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# Modeling the structural relationships among Chinese secondary school students' computational thinking efficacy in learning AI, AI literacy, and approaches to learning AI

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## Abstract

K-12 artificial intelligence (AI) education requires cultivating students' computational thinking in the school curriculum so as to transfer their computational thinking to diverse problems and authentic contexts. However, students may be limited by traditional computational thinking development activities because they may have a lower degree of computational thinking efficacy for persistent learning of AI when encountering difficulties (computational thinking efficacy in learning AI). Accordingly, this study aimed to explore the relationships among Chinese secondary school students' computational thinking efficacy in learning AI, their AI literacy, and approaches to learning AI. Structural equation modeling was adopted to examine the mediation effect. Data were gathered from 509 Chinese secondary school students, and the confirmatory factor analyses showed that the measures had high reliability and validity. The results revealed that AI literacy was positively related to students' computational thinking efficacy in learning AI, which was mediated by more sophisticated approaches to learning AI, contributing to the current understanding of learning AI. It is crucial to focus on students' AI literacy and deep approaches (e.g., engaging in authentic AI contexts with systematic learning activities for in-depth understanding of AI knowledge) rather than surface approaches (e.g., memorizing AI knowledge) to develop their high-level computational thinking efficacy in learning AI. Implications for designing the AI curriculum are discussed.

**Keywords** Computational thinking · Efficacy · AI literacy · Approaches to learning AI · Structural equation modeling

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## 1 Introduction

Students' self-efficacy, which refers to the confidence students perceive in their capacity to perform particular tasks and challenges in certain contexts (Bandura, 1997), has been regarded as a significant factor that relates to students' learning performance (Chen et al., 2021; Chou et al., 2022). Currently, students have a growing need to develop their computational thinking in artificial intelligence (AI) courses to actively experience AI performance, principles, application, and ethics (Huang, 2021; Lin et al., 2023a, b). K-12 students' computational thinking competency is increasingly regarded as a new dimension of key competencies of the future work environment (Huang, 2021; Shamir & Levin, 2022). Particularly, previous research pointed out that computational thinking is a key skill in the 21st century and has been integrated by countries around the world into K-12 education (Polat et al., 2021). For some secondary school students, the acquisition of computational thinking for learning computer science is an urgent need for their future careers. Recently, Polat et al. (2021) and Uslu (2022) indicated the urgent need to explore secondary school students' computational thinking performance and self-efficacy. Ng et al. (2021) found that AI literacy is considered to be the foundational learning outcome for all secondary school students, indicating that they need to not only master the basic AI knowledge but also engage in higher-level thinking activities (e.g., create AI products, design algorithms, debug, and check AI applications).

However, the existing literature associated with secondary school students' computational thinking self-efficacy (e.g., Polat et al., 2021; Uslu, 2022) did not reveal the inner relationships behind their computational thinking self-efficacy or include the learning AI context regarding computational thinking conditions. Without a clear understanding of the inner relationships of computational thinking learning, secondary school students may encounter difficulties developing computational thinking efficacy for learning AI because computational thinking is viewed as unapproachable in programming learning (Ballard & Haroldson, 2021). In addition, they are required to have a high-quality understanding of abstract AI mental models, or it will lead to a lower sense of self-efficacy which makes it difficult for them to persist in learning AI (Allen et al., 2022). Few studies have addressed effective pedagogical approaches for AI education in the K-12 curriculum, especially for filling the need to teach secondary school students some basic machine learning concepts (Tedre et al., 2021). Furthermore, the existing state of computational thinking among secondary school students shows that students' computational thinking efficacy has only been partially tested in previous studies. Although the importance of cultivating students' key competencies regarding computational thinking has been emphasized, there are still unsolved obstacles in Chinese AI education for teaching secondary school students due to the lack of overall approaches and suitable materials in AI education (Huang, 2021). To the best of our knowledge, there are few studies describing the computational thinking-related circumstances of the research subjects, particularly for Chinese secondary school students, by exploring the contributory factors of computational thinking efficacy to learning AI. To fill this research gap, there are obvious issues that necessitated this study for explicitly uncovering the relationships underlying Chinese secondary school students' development of computational thinking efficacy in learning AI. Computational thinking refers to thinking and acting by skills of algorithmic design, algorithms, and so on (Shute et al., 2017). AI is recognized as a scientific principle that concentrates on creating and presenting computer debugging (Wang et al., 2023). In this study, computational thinking efficacy in learning AI is defined as students' perceived belief in their capacity to successfully apply computational thinking skills to complete tasks when learning AI.

To identify the contributory factors of students' development of efficacy in learning AI, research evidence shows that AI literacy should be taken into consideration (Chai et al., 2023; Dai et al., 2020). AI literacy, which refers to students' degree of understanding and capability of applying AI in daily life, is positively related to self-efficacy (i.e., confidence) in learning AI (Dai et al., 2020). Nowadays, educators need to regard AI literacy as basic literacy to help students deal with AI-powered future challenges in the 21st century (Ng et al., 2021). Specifically, to develop AI literacy, the importance of cultivating students' AI capability of applying computational thinking in their everyday lives has been noted (Su et al., 2022). Chai et al. (2023) documented the positive relations between AI literacy and self-efficacy in learning AI. Therefore, we speculated that AI literacy might be a possible contributory factor to computational thinking efficacy in learning AI.

In addition, Bandura (1997) indicated that the major factor accounting for self-efficacy is mastery experiences. Derived from the gradual development of the lasting learning experience, students' approaches to learning could be characterized as individuals' tendencies that relate to their motivations and strategies in their learning processes (Chiou & Liang, 2012). Based on the above literature, this study proposed a similar idea that students' approaches to learning AI, which are recognized as individual perceptions of motivations and strategies of AI learning experiences (i.e., mastery experiences), could explain the development of their computational thinking efficacy in learning AI. The significance of students' approaches to learning has been proved in educational research, especially their approaches to learning computer science and earth science (Chou et al., 2021). Students' approaches to learning could be divided into two constructs: motivations such as intrinsic or extrinsic motivations, and strategies such as meta-cognitive or rote-like strategies (Chou et al., 2021). In addition, research evidence shows that these two constructs are positively related to self-efficacy (Chiou & Liang, 2012; Wei et al., 2021). For instance, the findings of Wei et al. (2021) indicated that understanding deeper approaches to learning programming (i.e., pair collaborative learning strategies) could provide insights into students' improvement of computational thinking and programming self-efficacy. Besides, the importance of harnessing students' intrinsic motivation to learn AI has been emphasized for facilitating their motivation during the AI learning processes (Lin et al., 2021). Students need to apply appropriate strategies for solving AI-related problems (Ng et al., 2022). The findings of Lin et al. (2021) and Ng et al. (2022) implied that more nuanced motivation and strategies are needed to foster students' AI learning achievements. Therefore, the role of approaches to learning AI should be maintained as a crucial facilitator of computational thinking efficacy in learning AI. This study included approaches to learning AI as a factor in the theoretical framework to help students cultivate computational thinking efficacy in learning AI and solve daily problems with computational thinking.

Regarding the fundamental role of computational thinking in secondary school students' efforts to learn AI (Jiang et al., 2022), we suppose it is a promising direction to explore the relationships behind generating computational thinking efficacy in learning AI. To pursue this goal, we argue that AI literacy and approaches to learning AI are two essential variables that can adequately explain the structure of computational thinking efficacy in learning AI based on the following theoretical foundations. However, it is still unclear how to construct a structural equation modeling (SEM) to explore students' computational thinking efficacy in learning AI, their AI literacy, and approaches to learning AI. Accordingly, the present study aimed to find precursory variables and explore their relations to computational thinking efficacy in learning AI in secondary school. The research questions (RQ) examined in this study are as follows:

RQ1: What are the relationships among secondary school students' computational thinking efficacy in learning AI, AI literacy, and approaches to learning AI?

RQ2: What is the role of AI literacy and approaches to learning AI in Chinese secondary school students' computational thinking efficacy in learning AI?

## 2 Literature review

### 2.1 Computational thinking efficacy in learning AI

Computational thinking has attracted researchers' attention as a concept that involves some higher-order thinking (e.g., critical thinking and complex problem-solving ability) in the 21st century for students (Tekdal, 2021; Lin et al., 2023a, b). Students are expected to develop their computational thinking competencies in machine learning courses, which is one way to implement AI (Shamir & Levin, 2022). In the meantime, activities aimed at developing students' computational thinking have been integrated into K-12 curricula in many countries (Angeli & Giannakos, 2020). In addition, students' computational thinking is evaluated by adopting the perspective of computer literacy (Tsai et al., 2020). Previous studies have developed validated measurement tools for computational thinking development (Tsai et al., 2019). As computational thinking is difficult to observe and predict, a new scale was developed by Kukul and Karatas (2019) to measure perceptions of the related presence of these skills (i.e., computational thinking self-efficacy).

It is necessary to leverage related concepts, such as computational thinking, to help students better understand AI knowledge to settle AI problems (Greenwald et al., 2021). In addition, Kim et al. (2021) showed that computational thinking is considered a necessary skill for students to acquire AI literacy. Considering that computational thinking is a high-level skill that is hard to observe (Kukul & Karatas, 2019), computational thinking efficacy in learning AI is worth measuring to acquire students' belief in successfully applying computational thinking to complete tasks when learning AI. Computational thinking self-efficacy is related to cognitive and psychological factors and is also involved in operational processes (Özmutlu et al., 2021).

However, the existing computational thinking measurements proposed by the above studies do not focus on the AI learning context, especially during the K-12 period (Chiu & Chai, 2020). Furthermore, previous research emphasized the urgency of studying secondary school students' computational thinking skills for their careers, as well as the development of K-12 curricula in countries around the world (Polat et al., 2021). An increasing number of studies have described the existing state of secondary school AI education in China (Chai et al., 2020, 2022) and Chinese secondary school students' computational thinking learning (Huang, 2021). In terms of secondary school AI education in China, the authorities and organizations have formulated policies and curricula to equip secondary school students with the AI-powered world (Chai et al., 2022). Previous research has emphasized that as the New Generation Artificial Intelligence Development Plan has been published by China's State Council, it is necessary to encourage secondary and elementary schools to develop AI curricula and promote AI literacy among students (Bhutoria, 2022; Ng et al., 2021). Scholars have conducted comprehensive research on AI education implementation in secondary school and have developed corresponding Chinese proposals (Chai et al., 2020), for example, developing individualized AI curriculum resources and effective AI instructional design to promote the intention and motivation of secondary school students, hence enabling students' innovative thinking and core literacy development (Lin et al., 2021).

From the perspective of Chinese secondary school students' computational thinking learning, Huang (2021) revealed the importance of further developing students' core competencies regarding computational thinking and the significance of tackling the main challenges in AI education at the Chinese fundamental education stage (e.g., the fragmentary nature of teaching content and the lack of an overall plan for the AI teaching process for secondary school students). Moreover, for the prospect of students' future professional development, Uslu (2022) revealed the correlation between secondary school students' latent profiles regarding future programming-related community identity (e.g., programming engagement, affiliation, actualization, and goal setting) and their computational thinking self-efficacy (e.g., reasoning, abstraction, decomposition, and generalization). Polat et al. (2021) implied the demand to cultivate secondary school students' computational thinking skills in visual programming lessons by incorporating systematic and comprehensive computational thinking activities into information technology course content. Based on the previous literature regarding Chinese secondary school students' computational thinking learning, the significance of this research lies in tackling the main challenges in Chinese AI education for secondary school students by investigating the computational thinking efficacy in learning AI from the perspective of Chinese K-12 or secondary school students learning AI. Since most secondary school students typically have a superficial understanding of computational thinking to address daily challenges, more research is required to explore strategies to further strengthen secondary school students' computational thinking. Regarding the lack of research to illustrate the relationships between Chinese secondary school students' computational thinking efficacy and related factors in learning AI, we were encouraged to measure and analyze the factors that correlate to students' computational thinking efficacy in learning AI. Further discovery of computational thinking efficacy in learning AI may benefit AI literacy education by examining two possible factors, namely students' AI literacy and approaches to learning AI. Although the existing research has noticed the importance of self-efficacy in learning, there is a need to understand self-efficacy as a dependent variable and to search for its contributory factors (Chiou & Liang, 2012).

## 2.2 Contributory factors of computational thinking efficacy in learning AI

### 2.2.1 AI literacy

The development of AI literacy is becoming a learning aim in AI education, which can be considered as a crucial contributory factor to computational thinking efficacy in learning AI (Chai et al., 2020, 2023; Dai et al., 2020). AI literacy refers to the knowledge and understanding of AI that is necessary for individuals to engage in applying AI in daily life and problem-solving activities (Chai et al., 2023; Southworth et al., 2023). Inspired by several reviews (e.g., Kong et al., 2021; Lee et al., 2021; Su et al., 2022), the necessity to investigate how to achieve desired goals of developing AI literacy has been noted. As a basic ability such as reading and writing literacy, the development of AI literacy aims to foster not only students' conceptual understanding of the basic AI knowledge, but also their ability of AI thinking to construct logic and algorithms for problem solving (Kong et al., 2021; Ng et al., 2021). Particularly, many studies have explored AI literacy from the perspective of concept understanding, which supports students' understanding of the basic concepts of AI in different contexts (Su et al., 2022), using AI concepts for understanding the real world (Kong et al., 2021), and accessing AI knowledge for high-level thinking activities or creating AI-related products (Ng et al., 2021). What's more, as an important facilitator of developing AI literacy, AI thinking has been noted to guide students in applying logic and algorithms in computational thinking learning (Ng et al., 2021), as well as using AI knowledge to solve problems (Lee et al., 2021).

The related studies have indicated that AI literacy education should be taken seriously to achieve the desired goals from two perspectives regarding AI empowerment to enhance learners' confidence in AI learning (Kong et al., 2021) and the basic ability to solve problems with AI knowledge (Lee et al., 2021). First, it is necessary to target the goal of AI empowerment, a comprehensive capacity for overcoming difficulties through acquiring confidence (i.e., self-efficacy) and supporting students' problem-solving through enhancing their computational thinking (i.e., logic and algorithms) through AI concepts, AI thinking, confidence, ethics, and social good (Kong et al., 2021; Ng et al., 2021). Empirical research involving 682 students indicated the need to measure self-efficacy that aimed at facilitating students' AI learning and identically fostering more autonomy in their AI literacy tasks (Chai et al., 2023). This indicated that AI literacy has the potential to play a positive role in computational thinking efficacy in learning AI. Second, some studies hold another perspective which sees AI literacy as a set of basic abilities that enable individuals to critically evaluate AI technologies, communicate, and collaborate effectively with AI (Long & Magerko, 2020). However, when students are stuck with difficulties, most might not apply the knowledge to make a judgment concerning AI independently because it requires certain approaches (Kong et al., 2021) which include the technical and conceptual understanding of basic AI knowledge. Accordingly, there is an emerging need to emphasize the importance of proper approaches (i.e., collaborative project-based learning) and effective tools (e.g., intelligent agents and hardware for AI literacy development) when solving problems in one's life to attain AI literacy (Ng et al., 2021).

#### 2.2.2 Approaches to learning AI

Students' approaches to learning refer to the combination of their intentions and the strategies they adopt to handle learning processes (Marton & Säljö, 1976). Furthermore, students' approaches have been divided into surface and deep approaches (Chou et al., 2021). For example, if students prefer surface approaches in their learning, they tend to be motivated by fear of poor performance and learn knowledge mainly by reproduction. On the other hand, students' deep approaches are associated with intrinsic motivation and meaningful learning experiences in their study (Chou et al., 2021), and emphasize that students could be guided by inquiry-based pedagogical, high-order learning or other deep strategies to accept challenging intellectual tasks, adopt deep approaches to learning, and intensely enjoy the process of learning (Xie et al., 2023). The difference between the two approaches could assess and optimize students' learning processes; hence previous research modified the original concept to apply it to the education of specific subjects (i.e., mathematics, mass communication subjects, and computer science) (Cai et al., 2019; Huang et al., 2018).

In AI literacy education, researchers have started to identify motives and strategies that play important roles in students' processes of learning AI. Chai et al. (2020, 2023) indicated that students' learning motivation is one of the essential parts of the AI learning process. These studies revealed that both factors, motive and strategy, involved in the framework of students' approaches to learning had attracted researchers' attention in AI education. It is appropriate to assess students' approaches to learning AI with a verified framework and to provide more information with an in-depth view. The previous research indicated that when students perceive deep learning strategies and motives, they will also achieve high-level self-efficacy (Phan, 2007; Shen et al., 2016). However, Chiou and Liang (2012) proposed that the surface motive students perceive in learning science may lead them to regard passing an examination or getting a reward as their basic goal and implement it, therefore feeling a sense of achievement and promoting their self-efficacy. These findings suggest that the exploration of the relationship between different levels of motive (i.e., deep motive and surface motive) and students' efficacy is a worthy direction for future research. Therefore, this study infers that students who perceive higher-level approaches to learning AI should try to learn better how to adjust their motives and strategies to learn AI.

### 2.3 Building a structural model: the relationships among AI literacy, approaches to learning AI, and computational thinking efficacy in learning AI

Proposed by Bandura (1997), the self-efficacy theory is constructed from four theoretical sources regarding enactive mastery experience, vicarious experience, verbal persuasion, and physiological and affective states. The fundamental goals of self-efficacy theory are to explain, predict, and evaluate differences caused by students' self-efficacy (Zakariya, 2021). The self-efficacy theory has been widely applied in learning in general domains, for example, statistics learning (Huang & Mayer, 2019), nursing (Kaldheim et al., 2021), reading (Peura et al., 2019), accounting (Beatson et al., 2018), and English courses (Truong & Wang, 2019). Self-efficacy is a belief in individuals integrating and performing specific tasks for success (Bandura, 1977, 1997). The level of one's self-efficacy has a powerful impact on one's achievement behaviors (Bandura, 1977). Students' self-efficacy positively correlates with autonomy learning and identically fosters more autonomy in their academic tasks (Ponton et al., 2005). However, students with low-level efficacy may show negative behaviors or feelings about the tasks, such as avoidance and stress (Terry, 1994). Educators have recognized the value of self-efficacy. It has been found that the relationships between students' self-efficacy and their achievements exist in different subjects, including mathematics (Kim et al., 2014), science (Burns et al., 2021), and computer programming (Tsai et al., 2019, 2020). However, the existing self-efficacy theory may be too simplistic to explain the contributory variables in the model and to gain a deeper understanding of how to learn AI. As self-efficacy is not only a general concept but is also domain-specific (Chiou & Liang, 2012), there is a need to investigate the specific computational thinking efficacy in learning AI. Taking the above views into account, below are several possible sources that could be inserted into the self-efficacy theory as external variables.

Of all of these sources, it can be seen that mastery experiences may be recognized as the major source of self-efficacy (Bandura, 1997). Accordingly, approaches to learning correlated with mastery experience tend to be a possible source that creates an optimistic connection to self-efficacy (Burns et al., 2021). This provides evidence in the context of learning AI to consider approaches to learning AI as a precursor for computational thinking efficacy in learning AI. Besides, AI literacy is considered a significant factor in exerting efficacy in learning AI (Chai et al., 2023). Therefore, both AI literacy and approaches to learning AI appear to be potential variables influencing students' computational thinking efficacy in learning AI. On the other hand, both approaches to learning and literacy were positively correlated with self-efficacy in various contexts. Existing studies have noted that students' approaches to learning significantly correlated to their self-efficacy (e.g., Chiou and Liang, 2012). Moreover, as a core definition of AI literacy, students' conceptions of increasing one's knowledge positively correlated to their approaches to learning computer science (Liang et al., 2015). Accordingly, there is a demand to pay immediate attention to two crucial variables (i.e., AI literacy and approaches to learning AI) regarding students' mastery experiences and computational thinking efficacy in learning AI for unlocking the possible sources of computational thinking efficacy in the AI learning area.

Therefore, based on the above theoretical foundations, it seems logical to hypothesize that students with more sophisticated AI literacy tend to use deep approaches to learning AI, which may in turn predict their higher degree of CT self-efficacy in learning AI.

### 2.4 Significance

This research might contribute to exploring the relationships among students' computational thinking efficacy in learning AI, their AI literacy, and approaches to learning

AI. Students' computational thinking efficacy was confirmed to play a potential role in developing students' computational thinking (Tang et al., 2020). Besides, examining students' AI literacy and approaches to learning AI provides an in-depth view of students' learning AI processes. Specifically, the developed model in this study highlighted the significance of building students' computational thinking efficacy cognitive development by integrating a cognitive basis of AI literacy as it revealed the crucial constructs which are positively associated with the sources of computational thinking efficacy in AI literacy education. Accordingly, this study should enrich our theoretical understanding of how to select appropriate approaches and motives to facilitate students' computational thinking efficacy in learning AI and learning AI achievement. These results should provide theoretical support to AI teachers and researchers to design appropriate, effective teaching of AI.

In the context of learning AI, the relationships between the two factors provide an insight into students' development process while learning computational thinking for solving AI-related problems. This study has further extended the existing self-efficacy theory by adding two variables, students' AI literacy and approaches to learning AI, to better adapt the classical theory to the learning AI context. The hypothesized model was established to depict the structural relationships among students' computational thinking efficacy in learning AI, their AI literacy, and approaches to learning AI (see Fig. 1 Hypothesized model), which have rarely been studied.

The literature on learning AI has focused on the relationship between students' AI literacy and confidence (Chai et al., 2020; Dai et al., 2020). Chai et al. (2020) suggested that students' AI literacy is significantly associated with their confidence. Dai et al. (2020) proposed that students' AI literacy positively correlates with AI confidence. Currently, it is important to help students acquire AI literacy as basic knowledge and skills for selecting suitable solutions according to targeted AI-related problems, solving students' uncertainty about learning AI and applying computational thinking to address complex difficulties in their everyday lives. As facilitating students' self-efficacy has the potential to give them the confidence to assimilate knowledge (Allen et al., 2022), we hypothesized the following:

H1: AI literacy is a significant contributory factor to computational thinking efficacy in learning AI (see Path H1 in Fig. 1).

Although the relationships between literacy and the approaches to learning have been extensively surveyed in different domains such as finance learning (Akben-Selcuk & Altiok-Yilmaz, 2014) and computer science learning (Liang et al., 2015), it has rarely been explored in the AI learning context. Akben-Selcuk and Altiok-Yilmaz (2014) proposed that deep learning approaches related to students' motives of deep personal satisfaction were positively correlated with financial literacy scores to help learners acquire the understanding and confidence to apply knowledge for making effective decisions. Moreover, students' higher-level learning conceptions (e.g., increasing their knowledge and understanding) were positively correlated to their surface motivations and deep approaches (i.e., deep motivations and strategies) to learning computer science (Liang et al., 2015). Taking these observations together, we assume that students with a high level of AI literacy tend to have more sophisticated approaches to learning AI. Thus, we formulated the following hypothesis:

H2: AI literacy is significantly related to approaches to learning AI (see Path H2 in Fig. 1).

Previous research has widely investigated students' approaches to learning as a predictor of self-efficacy. For example, Chiou and Liang (2012) found that students' approaches to learning science are significantly correlated to their science self-efficacy. Phan (2007) proposed that undergraduate students' usage of deep learning approaches positively correlated with their self-efficacy by performing a path analysis. Particularly, Zheng et al. (2018) found that a higher degree of deep approaches to learning science can be positively associated with the improvement of efficacy in learning science. However, a similar relationship between two factors regarding computational thinking in the context of AI has not been reported. Exploring this relationship can benefit students' acquisition of important computational thinking with appropriate approaches in AI education. Accordingly, this study assumed that students' learning approaches to learning AI have the potential to promote their computational thinking efficacy in learning AI. In other words, effective approaches would strengthen students' confidence in using computational thinking to address practical difficulties. Therefore, the following hypothesis was formulated:

H3: Approaches to learning AI are positively associated with computational thinking efficacy in learning AI (see Path H3 in Fig. 1).

It is also essential to clarify the structural relationships for cultivating students' computational thinking efficacy in learning AI and AI literacy in AI literacy education. These two factors are essential in AI education (Ng et al., 2021). On the one hand, the empirical findings indicated that it is insufficient to equip students with AI literacy to obtain knowledge of AI (Chai et al., 2023). On the other hand, computational thinking should not be limited by procedural operations at a classical level (i.e., debugging) (Tedre et al., 2021). Previous studies have noted that students' computational thinking at the thinking level (e.g., logical thinking and algorithm) also needs to be taken seriously (Ng et al., 2021). Accordingly, there is an urgent need to investigate the correlation between suitable approaches and students' computational thinking learning (e.g., algorithmic thinking and debugging) (Ballard & Haroldson, 2021). Moreover, Tang et al. (2020) indicated that students' higher self-efficacy might lead to greater computational thinking. Considering the practical need for computational thinking learning in AI literacy education, this study started with cultivating students' basic AI literacy and identifying the suitable approaches to learning AI matched with their computational thinking efficacy in learning AI.

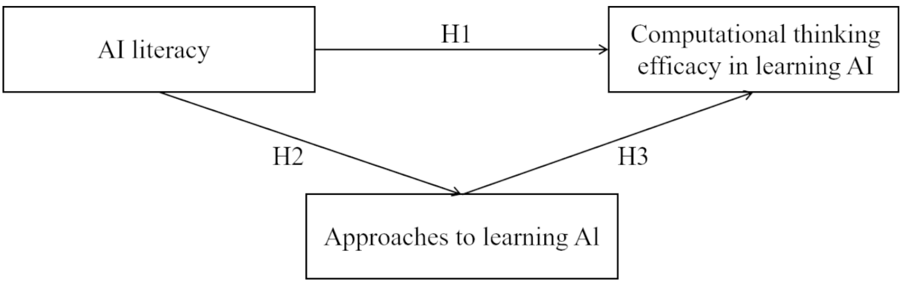


**Fig. 1** Hypothesized model

# 3 Method

## 3.1 Participants

A total of 509 secondary school students from six schools in southern China agreed to join this study, including 319 (62.7%) males and 190 (37.3%) females. The age of the students ranged from 14 to 17, and the mean age was 14.24 years ($SD = 1.24$). Among these students, 33.6% were in grade 7, 40.9% were in grade 8, 9.0% were in grade 9, 5.1% were in grade 10, and 11.4% were in grade 11. The higher the grade level, the greater the pressure of examinations, and thus fewer students at higher levels choose to enroll in AI courses, which might impact the composition of our sample. A convenience sample was drawn from different schools, which have various AI curriculums that were designed according to the same AI curriculum standards. For each school, two classes were randomly selected from each grade for the survey in the study. The students were selected as participants due to the emphasis on developing computational thinking and AI education for secondary school students in China. Considering the significant influence of participants' prior knowledge and experience on their perceptions, these selected students were ensured to have similar prior experience of participating in formal AI courses before completing the survey of this study.

## 3.2 Context

The study involved secondary school students completing a project that required them to code for a robotic car so that it could act autonomously as an intelligent fire engine. Each student had around 50 h (i.e., 90–120 min per lesson) of AI learning throughout the project, and the completion time of this project for different grades of students was similar. In the project, teachers used project-based learning with four instructional activities. The first activity was experiential learning. Teachers helped students gain AI knowledge in a favorable and authentic context to enrich their cognition and experience using AI (e.g., teachers guided students to experience facial recognition to understand the concept and meaning of face recognition technology). Under the guidance of teachers, students explored AI technologies and continuously improved their AI literacy. Activity two was discussion-based collaborative learning, where students talked freely in groups. Combined with their thinking, students discussed the events involving AI in society with their group members. This could boost their belief in using AI knowledge to improve the quality of life. The third activity was literacy learning, which enhanced students' self-rated understanding of foundational knowledge and skills about AI. Teachers explained the AI basics and functional modules (e.g., application of infrared sensors and timers) to help students know how to use AI. Students could learn AI to enhance their previous knowledge by interacting with teachers. The last activity was project-based programming learning, in which students reported their project progress to measure their perceived growth. Teachers asked students to complete an AI project with logical thinking. Students used logical scaffolding in their thinking process for analyzing problems and finding solutions via writing computer programs. With teachers' technological guidance and other students' advice, students debugged AI programs and optimized their projects.

## 3.3 Measures

### 3.3.1 Computational thinking efficacy in learning AI scale

The computational thinking efficacy in learning AI scale adopted from Tsai et al. (2019) was evaluated using confirmatory factor analysis with three latent variables (i.e., algorithm, logical thinking, and debugging). Reliability tests were executed. The finding indicated that the α value was 0.96. To adapt the scale to the context of the study, we chose three sub-scales of computational thinking efficacy in learning AI, and we retained 11 of the original 25 items. These 11 items were divided into three dimensions: algorithm, logical thinking, and debugging. The details are as follows:

- Algorithm refers to learners' perspectives of their capacity for thinking about how to solve programming problems with discrete steps. This dimension consists of four items (e.g., I can comprehend the step-by-step procedures of the programming to accomplish specific tasks).
- Logical thinking is generally understood to mean students' ability to apply logic to their thinking process for solving problems and selecting appropriate plans. There are four items in this dimension (e.g., I can address difficulties and find suitable solutions with logic through writing computer programs).
- Debugging has been applied to learners' perspectives of their capacity to revise program errors. This dimension contained three items (e.g., I'm able to learn more about programming via the process).

### 3.3.2 AI literacy scale

The AI literacy scale was designed to assess the students' ability to apply AI-related knowledge and skills to accomplish the given tasks. The scale retained six items from Chai et al. (2020). The expert validity test for AI literacy showed the appropriateness of the content, which indicated that these items of AI literacy have satisfactory reliability and effectiveness. A sample item is "I know how AI can be used to predict possible outcomes through statistics." According to the original scale, the reported alpha reliability was 0.90.

### 3.3.3 Approaches to learning AI scale

The approaches to learning AI scale was modified from Umapathy et al. (2020) for investigating students' ability to handle learning tasks. Four dimensions (i.e., deep motive, deep strategy, surface motive, and surface strategy) were selected to represent the latent variable of approaches to learning AI, with the scale comprised of 16 items. The reliability of the original scale was 0.73. After revising some minor wording, the content validity of the approaches to learning AI scale was established. The details are as follows:

- Deep motive refers to students' intrinsic motivation to learn AI, which is triggered by their intense curiosity and the knowledge and enjoyment that they bring. This dimension consists of four items (e.g., Sometimes I feel very happy and fulfilled when taking AI courses).
- Deep strategy is generally understood to mean that learning AI through high-order learning indicates that students tend to adopt metacognitive strategies such as analysis, synthesis, evaluation, and application, and utilizes more meaningful ways to learn AI, like understanding and integrating the new learning materials with existing ideas, ensuring coherent understanding, and applying knowledge to use. This dimension consists of four items (e.g., I try to understand the meaning of related concepts in the course content when I take an AI course).
- Surface motive means that learning AI in the courses is triggered by extrinsic motivations such as passing an examination, pursuing good course grades, meeting others' expectations or the degree requirement, and getting a better job. This dimension consists of four items (e.g., I want good AI achievement to get a better job in the future).
- Surface strategy has been applied to learning AI in courses by rote learning, solely memorizing and reproducing the most important learning materials (e.g., concepts, rules, and codes) to achieve narrow targets (e.g., high exam scores). This dimension consists of four items (e.g., I will study according to the focus of AI courses as I think it is unnecessary to devote too much time to AI learning).

### 3.4 Data collection and analysis

Three steps were arranged for data collection and analysis. First, to confirm the accuracy and credibility of the students' computational thinking efficacy in learning AI, AI literacy, and approaches to learning AI instruments, the measurements were sent to three professors in the field of educational technology and AI education for expert verification. According to the recommendations of the experts, we revised and polished the wording and the scale items to design a paper-based survey. Participants received the surveys during break time. The surveys were administered anonymously and could be completed in 15–20 min.

Second, the data preprocessing of this study involved two analytical methods conducted using SPSS version 21.0: descriptive statistical analysis and factor analysis. Descriptive statistics were used to preliminarily sort out and summarize original data to get each dimension's average and standard deviation values. Samples with extreme data were deleted in the process. In the factor analysis, the samples ($N=509$) were randomly divided into two subsets for the exploratory factor analysis (EFA) ($n=165$) and confirmatory factor analysis (CFA) ($n=344$) for further data cleaning. EFA was performed with principal axis factoring analysis and the direct oblimin rotation method for clarifying the factor structure of the survey. Items with cross-loadings or factor loadings of $<0.50$ were omitted. For CFA, we selected a factor loading of less than 0.70 and composite reliability (CR) of more than 0.50 items. Then, the item validity of the three measurements used in this study was ensured.

Third, the SEM model was tested with AMOS 22.0 to explore the relationships among computational thinking efficacy in learning AI, AI literacy, and approaches to learning AI. We used chi-square/degree of freedom ($\chi 2$/df), goodness of fit index (GFI), adjusted goodness of fit index (AGFI), comparative fit index (CFI), normed fit index (NFI), and root mean square error of approximation (RMSEA) to evaluate the model fit metrics. A value of GFI, AGFI, CFI, and NFI at least 0.90 and an RMSEA of less than 0.08 would suggest a good fit between the hypothesized model and the data (Hair et al., 2010).

## 4 Result

### 4.1 Exploratory factor analysis of the measurement model

We performed EFA to clarify the structure of the factors. The factor analysis results indicated that the measures of sampling adequacy were acceptable: the Kaiser–Meyer–Olkin value was 0.82, Bartlett's test of sphericity = 6281.873 ($df$ = 231, $p < 0.001$), and 68.533% of the total variance was explained. These results indicated that the eight factors had good explanatory power concerning the perceptions of AI learning. A total of 33 items remained in the final version of the scales. However, after removing one of the items from the deep motive factor due to low factor loading ($\lambda < 0.3$), the EFA extracted 32 items with factor loadings greater than 0.5 in the final version of the eight-factor measurement model, which is shown in Table 1. The overall α value was 0.79, suggesting that these factors had satisfactory reliability and were suitable for measuring perceptions of AI learning.

### 4.2 Confirmatory factor analysis of the measurement model

The factor validity of computational thinking efficacy in learning AI, AI literacy, and approaches to learning AI was verified by the CFA analysis. Table 2 shows that all parameters of the test items were statistically significant. The examination of the composite reliability of dimensions was in the range of 0.77 to 0.88, showing the satisfactory composite reliability of dimensions. Moreover, the value of the average variance extracted (AVE) of each item exceeded 0.50. They indicate a good convergent validity and a sufficient fit of all instruments. The Cronbach's α for each dimension was in the range of 0.79 to 0.88 (Cronbach's α values > 0.7), which provided evidence of internal consistency and reliable measures.

### 4.3 Correlations and discriminant indexes

Table 3 shows the Pearson correlation analysis among the eight factors, allowing us to better understand their relationships. As noted in Table 3, AI literacy and deep motive were significantly and positively correlated with algorithm, logical thinking, and debugging of computational thinking efficacy in learning AI (from $r = 0.15$ to $r = 0.28$, $p < 0.05$). In addition, this finding provided evidence for deep strategy positively related to logical thinking and debugging of computational thinking efficacy in

**Table 1** The EFA analysis

| Construct | Factor | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| AI literacy | | | | | | | | |
| AI literacy3 | 0.83 | | | | | | | |
| AI literacy4 | 0.79 | | | | | | | |
| AI literacy2 | 0.78 | | | | | | | |
| AI literacy7 | 0.74 | | | | | | | |
| AI literacy6 | 0.71 | | | | | | | |
| AI literacy5 | 0.59 | | | | | | | |
| Deep motive | | | | | | | | |
| Deep motive4 | | 0.86 | | | | | | |
| Deep motive2 | | 0.76 | | | | | | |
| Deep motive3 | | 0.64 | | | | | | |
| Deep strategy | | | | | | | | |
| Deep strategy1 | | | 0.83 | | | | | |
| Deep strategy4 | | | 0.80 | | | | | |
| Deep strategy3 | | | 0.79 | | | | | |
| Deep strategy2 | | | 0.72 | | | | | |
| Surface motive | | | | | | | | |
| Surface motive4 | | | | 0.81 | | | | |
| Surface motive1 | | | | 0.80 | | | | |
| Surface motive2 | | | | 0.73 | | | | |
| Surface motive3 | | | | 0.72 | | | | |
| Surface strategy | | | | | | | | |
| Surface strategy1 | | | | | 0.82 | | | |
| Surface strategy3 | | | | | 0.77 | | | |
| Surface strategy4 | | | | | 0.76 | | | |
| Surface strategy2 | | | | | 0.75 | | | |
| Algorithm | | | | | | | | |
| Algorithm3 | | | | | | 0.87 | | |
| Algorithm4 | | | | | | 0.84 | | |
| Algorithm1 | | | | | | 0.77 | | |
| Algorithm2 | | | | | | 0.72 | | |
| Logical thinking | | | | | | | | |
| Logical thinking1 | | | | | | | 0.85 | |
| Logical thinking3 | | | | | | | 0.81 | |
| Logical thinking2 | | | | | | | 0.79 | |
| Logical thinking4 | | | | | | | 0.70 | |
| Debugging | | | | | | | | |
| Debugging1 | | | | | | | | 0.84 |
| Debugging2 | | | | | | | | 0.79 |
| Debugging3 | | | | | | | | 0.79 |

Note. KMO = 0.82, overall α = 0.79, total variance explained = 68.533%

learning AI ($r = 0.31$, $p < 0.001$; $r = 0.17$, $p < 0.05$). Besides, surface motive positively correlated to AI literacy and logical thinking of computational thinking efficacy in learning AI ($r = 0.16$, $p < 0.05$; $r = 0.16$, $p < 0.05$). The result indicated that promoting secondary school students' AI literacy, deep motive, and deep strategy might

**Table 2** The CFA analysis

| Scale | Items | Mean | *SD* | Unstd. | S.E. | *t*-values | *p*-values | std. | SMC | CR | AVE | α |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AI literacy | AI literacy2 | 4.01 | 1.30 | 1.00 | | | | 0.79 | 0.62 | 0.88 | 0.56 | 0.88 |
| | AI literacy3 | 3.92 | 1.37 | 1.08 | 0.07 | 15.81 | *** | 0.81 | 0.66 | | | |
| | AI literacy4 | 3.97 | 1.26 | 0.93 | 0.06 | 14.65 | *** | 0.76 | 0.58 | | | |
| | AI literacy5 | 4.21 | 1.26 | 0.84 | 0.06 | 13.12 | *** | 0.69 | 0.48 | | | |
| | AI literacy6 | 4.33 | 1.27 | 0.78 | 0.07 | 11.68 | *** | 0.63 | 0.40 | | | |
| | AI literacy7 | 3.79 | 1.04 | 0.78 | 0.05 | 15.01 | *** | 0.78 | 0.61 | | | |
| Deep motive | Deep motive2 | 4.04 | 1.20 | 1.00 | | | | 0.77 | 0.59 | 0.77 | 0.53 | 0.79 |
| | Deep motive3 | 4.02 | 1.36 | 0.95 | 0.09 | 10.11 | *** | 0.64 | 0.41 | | | |
| | Deep motive4 | 3.90 | 1.34 | 1.13 | 0.10 | 10.87 | *** | 0.77 | 0.59 | | | |
| Deep strategy | Deep strategy1 | 4.29 | 1.25 | 1.00 | | | | 0.70 | 0.49 | 0.83 | 0.55 | 0.82 |
| | Deep strategy2 | 4.13 | 1.21 | 1.01 | 0.09 | 11.64 | *** | 0.73 | 0.53 | | | |
| | Deep strategy3 | 4.16 | 1.18 | 1.13 | 0.09 | 12.71 | *** | 0.84 | 0.71 | | | |
| | Deep strategy4 | 4.15 | 1.29 | 1.01 | 0.09 | 11.02 | *** | 0.68 | 0.47 | | | |
| Surface motive | Surface motive1 | 3.82 | 1.27 | 1.18 | 0.08 | 14.37 | *** | 0.80 | 0.66 | 0.85 | 0.59 | 0.85 |
| | Surface motive2 | 3.49 | 1.12 | 1.00 | | | | 0.77 | 0.61 | | | |
| | Surface motive3 | 4.24 | 1.13 | 1.01 | 0.07 | 13.97 | *** | 0.78 | 0.62 | | | |
| | Surface motive4 | 3.71 | 1.29 | 1.09 | 0.08 | 13.10 | *** | 0.73 | 0.58 | | | |
| Surface strategy | Surface strategy1 | 3.00 | 0.93 | 1.00 | | | | 0.78 | 0.61 | 0.86 | 0.60 | 0.85 |
| | Surface strategy2 | 3.49 | 1.20 | 1.27 | 0.09 | 14.01 | *** | 0.77 | 0.59 | | | |
| | Surface strategy3 | 2.88 | 1.22 | 1.31 | 0.09 | 14.20 | *** | 0.78 | 0.61 | | | |
| | Surface strategy4 | 3.04 | 1.38 | 1.46 | 0.10 | 14.03 | *** | 0.77 | 0.59 | | | |
| Algorithm | Algorithm1 | 3.97 | 1.12 | 1.00 | | | | 0.76 | 0.58 | 0.86 | 0.60 | 0.86 |
| | Algorithm2 | 3.60 | 1.21 | 1.07 | 0.08 | 13.29 | *** | 0.75 | 0.56 | | | |
| | Algorithm3 | 3.47 | 1.00 | 0.98 | 0.07 | 14.49 | *** | 0.83 | 0.69 | | | |
| | Algorithm4 | 3.42 | 1.13 | 1.01 | 0.08 | 13.46 | *** | 0.76 | 0.58 | | | |

**Table 2** (continued)

| Scale | Items | Mean | *SD* | Unstd. | S.E. | *t*-values | *p*-values | std. | SMC | CR | AVE | α |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Logical thinking | Logical thinking1 | 3.78 | 1.22 | 1.00 | | | | 0.79 | 0.62 | 0.83 | 0.55 | 0.84 |
| | Logical thinking2 | 4.13 | 1.22 | 0.87 | 0.07 | 12.20 | *** | 0.69 | 0.48 | | | |
| | Logical thinking3 | 3.49 | 0.96 | 0.80 | 0.06 | 13.94 | *** | 0.80 | 0.64 | | | |
| | Logical thinking4 | 3.89 | 1.28 | 0.92 | 0.08 | 12.28 | *** | 0.69 | 0.48 | | | |
| Debugging | Debugging1 | 3.75 | 1.12 | 1.00 | | | | 0.80 | 0.64 | 0.83 | 0.61 | 0.83 |
| | Debugging2 | 3.53 | 1.29 | 1.05 | 0.08 | 12.67 | *** | 0.77 | 0.59 | | | |
| | Debugging3 | 3.70 | 1.12 | 0.91 | 0.07 | 12.66 | *** | 0.78 | 0.61 | | | |

Note. ***$p < 0.001$

**Table 3** Correlations in the measured model

| Scale | AI literacy | Deep motive | Deep strategy | Surface motive | Surface strategy | Algorithm | Logical thinking | Debugging |
|---|---|---|---|---|---|---|---|---|
| AI literacy | **0.75** | | | | | | | |
| Deep motive | 0.24*** | **0.73** | | | | | | |
| Deep strategy | 0.13* | 0.24*** | **0.74** | | | | | |
| Surface motive | 0.16* | 0.19** | 0.06 | **0.77** | | | | |
| Surface strategy | -0.15* | -0.15* | -0.21** | -0.16* | **0.77** | | | |
| Algorithm | 0.19** | 0.28*** | 0.08 | 0.09 | -0.22*** | **0.77** | | |
| Logical thinking | 0.19** | 0.24*** | 0.31*** | 0.16* | -0.17** | 0.11 | **0.74** | |
| Debugging | 0.15* | 0.21** | 0.17* | 0.06 | -0.19** | 0.09 | 0.30*** | **0.78** |

Note. *$p<0.05$; **$p<0.01$; ***$p<0.001$. The diagonal elements represent the square roots of AVE values, and the off-diagonal elements represent the correlation estimates. The square roots of the AVEs upon the diagonals are depicted in bold

facilitate their computational thinking efficacy in learning AI. However, the surface strategy was negatively associated with the other seven factors (from $r$ = -0.22 to $r$ = -0.15, $p<0.05$). To validate the discriminant validity, the square root of the AVE value needs to be greater than 0.50 (Fornell & Larcker, 1981). Moreover, the square root of each facet of AVE is higher than the correlation coefficients between that scale and other scales, according to Chin (1998). Table 3 shows that all constructs satisfied the criteria, supporting discriminant validity.

### 4.4 The relationships among computational thinking efficacy in learning AI, AI literacy, and approaches to learning AI

This study tested the hypotheses through SEM. The SEM model exhibited a suitable goodness of fit: $\chi^2/df=1.44$ (<3.00), GFI=0.93 (>0.90), AGFI=0.95 (>0.90), CFI=0.97 (>0.90), and NFI=0.98 (>0.90), and RMSEA=0.03 (<0.08). As shown in Table 4, in the direct model without mediators, students' AI literacy created an optimistic connection to their algorithm, logical thinking, and debugging ($\beta=0.18$, $\beta=0.20$, $p<0.001$; $\beta=0.25$, $p<0.01$). Regarding the direct model with mediators, statically significant relationships were only revealed between students' AI literacy and debugging ($\beta=0.18$, $p<0.01$). Regarding the indirect model, statistical significance exists for the relationship between the students' AI literacy and algorithm ($\beta=0.04$, $p<0.001$) with deep motive as a mediator. In addition, with deep motive as a mediator, students' AI literacy was positively and significantly correlated with logical thinking ($\beta=0.03$, $p<0.001$). Surface motive mediated the positive relationship between the students' AI literacy and logical thinking ($\beta=0.02$, $p<0.001$). Surface strategy had a mediation effect in the relationship between the students' AI literacy and algorithm, logical thinking, as well as debugging ($\beta=0.03$, $p<0.001$; $\beta=0.03$, $p<0.001$; $\beta=0.03$, $p<0.001$). The final results of the mediation tests indicated that students' AI literacy related to their computational thinking efficacy in learning AI

**Table 4** Bootstrap analyses of the magnitude and statistical significance

| Relationships | Direct model without mediator | Direct model with mediator | Indirect model | Medi-ate effect |
|---|---|---|---|---|
| AI literacy-Deep motive-Algorithm | 0.18*** | 0.10 | 0.04*** | 22.22% |
| AI literacy-Surface strategy-Algorithm | 0.18*** | 0.10 | 0.03*** | 16.67% |
| AI literacy-Deep motive-Logical thinking | 0.20*** | 0.09 | 0.03*** | 15.00% |
| AI literacy-Deep strategy-Logical thinking | 0.20*** | 0.09 | 0.04*** | 20.00% |
| AI literacy-Surface strategy-Logical thinking | 0.20*** | 0.09 | 0.03*** | 15.00% |
| AI literacy-Surface motive-Logical thinking | 0.20*** | 0.09 | 0.02*** | 10.00% |
| AI literacy-Deep strategy-Debugging | 0.25** | 0.18** | 0.02*** | 8.00% |
| AI literacy-Surface strategy-Debugging | 0.25** | 0.18** | 0.03*** | 12.00% |

Note. **$p<0.01$; ***$p<0.001$

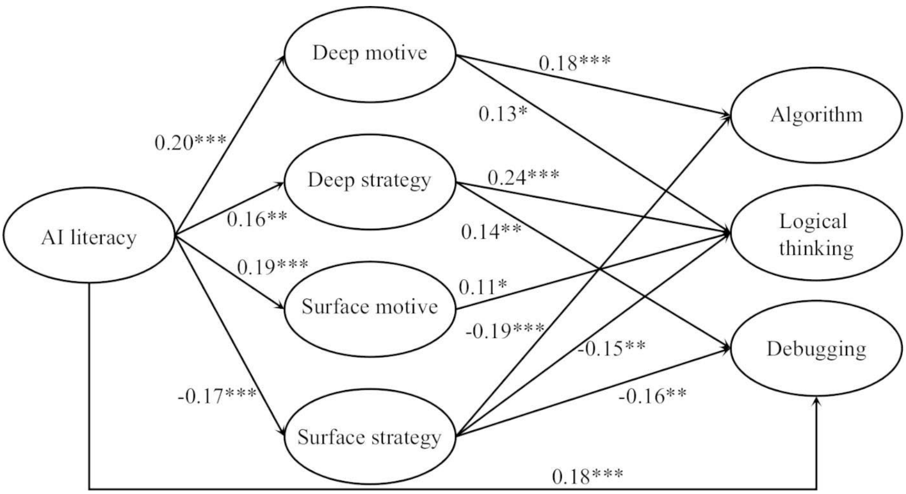


**Fig. 2** SEM model. *$p<0.05$, **$p<0.01$; ***$p<0.001$

through the partial mediation of approaches to learning AI. Furthermore, the size of the mediating effect accounted for 8.00-22.22% of the total effects.

As shown in Fig. 2, hypotheses were partially confirmed, indicating that AI literacy positively associates with all the approaches to learning AI dimensions except surface strategy, which also negatively relates to computational thinking efficacy in learning AI. In addition, AI literacy positively correlated with debugging, which is the dimension of computational thinking efficacy in learning AI. The SEM analysis and mediation testing suggested some relationships between computational thinking efficacy in learning AI, AI literacy, and approaches to learning AI, and further showed partial mediation for all paths.

## 5 Discussion and conclusions

The present study explored the relationships among secondary school students' AI literacy, perceived approaches to learning AI, and computational thinking efficacy in learning AI by adopting an SEM analysis, which was in response to RQ1. The results of the SEM analysis revealed that secondary school students' perceived AI literacy could improve their approaches to learning AI (i.e., deep motive, deep strategy, and surface motive), which indirectly promoted their computational thinking efficacy in learning AI. The correlations echo the findings of previous research, which indicated that students' learning approaches have positive relationships with efficacy (Chiou & Liang, 2012). As these interpretative relations have not been revisited and verified in the AI learning context, this study fills the research gap by identifying nuanced relationships between secondary students' AI literacy and computational thinking efficacy in learning AI. Specifically, secondary school students who adopted more surface approaches in AI learning cannot generate high-level computational thinking efficacy, which is partly consistent with the findings of Tedre et al. (2021). In another way, the present study noted that proper approaches to learning AI are vital for reaching higher-level computational thinking efficacy in learning AI, such as logical thinking and algorithmic thinking. The results of this study also show that literacy plays an important role in learning AI, which is in line with the results of Chai et al. (2023).

On the other hand, AI literacy and approaches to learning AI (i.e., deep motive, deep strategy, and surface motive) could be the most critical aspect of students' computational thinking efficacy in learning AI. Approaches to learning AI can function as a partial mediation variable for AI literacy on computational thinking efficacy in learning AI in this study, which confirms RQ2. By adopting students' approaches to learning AI as the mediator, it appears that when students exhibit a higher degree of AI literacy, they may perceive a high level of deep approaches (deep motive & deep strategy), indirectly increasing their perceived computational thinking efficacy in learning AI. Instead, through a lower degree of AI literacy, students tend to have fewer chances of applying the surface motive and strategy, which in turn decreases their computational thinking efficacy in learning AI. Moreover, in line with Chiou and Liang (2012), mixed motives can also positively associate with the relationships between AI literacy and computational thinking efficacy in learning AI. In other words, the students may need to flexibly trigger deep or surface motives to learn AI varying from actual learning tasks. Specifically, with the use of surface strategies (i.e., memorizing AI knowledge), students tend to focus on the AI learning materials instead of paying attention to practicing their programming skills for meaningful learning, which suggests that teachers should not pay much attention to surface strategies in the daily teaching of AI contexts. However, students tend to have low self-efficacy in AI learning environments (Ballard & Haroldson, 2021). Although students have already acquired the basic knowledge, they still perceive a low level of self-efficacy, which may be due to the improper application of approaches. The structural relationships of these findings identify the benefits of considering both students' AI literacy and appropriate approaches when designing AI learning activities so as to form a complete and systematic AI learning activity. Accordingly, it is crucial for teachers to take both students' AI literacy and deep approaches into account when developing their computational thinking efficacy in learning AI. Deep motive is developed in the process of using AI literacy to complete tasks in the AI learning context. More specifically, this study takes “recognizing the value and purpose of AI image recognition” as an example to articulate how students engage in systematic AI learning activities that depend on authentic AI contexts to strengthen their intrinsic motivations for AI literacy learning. In this learning situation, students are guided in collaborative inquiry to explore the significance of AI image recognition technology and to learn about its principles and algorithms in a problem-oriented, contextualized context. For example, by displaying videos of toxic plants recognized by AI on smartphones, students are able to realize the usefulness of how AI recognition can help people avoid harm in real life, thus motivating them to learn and apply their AI knowledge.

Thus, to cultivate computational thinking efficacy in learning AI, the findings of this research suggest that AI teachers might focus on AI literacy and deep motive. This result highlights the significance of incorporating AI literacy and approaches to learning AI into the school AI curricular reform. What’s more, the present findings enrich the existing theoretical understanding of self-efficacy theory from Bandura (1997) by advancing the development of computational thinking for AI literacy education. The full model in the present study included both students’ AI literacy and approaches, and they were effectively proved for students’ development of computational thinking efficacy in learning AI, which supports the positive effect of problem-solving instructional strategies on students’ motivation and retention of students’ computational thinking efficacy (Ma et al., 2021). It can be concluded that the application and reconstruction of the self-efficacy theory in a new context were theoretically proved by testing the framework constructed with K-12 students’ computational thinking efficacy in learning AI, AI literacy, and approaches to learning AI.

## 6 Implications and Limitations

This study investigated the relationships between computational thinking efficacy in learning AI, AI literacy, and approaches to learning AI by adopting a mediational model approach. The findings of this study have some important implications.

First, the study has some theoretical contributions to the classical self-efficacy theory on learning AI in the following ways: (a) Extending the self-efficacy theory based on Bandura (1997), this study proposes a modified structural model by integrating students’ AI literacy and approaches to learning AI into its construction to better adapt the classical self-efficacy theory to the AI learning context. (b) This paper extends the scope of previous studies by adopting AI literacy (e.g., AI concepts and AI thinking) and approaches to learning AI (e.g., motive and strategy) to investigate students’ computational thinking efficacy in learning AI. That is, this study further refines the self-efficacy theory with AI empowerment to ensure that it serves as an internal hierarchical structural model to cultivate students’ basic abilities of AI literacy to critically evaluate deep motive and strategy, which in turn enhances their computational thinking efficacy in learning AI. (c) This study has identified a synthetic theoretical model for studying students’ computational thinking efficacy in learning AI, which provides theoretical perspectives and empirical evidence for educators to understand what to prepare for facilitating students' AI literacy, and how to design suitable approaches for avoiding difficulties in traditional computational thinking learning.

Second, the result also gives practical suggestions for the pedagogical design of the K-12 AI curriculum. Teachers should reconsider students' learning methods to improve this situation. To address the practical problems, teachers need to pay attention to students' AI literacy in acquiring and using AI knowledge correctly to address students' uncertainty about learning CT. By engaging in authentic AI contexts with systematic learning activities, students can be guided by inquiry-based pedagogical methods, which encourage them to evaluate and create AI artifacts (deep strategy) as well as realize AI ethics and its social impacts (i.e., deep motive) (Ng et al., 2022). The model presents the different relationships between students' efficacy of different types of computational thinking knowledge, which indicates that teachers should consider specific pedagogies for different content of AI courses. The suggestion based on the result of this study is that instructors should not superficially implement learning activities such as simply demanding that students understand concepts and write down code, but need to have a deep motive and deep strategy to reach higher cognitive levels such as guiding students to split computational thinking tasks and transfer the knowledge learned to another new task.

Nonetheless, this research also has certain limitations. First, these findings may not fully represent other mediators or moderators like learning engagement in the AI curriculum, which relate to computational thinking efficacy; these remain to be addressed. Second, as this study mainly focused on revealing the relationships among students' computational thinking efficacy in learning AI, AI literacy, and approaches to learning AI, future research could pay more attention to proving the effect of computational thinking learning with AI literacy on AI education with regard to experimental study and practice. Third, this study used a self-report questionnaire, which provides a limited understanding of the particular situation. The distribution of participants was mainly low-grade (grades 7–8) secondary school students; therefore, it might be improper to generalize the findings to other grades of students with different learning AI experiences. To confirm the applications of our findings, future research may collect data from log files with AI platforms, and investigate students of different grades for a longer period. Thus, further studies should involve more senior high school and vocational high school students because this group is more suitable for the AI learning context considering their possible interest in continuing their future professional development.

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**Data Availability** The datasets used and/or analyzed during the current study are not publicly available due to their personal and private nature but are available from the corresponding author on reasonable request.

**Declaration of conflicting interests** The authors declare no conflict of interest. Data is available upon request from the first author.

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