mirroring sophisticated, human-like interactions (Clavié et al., 2023; Y. Liu et al., 2023; White et al., 2023). Moreover, they stated that CT can give users an intuitive understanding of AI models, at least at a rudimentary level, helping them heuristically leverage the underlying mechanisms that drive the models' behavior and adaptability. For instance, Mr. Jasper, a student of Bachelor of Arts and Sciences (BASc) in applied AI, stated,

With the invention of ChatGPT and Bing AI, when you run into a problem, if you ask it a question like a human, you're not going to get the best possible answer… But if you're a programmer and you know that this is how it [AI] works, it looks at these words, it makes this connection… You probably will be able to give it a much better prompt and get a much better response. So, I think today, especially, it's more important for everyone in this field to learn CT.

Mr. Ethan, a trainee pursuing a BEng in computer science, suggested, "I think the concept of prompt engineering is a very CT-based concept. You design things in such a manner that the computer or the AI really understands it and does what you want."

Another trainee, Ms. Orion, doing a BEng in computer science, expressed,

I think that computational thinking is the base that is required for individuals to be able to use AI technology… I think prompt engineering is a lot about how to phrase what you say and how to understand the design behind the AI and to understand that it is AI at the end; it's not human. And, as a user, I need to know, like the programmer who designed that AI, "What thinking did they put into building that AI?" And by thinking that it's my CT, I did either knowingly or unknowingly.

Likewise, Mr. Graham, a BSc in biological sciences student, proffered,

In CT, we need to remove all noise. Similarly, when we talk to a chatbot, we need to remove all unnecessary information… I think the student with CT skills will have an advantage. Like, he understands better, at least like, how a computer processes answers, so he'll be able to refine his input better or refine them.

Mr. Mateo, studying a Bachelor of Social Sciences (BSocSc) in education psychology and BEd, remarked,

I think CT would empower students to make better use of AI or different types of chatbots. Like, because our AI is not as smart as a human being yet. When we expect the AI to provide a detailed answer, sometimes it makes mistakes or misunderstands our prompt. CT would help students understand why we should instruct the AI about our tasks in a certain way… How to decompose our task requirements, [and] abstract them, like how to communicate them to the

AI. We can explain our task requirements to the AI in different ways.

Mr. Bennett said,

I think one aspect is that we need to have CT to understand how AI works. And if we understand how AI works, we can control it and make use of it. For example, we need to know how ChatGPT processes information so we can ask accurate questions and guide the AI model to the correct outcome. Another example is that if we have an AI that generates drawings, we need to understand the algorithm behind it in order to generate a photo or a picture accurately.

Likewise, Mr. Beckett mentioned, "CT can help you to think more like a computer. So, when you have learned CT, you can understand what kind of information to extract from ChatGPT."

Mr. Nolan noted,

I think with CT, you're better able to understand AI models, any machine at that… You don't know how this model was created. You don't know whether you should be afraid of it. You don't know whether you should be fond of it. But I think CT gives you a very basic idea of what's happening behind the scenes.

3.4. Recognize the Challenges of Adopting AI Models

The trainees perceived various challenges when asked about adopting AI models for their current and future T&L. These challenges include (a) limited guidance and experience in integrating AI models within educational settings, (b) conflicting reasons among students when it comes to utilizing AI models, (c) difficulties in designing assessment tasks that ensure transparent and honest use of AI models, and (d) adverse effects on learning transactions in classroom settings. These challenges are evident from the following quotes:

(a) Mr. Bennett acknowledged,

These [AI models] are very useful tools for generating ideas in education. But how to apply AI in our education? Currently, I do not have a very clear concept or idea because I haven't had the chance to apply it.

(b) Mr. Carter expressed,

I would argue that people who are less adept at solving problems would rely more on AI models, or these AI bots, to solve their problems… On the other hand, you could argue that the smartest students, who want to save their time, would also utilize AI. So, I think it just goes both ways, and it's a discussion that could continue indefinitely.

(c) Mr. Blaine relayed,

In teaching parts, it gets more challenging. Because I have to design an assessment that AI can, I won't say cannot, but it is more difficult for AI to finish. Because, yeah, we have ChatGPT. We also have more and more of those language models. So, if I still continue with very simple questions that students can copy and paste.

(d) Mr. Graham noted,

In the past, before when students had a question, they might raise their hand. Or ask teachers or use Google search. But now, I think they're more likely to ask just AI… But when they ask AI, like the AI might not be able to see these problems and [might] provide an answer the student wasn't needing.

4. DISCUSSION

4.1. Latent Synergies Between AI Models and CT

The pre-service teacher trainees' perspectives on AI models and CT reveal latent synergies or interrelationships between the two. On one side, their perspectives recognized that AI models can seemingly deploy CT-like problem-solving when dealing with complex problems (Kojima et al., 2023; Wei et al., 2022; Yao et al., 2023). Conversely, they accentuated the importance of CT for human users to instruct and interact with AI models effectively. These latent synergies are no mere coincidence; it stands to reason that the AI models directly resulted from the CT employed by computer scientists—they are the outcome of CT—writ large (Celik, 2023; Lin et al., 2023; Yilmaz & Karaoglan Yilmaz, 2023). Likewise, since AI models (i.e., transformers) are trained on copious amounts of human data, they have acquired human-like reasoning and problem-solving abilities, such as CT (Huang & Chang, 2023; Qiao et al., 2023). However, one question remains: Why did the trainees recognize CT for effectively instructing and interacting with AI models, or what is the interrelationship between prompting and CT? This question has not been researched (to the best of our knowledge) from either an a priori or a posteriori standpoint. This highlights a research gap, but the question is, why is answering this question significant from a real-world point of view?

4.2. Prompting AI Models: A Novel Approach for Cultivating CT

The current trends in CT education, especially at the K–12 level, can be divided into plugged or unplugged T&L approaches. The plugged approaches include educational robotics, block-based and text-based programming, and digital gamification (e.g., Kong et al., 2020; Rich et al., 2021; Umutlu, 2021). The unplugged approaches include algorithm assembly and pattern recognition puzzles, board games based on CT concepts (e.g., functions, conditionals, iteration), and physical programming robots (e.g., Bell & Lodi, 2019; Delal & Oner, 2020; Ung et al., 2022). Regardless, the elephant in the room remains, as these approaches are arduous to integrate within formal T&L environments across different K–12 subject areas and contexts (Ali, 2021; Angeli & Giannakos, 2020; Lodi & Martini, 2021; Shute et al., 2017). Subsequently, the cultivation of CT has been traditionally relegated to specialized STEM-based lessons, projects, or competitions. So, one may argue that prompting or prompt engineering could emerge as a novel approach that potentially addresses this issue and revolutionizes CT education.

The crux of prompting lies in its fluid adaptability and its necessity to be taught across K–12. As AI models become ever more prevalent, it becomes crucial for both students and teachers to learn how to harness them effectively (Casal-

Otero et al., 2023; Chiu, 2023; Lozano & Carolina Blanco, 2023). Recognizing this, a promising opportunity exists to integrate CT into the formal curricula to teach prompting. This hinges on first investigating CT's role as a foundational skill for effective prompting. If rigorously evidenced, this could allow seamless integration of CT across computer-based and noncomputer-based subject areas, mainly thanks to increasingly affordable and ubiquitous access to AI models (ChatGPT, Bing AI, Stable Diffusion, etc.). This could democratize CT education and help overcome its dependence on expensive, specialized equipment. In this manner, CT and its practices could be cultivated regardless of a school's resources, becoming a proper egalitarian prerogative for all K–12 students and teachers.

In brief, prompt engineering's versatility as a novel approach could bridge the divide between CT and general education. It could foster a generation of learners trained to apply CT and its practices across diverse academic disciplines and real-world scenarios. Most importantly, it could prepare them to be AI-ready and excel in an increasingly digital and automated world.

5. CONCLUSION

The study reveals latent synergies between AI models and CT that beckon further exploration in future research. It highlights the potential of prompt engineering as a novel approach to cultivating CT in K–12 education and teacher education. The teacher trainees acknowledged the significance of CT in developing AI models and its necessity for effectively harnessing them. Nevertheless, future studies should pragmatically investigate this interplay, particularly the extent and roles of different CT practices during prompting and their implications across different prompt engineering techniques.

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