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Research Article:

Computational Thinking in STEM Education among Matriculation Science Students

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ABSTRACT

In the advent of the rapid technological advancement of The Fourth Industrial Revolution (4IR), computational thinking is recognised as an essential skill in the 21st century across all disciplines, especially in STEM, as it trains students to have the cognitive flexibility to deal with complex problem-solving. Computational thinking (CT) is naturally embedded in STEM practices in the reflection of creativity, algorithmic thinking, critical thinking, problem solving and cooperation skills. This study aimed to measure the level of computational thinking in science matriculation students and examine the effect of academic achievement in STEM on CT. The convenient sampling strategy was used to identify one matriculation college in the northern region of Malaysia to participate in the study. Computational thinking scale (CTS) instrument was employed on 153 science students. Descriptive analysis was used to evaluate the level of CT. One-way multivariate analysis of variance (MANOVA) was performed to analyse the main effect of academic achievement in STEM on CT, followed by univariate analysis of variance (ANOVA) to determine the effect on each of the dimensions of CT. The result indicates that students have a medium high level of CT with an overall mean of 3.51. In addition, the findings showed that there was a statistically significant effect of academic achievement in STEM on CT. The mean score for academic achievement revealed that good students scored the highest, followed by average students and weak students in all dimensions of CT except for cooperation. This study will provide insight into the impact of STEM learning outcomes on the development of CT to inform instructional design.

Keywords: Academic achievement, computational thinking, matriculation, STEM

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INTRODUCTION

The Fourth Industrial Revolution (4IR) is changing the world in every aspect through the fusion of technologies that blur the lines between the physical, digital and biological world (Schwab, 2016). The technological advancement brought by 4IR permeates every aspect of our lives through digitally connected products, smart cities and factories, and automation of tasks. The transformation is beyond rapid technological advancement as 4IR shapes the way we live and experience the world (Schwab, 2018). This calls for a cognitive process or way of thinking that allows for better understanding and engagement with such technologies creatively and meaningfully in an increasingly digitised world.

In this context, computational thinking (CT) plays an essential role as a cognitive process for structuring and formulating problems that can be effectively carried out by computational devices or other information processing agents (Wing, 2010). Despite originating from the concept of computer science, CT is a general broad set of skills applicable across disciplines to solve the problem as the human brain is seen as an information processing system too (Curzon et al., 2019). Therefore, Wing (2014) advocated that everyone should acquire CT at a basic level, just like reading, writing, and arithmetic skills to function in a digital age. Subsequently, CT is gaining recognition as an essential characteristic of 21st century learning as well as requite skills for the modern economy (Curzon et al., 2014; Weintrop et al., 2016).

CT skills have long been practised by science, technology, engineering, and mathematics (STEM) professionals as a computational tool and ways for discoveries (Denning, 2009). Naturally, CT and STEM are connected (Li et al., 2020) because at its core, both CT skills and STEM education view of problem-solving focuses on transdisciplinary and complex problem-solving in real-world situations (Khine, 2018; Li et al., 2019; Li et al., 2020). The transdisciplinary aspects and real-world context lead students to investigate the contextual environment using skills such as cooperation and communication in addition to scientific thinking and creative thinking skills (Juškevičienė et al., 2021; Sırakaya et al., 2020). The complexity of the problem necessitates thinking to apply science, technology, engineering, and mathematics knowledge appropriately to find solutions for the problem. The thinking skills embraced within the context of solving STEM-related problems are algorithmic thinking, critical thinking, creativity, cooperation, and problem-solving (Sırakaya et al., 2020). These thinking skills are collectively known as CT (International Society for Technology in Education (ISTE), 2015, Korkmaz et al. 2017; Yağcı, 2019).

The CT skills are imperative for matriculation level students. Particularly for the students enrolled in STEM courses at the matriculation level. This is because matriculation STEM courses play a critical role in building a strong CT-integrated STEM workforce in a digitised world (Lee & Malyn-Smith, 2020; Augustine, 2005). The importance of computing and CT in the STEM profession is widely acknowledged (Denning, 2007; Froyd et al., 2012). Knowledge of CT and understanding the concept of CT in STEM encourages students to study CT-integrated courses in university and pursue STEM careers to contribute to the 4IR workforce. Despite the importance of CT in STEM education, there are minimal studies at the matriculation level (Li et al., 2020).

Academic achievement has a strong correlation with computational thinking (Cai et al., 2017). According to research, academic success significantly impacts CT (Durak & Saritepeci, 2018; Kalelioglu et al., 2016; Lei et al., 2020). In the literature, the impact of CT on STEM (Günbatar & Bakırcı, 2019; Repenning et al., 2017; Wilensky & Reisman, 2006) and the importance of CT in STEM have been well documented (García-Peñalvo & Mendes, 2018; Henderson et al., 2007; Sengupta et al., 2013; Wilensky & Reisman, 2006). Studies showed CT deepen students' understanding of STEM (Grover & Pea, 2013; Riley & Hunt, 2014; Sırakaya et al., 2020). Conversely, STEM classroom activities are able to facilitate the acquisition and development of students' CT too (Sırakaya et al., 2020), since both STEM and CT are transdisciplinary (Li et al., 2020). However, in the context of STEM education, research on the relationship between CT skills and academic achievement is lacking particularly at the matriculation level.

In acquiring and developing CT, academic achievement is the variable that should be addressed. Hence, this study aims to determine the level of CT and investigate the effect of academic achievement in STEM on the development of CT in the context of Malaysian matriculation. The empirical data obtained from this study broadened the view of CT as a transdisciplinary thinking process and practice aligned with the characteristic of STEM education in science matriculation students. The findings from this study are hoped to give an informed perspective on the effect of STEM learning outcomes on CT. Furthermore, it will provide insight to better plan strategies or pedagogies to create an inclusive learning environment to foster CT skills in STEM education among matriculation students.

LITERATURE REVIEW

STEM Education

In the midst of 4IR, the increasing need and implementation of computation in modern scientific research and experimentation amplify the importance of CT skills in the STEM field (Buckley, 2012). The increasing connectivity and collaboration between STEM disciplines and CT to innovate and solve global problems repositioned the role of CT in STEM education. STEM education approach integrates four core disciplines: science, technology, engineering, and mathematics, which promote boundaries crossing to create a relevant real-world learning experience (Vasquez et al., 2013).

STEM Integration Framework in the Classroom developed by Moore and colleague (Moore et al., 2021; Moore, Guzey, et al., 2014; Moore, Stohlmann, et al., 2014) serve as guidance for the implementation of STEM activities through seven primary elements to ensure the comprehensive learning environment of content across the discipline. The first element implies integration of STEM across the disciplines should create a motivating and engaging learning environment so learning will be personally meaningful. The second element encourages exploration of relevant technology, technological progress, and engineering thinking and design to solve real-world problems to foster problem solving, creativity and higher-order thinking skills. The third element states that students should be allowed to practise engineering thinking through learning from failure and redesign based on what is learned. The fourth element indicates that STEM project-based or problem-based activities should be aligned with the standard science and mathematics curriculum. The fifth element states that instruction should be student-centred. The sixth element emphasised promoting collaborative and communication skills. Lastly, the seventh element is to ensure all the aspects of STEM are integrated throughout the activities.

STEM Education in Matriculation

STEM for matriculation Module 1 course offers Chemistry, Mathematics, Biology and Physics subject. The Malaysia Education Blueprint 2013–2025 aimed to strengthen STEM delivery in all levels of education in three waves of transformation (Ministry of Education Malaysia (MOE), 2013). The first and second wave focuses on strengthening and building the STEM foundation by implementing new curriculum and enhanced teaching approaches. From 2021 to 2025, the third wave measure effectiveness of the previous initiatives can be evaluated to facilitate the development of a road map for the future. In 2018, the new curriculum was implemented in matriculation to reform STEM education. The current matriculation STEM education approach moves towards removing the traditional boundaries separating the disciplines and integrating them into real-world relevant learning experiences for students instead of the traditional siloed approach. The STEM curriculum specifications include learning outcomes to develop the ability to solve STEM-related problems by applying basic concepts and principles through investigation and exploration (Matriculation Division, 2018).

Computational Thinking

CT is an umbrella term referring to a set of cognitive skills involved in computational tasks and activities (Doleck et al., 2017). The traditional view of CT as a skill centres around computers science with a concept such as abstraction, decomposition, algorithm, and generalisation (Angeli et al., 2016; Barr et al., 2011; Selby & Woollard, 2014; Shute et al., 2017). However, Wing's (2010) view of CT as the thought process involved in formulating problems and solutions. The solutions are represented in a form that can be effectively carried out by an information processing agent, which can be human, or machine broaden the conception of CT to be applied across disciplines. The essence of CT comes from thinking like a computer scientist when faced with transdisciplinary problems (Grover & Pea, 2013; Riley & Hunt, 2014).

CT skills are not limited to science computers but a broad set of skills applicable to various disciplines which train students to have the cognitive flexibility to deal with complex problem solving (Curzon et al., 2019; Wing, 2006). This can be associated to Brennan and Resnick's framework that addresses CT in three dimensions which are CT fundamental concepts, CT practices and CT perspectives. CT fundamental concept consists of knowledge of core concepts related to programming or computer science-oriented practices such as pattern recognition, abstraction, decomposition and parallelism. In contrast, CT practices develop from engaging with concepts such as collecting and sorting data, designing, debugging, modelling and simulation. Finally, CT perspectives include students' understanding of themselves, computer and information technologies, and their relationships. This highlights the importance of expression, connecting, and questioning in CT practices, translated into critical thinking, cooperation, and creativity. Align with this view, Bers (2008) suggested that CT has the potential to be used in STEM for communication, creativity and expression. Furthermore, Tang et al. (2020) recently conducted a review on CT and found that majority of the studies assessed cognitive constructs, including CT concepts and skills. This study defines CT skills as algorithmic thinking, creative thinking, critical thinking, problem-solving, and cooperation (ISTE, 2015, Korkmaz et al. 2017; Yağcı, 2019).

Algorithmic thinking

Algorithmic thinking is the basic idea of CT (Aho, 2012; Denning, 2009). In computation, algorithmic thinking refers to the process required to formulate an algorithm that consists of a series of sequential logic written in a programming language that can be executed to solve a problem (Katai, 2015). In a real-life situation, the concept of the algorithm is very practical for solving a problem as it involves following simple and discrete steps (Labusch et al., 2019; Yadav et al., 2017). Therefore, the inclusion of algorithmic thinking in other subjects is strongly encouraged (Barr & Stephenson, 2011). Basically, the thinking process required to develop an algorithm consists of a systematic series of steps that is easy to comprehend as a guide to solve a problem. In STEM education, algorithmic thinking is being practised by writing instructions for an experiment or formulating steps for the mathematical solutions. By doing so, the student practices logical reasoning used in writing an algorithm (Labusch et al., 2019).

Critical thinking

Critical thinking is an important dimension in CT to evaluate a problem on a deeper level of thinking in order to engage in problem-solving (Doleck et al., 2017). CT skills train students to have the cognitive flexibility to deal with complex problem solving (Curzon et al., 2019). The ability to think critically in order to analyse, reason logically, discriminate, predict, and transform knowledge is required in solving complex problems (Lamb et al., 2018). In computing, critical thinking is crucial to unfold the layers of problems and apply multidiscipline knowledge to form a suitable algorithm or solution (Buckley, 2012). In STEM education, critical thinking skills are a key cognitive attribute associated with solving transdisciplinary real-world problems through inquiry-based learning (Li et al., 2019).

Creativity

Creative thinking is one of the key dimensions in CT skills (Grover & Pea, 2018). One of CT's objectives is to build students' cognitive capability and creativity (Weintrop et al., 2016). Hence, critical thinking and creativity are closely related. A certain degree of creative thinking is required to solve the problem (Snalune, 2015), especially when considering solutions from different perspectives and imagining all possible outcomes. Creative thinking makes students a better problem-solvers, especially in complex and transdisciplinary problems by challenging their curiosity and imagination with the capabilities of intelligence machines and knowledge in STEM. Creativity in the STEM field plays an important role to drive innovation and breakthroughs of the future (Hunter-Doniger & Sydow, 2016; Li, et al., 2019). STEM education aims to produce creative problem solver that is able to apply fundamental STEM knowledge across disciplines. Creativity in STEM education is practised by providing a learning environment that required disciplinary boundaries to be crossed by exploring technologies and engineering design using the fundamental knowledge of science and mathematics as problem-solving strategies (Moore et al., 2021).

Problem-solving

Barr and Stephenson (2011) highlighted that problem solving is a core dimension in CT. As Wing (2006) defined, CT is an approach to solving the problem that draws on the concept fundamental to computing. Computational thinking allows students to conceptualise, analyse and solve complex problems using appropriate strategies and tools, both virtually and in the real world (Computer Science Teachers Association [CSTA], 2011). Similarly, STEM education is defined as solving a complex problem that draws on fundamental knowledge of science, mathematics, engineering by using suitable technology (Shaughnessy, 2013). Moreover, developing problem-solving abilities is emphasised in the Framework for STEM Integration in the classroom proposed by Moore et al. (2021).

Cooperation

Collaborate socially is another key dimension in CT (Farris & Sengupta, 2014; Grover & Pea, 2018). Social cooperation will increase in importance as technology advance the world becomes more connected than before enabling global networking and sharing complex data application (Doleck et al., 2017). Parallel with STEM education, the fifth dimension in the Integrated STEM framework is to promote collaborative and communicative skills through an instructional approach that encourages teamwork such as project-based learning (Moore et al., 2021). Students working together to complete a project engage in a collaborative environment to increase comprehension, problem-solving skills (Sullivan & Wilson, 2015; Yuen et al., 2014), and collaborative skills (Kong et al., 2018). As a team, these students might exert more effort, develop better collaborative skills and collaborate more effectively to solve complex problems creatively (Kong et al., 2018).

Academic Achievement and Computational Thinking

The thought process resulting from computational thinking can deepen students' understanding of STEM (Grover & Pea, 2013; Riley & Hunt, 2014) and vice versa (Sırakaya et al., 2020). STEM education connects content knowledge to a real-world situation and CT provide a cognitive framework for learning that connection (Sırakaya et al., 2020). Referring to Sırakaya et al. (2020) findings, the opposite might be possible where STEM disciplines are able to facilitate acquisition and development of students' CT skills too. Therefore, students who perform academically in STEM might have a higher level of CT. In line with this, studies have shown academic success significantly affects CT skills (Durak & Saritepeci, 2018; Kalelioglu et al., 2016). Likewise, a correlational study performed by (Cai et al., 2017) reported academic achievement has a strong correlation with computational thinking. The study by Gülmez and Özdener (2015) using the computational thinking scale (CTS) administered in Turkish schools, showed a significant relationship between students' computational thinking and academic achievement. However, Doleck et al. (2017) study on matriculation science students in Canada using CTS showed no significant relationship between academic achievement and dimensions of CT except for cooperativity. The difference in grade level can explain the inconsistent finding. In a study conducted by Lei et al. (2020), the correlation between academic achievement and CT is weaker as grade level increases. The influence of academic achievement on CT is the strongest among primary students, moderate for secondary students, and weakest for university students. Studies of the effect of academic achievement on computational thinking on matriculation in Malaysia are yet to be done. There is a need to investigate the relationship between academic achievement and the level of computational thinking to provide more empirical research insight into the potential influence of academic achievement on CT in Malaysia.

METHODOLOGY

This study employs a cross-sectional survey design to determine the level of computational thinking and its effect on academic achievement among science matriculation students in Malaysia. The convenience sampling approach was employed to identify one matriculation college in the northern region of Malaysia to participate in the study (Gay et al., 2012). The convenience sampling approach is appropriate because teaching and learning in Matriculation in Malaysia closely abide the Curriculum Specification from the Division of Matriculation, Ministry of Education. A statistical power analysis was performed to determine the sample size using G* Power software (Faul et al., 2007; 2009). The power analysis indicates that a minimum of 92 students is required to detect a medium effect size of d=.15 (Cohen, 1988) with 80% power using MANOVA analysis with the significant level at 5% considering three groups, five predictors and one response variable. In this study, the sample size N = 153 is sufficient and fulfill the minimum sample size requirement.

This study consists of science students who study Biology, Mathematics, Physics, and Chemistry. Cumulative Grade Point Average (CGPA) is used as a measure of students' academic achievement. The CGPA consists of four STEM subject which is Chemistry, Mathematics, Physic, and Biology. The CGPA is categorised into three categories, namely, Good (3.50–4.00), Average (3.00–3.49), and Weak (2.50–2.99). The distribution of good, average and weak students is 44 (28.76%), 70 (45.75%) and 39 (25.49%), respectively.

The CTS develop by Korkmaz et al. (2017) was used in this study. The CTS consists of two sections. The first section consists of respondent demographic data such as gender, academic achievement, and course enrolment. The second section consists of 29 items divided into five dimensions: creativity, algorithmic thinking, cooperation, critical thinking, and problem-solving to evaluate students' CT. A five-point Likert scale ranging from 1 for "never", 2 for "rarely", 3 for "sometimes", 4 for "generally" and 5 for "always" were used for students to express their views about the frequencies of practices in STEM class. Table 1 includes categories of items in each of the dimensions.

Table 1. Dimensions of CTS

Dimensions	Description	Example of item
Creativity	Self-recognition of students and ability to develop genuine ideas different from the ordinary and find different solutions to a problem.	I like the people who are sure of most of their decisions.
Algorithmic thinking	The skill of understanding, applying, assessing and producing the algorithm.	I have a special interest in the mathematical processes.
Cooperation	Working together to achieve/complete a task.	In cooperation learning, I think that I attain/will attain more successful results because I am working in a group.
Critical thinking	The skill to analyse, make conscious judgements and using these to reach a decision.	I use systematic method to compare available options in order to reach a decision.
Problem-solving	The skills to plan and execute the solution.	I cannot apply the solution ways. I plan respectively and gradually.

Six experienced chemistry lecturers validated the CTS questionnaire on the items' clarity of meaning and language used. The I-CVI results were 1.00. The minimum value recommended for S-CVI is 0.80 for reflecting content validity (Polit & Beck, 2006). The CTS was administered in Turkey and all five dimensions have Cronbach's alpha values between 0.73 and 0.87 with an overall value of 0.82 (Korkmaz et al., 2017). In another study, CTS was administered in Canada and the composite reliability reported ranges from 0.83 to 0.91 (Doleck et al., 2017). A pilot study has been conducted with 50 science matriculation students excluded from the sample to determine the instrument's reliability. For each category, the value of Cronbach's alpha ranges from 0.72 to 0.83, and the overall is 0.80. Overall, CTS has demonstrated a high internal consistency with all

Cronbach alpha values above 0.70 (Hair et al., 2014). Table 2 provide details of the CTS and the alpha Cronbach value.

Table 2. Computational thinking scale (CTS)

Dimensions	Number of items	Item number	Cronbach alpha
Creativity	8	1–8	0.72
Algorithmic thinking	6	9–14	0.89
Cooperation	4	15–18	0.82
Critical thinking	5	19–23	0.79
Problem solving	6	24–29	0.83
Computational thinking	29	–	0.80

Nunnally and Bernstein (1994) interpretation of the mean score is used to categorise CTS mean score into four levels. Table 3 demonstrates the interpretation of the mean score according to the level.

Table 3. Categorisation of mean score

Mean score	Level
1.00–2.00	Low
2.01–3.00	Medium low
3.01–4.00	Medium high
4.01–5.00	High

The data collected are analysed using the IBM Statistical Packages for Social Science (IBM SPSS) software version 24.0. All items under problem-solving were negatively worded therefore, they were coded reversely. Descriptive statistic was used to determine the computational thinking skills and distribution of CGPA. For inferential statistics, one-way multivariate analysis (MANOVA) was used to determine the main effect of academic achievement on CT's five dimensions. Further univariate analysis of variance (ANOVA) was conducted for each case where the effects were significant. One-way MANOVA analysis is appropriate because the five dimensions of CT are positively correlated (Korkmaz et al., 2017). Prior to the MANOVA, multivariate normality and homogeneity of variance and covariance matrices were checked. Shapiro-Wilk test for normality was significant ($p < 0.05$), hence violating the assumption of multivariate normality. Multivariate Central Limit Theorem stated that violation of this assumption has minimal impact for large sample size (> 30 for each dependent × independent group) (Altman & Bland, 1995; Heyde, 2014). In the study, the sample size of each variable combination group is more than 30, therefore MANOVA can be conducted (Elliot & Woodward, 2007). There are no violations of assumptions for homogeneity. Levene's test showed that all five dimensions of CT are insignificant with $p > 0.05$, thus the assumption of homogeneity of variances is met.

RESULTS

The level of CT among science matriculation students is determined by the overall mean score (M = 3.51, SD = 0.44) that falls under the medium high level. All the dimensions of CT are in the medium high mean score level ranging from 3.13 to 3.69. The highest mean score is creativity (M = 3.69, SD = 0.48), followed by cooperation (M = 3.67, SD = 0.64), critical thinking (M = 3.56, SD = 0.58), problem solving (M = 3.33, SD = 0.72) and lowest is algorithmic thinking (M = 3.31, SD = 0.68). Table 4 shows the total mean score of each dimension of CT and its level.

Table 4. Mean scores of CT

Dimensions	Mean	SD	Level
Algorithmic thinking	3.31	0.68	Medium high
Creativity	3.69	0.48	Medium high
Cooperation	3.67	0.64	Medium high
Critical thinking	3.56	0.58	Medium high
Problem solving	3.33	0.72	Medium high
Computational thinking (Overall)	3.51	0.44	Medium high

In terms of academic achievement in STEM, there is a substantial difference in the mean score for each dimension between the groups. For algorithmic thinking, creativity, critical thinking, and problem-solving, the mean score trend revealed that good students scored the highest, followed by average students and weak students. The biggest difference in mean score is evident in problem-solving as the academic achievement group falls into different levels of CT. Problem-solving for good students is high, average students are medium high and weak students is medium low. However, average students scored the highest for cooperative skills, while good and weak students obtained the same score. The mean scores based on academic achievement in STEM for the five dimensions are presented in Table 5.

The results of the one-way MANOVA showed significant main effect for academic achievement in STEM (Pillai's trace = 0.656, $F\ (10, 294) = 14.343$, $p < 0.05$, partial $\eta^2 = 0.328$) on all five dimensions of CT. ANOVA results for academic achievement in STEM on dimensions of CT showed there was a significant effect on algorithmic thinking $F\ (2, 150) = 99.254$, $p < 0.05$, partial $\eta^2 = 0.570$; creativity $F\ (2, 150) = 29.627$, $p < 0.05$, partial $\eta^2 = 0.283$ critical thinking $F\ (2, 150) = 9.387$, $p < 0.05$, partial $\eta^2 = 0.111$ and problem solving $F\ (2, 150) = 96.90$, $p < 0.05$, partial $\eta^2 = 0.056$. There was no significant effect of academic achievement on cooperation $F\ (2, 150) = 0.632$, $p > 0.05$, partial $\eta^2 = 0.008$. The statistical results showed academic achievement in STEM affected four dimensions of CT: algorithmic thinking, creativity, critical thinking and problem solving. In algorithmic thinking, good students scored the highest (M = 3.96, SD = 0.51), followed by average students (M = 3.30, SD = 0.41) and weak student (M = 2.59, SD = 0.41) while for creativity good students obtained the highest score (M = 4.02, SD = 0.37), followed by average students (M = 3.69, SD = 0.36) and weak students (M = 3.33, SD = 0.51). Similarly, for critical thinking the score according to the academic achievement is as follows: good students, (M = 3.84, SD = 0.55); average students (M = 3.51, SD = 0.47); weak students (M = 3.34, SD = 0.45) whereas for problem solving the scores as follows: good students, (M = 4.02, SD = 0.45); average students (M = 3.32, SD = 0.46); weak students, (M = 2.56, SD = 0.52). In general, students with higher academic achievement had higher scores for all the three significant components of CT. The partial eta square value indicates academic achievement in STEM has a 57.0% effect on algorithmic thinking, 28.3% on creativity, 11.1% on critical thinking, and 56.4% effect on problem solving to the study population. The results suggest that academic achievement in STEM has a substantial effect to the changes in dimensions of CT. Table 6 summarised the ANOVA analysis for academic achievement in STEM on all dimensions of CT.

Table 5. Descriptive statistic for components of CT based on academic achievement in STEM

Components of CT	Academic achievement	Mean	SD	Level
Algorithmic thinking	Good	3.96	0.51	Medium high
	Average	3.30	0.41	Medium high
	Weak	2.59	0.41	Medium low
Creativity	Good	4.02	0.37	High
	Average	3.69	0.36	Medium high
	Weak	3.33	0.51	Medium high
Cooperative	Good	3.61	0.55	Medium high
	Average	3.72	0.63	Medium high
	Weak	3.61	0.58	Medium high
Critical thinking	Good	3.84	0.55	Medium high
	Average	3.51	0.47	Medium high
	Weak	3.34	0.65	Medium high
Problem solving	Good	4.02	0.45	High
	Average	3.32	0.46	Medium high
	Weak	2.56	0.52	Medium low
Computational thinking (Overall)	Good	3.89	0.41	Medium high
	Average	3.51	0.29	Medium high
	Weak	3.09	0.28	Medium high

Table 6. ANOVA findings for dimensions of CT based on academic achievement in STEM

Dimensions of CT	Academic achievement			F	Sig	η^2
	Good mean (SD)	Average mean (SD)	Weak mean (SD)			
Algorithmic thinking	3.96 (0.51)	3.30 (0.41)	2.59 (0.41)	29.627	0.000	0.570
Creativity	4.02 (0.37)	3.69 (0.36)	3.33 (0.51)	99.254	0.000	0.283
Cooperation	3.61 (0.55)	3.72 (0.63)	3.61 (0.58)	0.632	0.533	0.008
Critical thinking	3.84 (0.55)	3.51 (0.47)	3.34 (0.65)	9.387	0.000	0.111
Problem solving	4.02 (0.45)	3.32 (0.46)	2.56 (0.52)	96.900	0.000	0.564

Note: Means were based on CGPA 1.00 to 4.00. Pillai's trace = 0.656, F (10, 294) =14.34, $p < 0.05$, partial $\eta^2 = 0.328$.

DISCUSSION

The expansion of the definition of CT as a cognitive process to form a solution to a problem (Wing, 2010) broadens the conception of skills in CT, leading to the integration of CT with various disciplines. The transdisciplinary approach to problem-solving in CT and STEM allows both to be intertwined naturally (Li et al., 2020; Sırakaya et al., 2020). Based on the literature, CT (Doleck et al., 2017; ISTE, 2015; Korkmaz et al., 2017) and STEM education (Moore et al., 2021) share common characteristics such as algorithmic thinking, creativity, critical thinking, cooperation, and problem-solving. These are the five dimensions that define CT in this study. The analysis showed that science matriculation students have a medium high level of CT with a mean value of 3.51.

Referring to the MANOVA analysis result, there is a significant main effect for academic achievement in STEM on CT skills among science matriculation students. The current findings are consistent with the findings of Cai et al. (2017), Gülmez and Özdener (2015), and (Lei et al., 2020). Students who excel academically in STEM have a higher level of CT as compare to average achievers and low achievers (Durak & Saritepeci, 2018; Kalelioglu et al., 2016; Lei et al., 2020). This supports the assertion that STEM is able to facilitate the acquisition and development of students' CT skills (Sırakaya et al., 2020). STEM lessons and activities facilitate CT's development as students explore beyond the disciplinary boundaries of science, technology, engineering, and mathematics.

Further analysis of each dimension of CT found academic achievement in STEM had a significant effect for four dimensions in CT: creativity, algorithmic thinking, critical thinking, and problem-solving. This signifies that algorithmic thinking, creativity, critical thinking and problem solving are the CT skills integrated into STEM, supporting the view that CT is naturally embedded in STEM as Li et al. (2020) proposed. The average mean score for each dimension from highest to lowest is problem-solving, creativity, algorithmic thinking and critical thinking. In contrast, academic achievement is found to have no significant effect on cooperation. Average students have a higher score than good and weak students, while good and weak students obtained the same mean score.

This implies students who valued the shared benefits and recognised the common aim of working together are unaffected by academic performance.

In the context of matriculation, the finding demonstrated students benefited from the STEM activities such as laboratory activates and project work that foster CT skills in the dimension of problem-solving, algorithmic thinking, creativity and critical thinking. This signifies the implementation of STEM is in line with the STEM Integration Framework in the Classroom proposed by Moore et al. (2021). However, there was a significant gap between different groups of academic achievers, particularly in problem-solving. This suggests that the learning outcomes and instructional design favour the development of CT skills in high achieving students. Following the study by Jajuri et al. (2019), employing the proper teaching and learning strategies in STEM activities can strengthen students' skills, especially in creativity, problem-solving, and collaborative skills. Therefore, lecturers in matriculation should take the students' academic achievement into account when considering STEM teaching and learning strategies to ensure the development of CT among students.

CONCLUSION

The findings of this study suggest that academic achievement has a significant main effect on the development of CT among science matriculation students. ANOVA analysis further suggests that academic achievement significantly affects four dimensions of CT: algorithmic thinking, creativity, critical thinking, and problem-solving. The effect of academic achievement is not significant. It is found that students with higher academic achievement have higher CT skills. The significant effect of academic achievement on the development of CT has several implications for STEM educators in designing classroom instructions and pedagogies. Since the class is more diverse at the post-secondary level, the difference in academic ability must be considered by creating a supportive learning environment for all students. Malaysia, like other developing countries, is attempting to push CT and STEM education to the forefront of the national agenda to prepare students to meet the challenges and human capital demand in the advent of 4IR. These findings provide insight into the current development of CT in STEM education to inform relevant institutions and policymakers to realign existing STEM instruction to make CT inclusive to all students.

This study has several limitations. The sample of the study comprised science students from a matriculation college in a Northern zone. Hence, the results obtained from this study are unable to represent the whole population. A large sample including different matriculation colleges and types of matriculation programmes offered is suggested for future studies to improve the generalisability of the results obtained. In future, it is recommended to expand the study to measure other factors such as gender, location of secondary school, home environment or attitude.

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REFERENCES

Aho, A. V. (2012). Computation and computational thinking. *The Computer Journal*, *55*(7), 832–835. https://doi.org/10.1093/comjnl/bxs074

Altman, D., & Bland, J. (1995). Statistics notes: The normal distribution. *BMJ (Clinical Research Ed)*, *310*(6975), 298. https://doi.org/doi.org/10.1136/bmj.310.6975.298

Angeli, C., Voogt, J., Fluck, A., Webb, M., Cox, M., Malyn-Smith, J., & Zagami, J. (2016). A K-6 computational thinking curriculum framework: Implications for teacher knowledge. *Journal of Educational Technology & Society*, *19*(3), 47–57. http://www.jstor.org/stable/jeductechsoci.19.3.47

Barr, D., Harrison, J., & Conery, L. (2011). Computational thinking: A digital age skill for everyone. *Learning & Leading with Technology, 38*(6), 20–23.

Barr, V., & Stephenson, C. (2011). Bringing computational thinking to K-12: What is involved and what is the role of the computer science education community? *ACM Inroads*, *2*(1), 48–54. https://doi.org/10.1145/1929887.1929905

Bers, M. U. (2008). *Blocks to robots learning with technology in the early childhood classroom*. Teachers College Press.

Brennan, K., & Resnick, M. (2012). New frameworks for studying and assessing the development of computational thinking. In *Proceedings of the 2012 Annual Meeting of the American Educational Research Association (AERA)* (Vol. 1, pp. 25), Vancouver, Canada. https://web.media.mit.edu/~kbrennan/files/Brennan_Resnick_AERA2012_CT.pdf

Buckley, S. (2012). *The role of computational thinking and critical thinking in problem solving in a learning environment*. Paper presented at the 11th European Conference on E-Learning (ECEL), Groningen, Netherlands, 26–27 October, 63–70.

Cai, Z., Fan, X., & Du, J. (2017). Gender and attitudes toward technology use: A meta-analysis. *Computers & Education*, *105*, 1–13. https://doi.org/10.1016/j.compedu.2016.11.003

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Computer Science Teachers Association (CSTA). (2011). *K-12 computer science standard*. Retreived from https://www.csteachers.org/page/about-csta-s-k-12-nbsp-standards

Curzon, P., Bell, T., Waite, J., & Dorling, M. (2019). Computational thinking. In S. A. Fincher, & A. V. Robins (Eds.), *The Cambridge handbook of computing education research* (pp. 513–546). Cambridge University Press. https://doi.org/10.1017/9781108654555.018

Curzon, P., Dorling, M., Ng, T., Selby, C., & Woollard, J. (2014). Developing computational thinking in the classroom: A framework. *Computing at School*, *June*, 1–6. http://eprints.soton.ac.uk/369594/10/DevelopingComputationalThinkingInTheClassroomaFramework.pdf

Denning, P. J. (2007). Computing is a natural science. *Communications of the ACM*, *50*(7), 13–18. https://doi.org/10.1145/1272516.1272529

Denning, P. J. (2009). The profession of IT Beyond computational thinking. *Communications of the ACM*, *52*(6), 28–30.

Doleck, T., Bazelais, P., Lemay, D. J., Saxena, A., & Basnet, R. B. (2017). Algorithmic thinking, cooperativity, creativity, critical thinking, and problem solving: exploring the relationship between computational thinking skills and academic performance. *Journal of Computers in Education*, *4*(4), 355–369. https://doi.org/10.1007/s40692-017-0090-9

Durak, H. Y., & Saritepeci, M. (2018). Analysis of the relation between computational thinking skills and various variables with the structural equation model. *Computers & Education*, *116*, 191–202. https://doi.org/10.1016/j.compedu.2017.09.004

Elliot, A., & Woodward, W. (2007). *Statistical analysis quick reference guidebook with SPSS examples* (1st ed.). Sage Publication. https://doi.org/10.4135/9781412985949

Farris, A. V., & Sengupta, P. (2014). *Perspectival computational thinking for learning physics: A case study of collaborative agent-based modeling*. Paper presented at the 11th International Conference of the Learning Sciences (ICLS), Boulder, United States, 23–27 June, 1102–1106.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Froyd, J. E., Wankat, P. C., & Smith, K. A. (2012). Five major shifts in 100 years of engineering education. *Proceedings of the IEEE*, *100*(Special Centennial Issue), 1344–1360. https://doi.org/10.1109/JPROC.2012.2190167

García-Peñalvo, F. J., & Mendes, A. J. (2018). Exploring the computational thinking effects in pre-university education. *Computers in Human Behavior*, *80*, 407–411. https://doi.org/10.1016/j.chb.2017.12.005

Gay, L. R., Mills, G. E., & Airasian, P. W. (2012). *Educational research: Competencies for analysis and applications* (10th ed.). Pearson.

Grover, S., & Pea, R. (2013). Computational thinking in K–12: A review of the state of the field. *Educational Researcher*, *42*(1), 38–43. https://doi.org/10.3102/0013189X12463051

Grover, S., & Pea, R. (2018). Computational thinking: A competency whose time has come. In S. Sentence, E. Barendsen, & C. Schulte (Eds.), *Computer science education: Perspectives on teaching and learning in school* (pp. 19–38). Bloomsbury Publishing.

Gülmez, I., & Özdener, N. (2015). Academic achievement in computer programming instruction and effects of the use of visualization tools at the elementary school level. *British Journal of Education, Society and Behavioural Science*, *11*(1), 1–18. https://doi.org/10.9734/BJESBS/2015/18316

Günbatar, M. S., & Bakırcı, H. (2019). STEM teaching intention and computational thinking skills of pre-service teachers. *Education and Information Technologies*, *24*(2), 1615–1629. https://doi.org/10.1007/s10639-018-9849-5

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (7th ed.). Pearson Education Limited.

Henderson, P., Cortina, T. J., & Wing, J. M. (2007). Computational thinking. *ACM SIGCSE Bulletin*, *39*(1), 195–196. https://doi.org/10.1145/3263098

Heyde, C. C. (2014). Multidimensional central limit theorems. In *Wiley StatsRef: Statistics reference online*. John Wiley & Sons. https://doi.org/10.1002/9781118445112.stat02951

Hunter-Doniger, T., & Sydow, L. (2016). A journey from STEM to STEAM: A middle school case study. *The Clearing House: A Journal of Educational Strategies, Issues and Ideas*, *89*(4–5), 159–166. https://doi.org/10.1080/00098655.2016.1170461

International Society for Technology in Education (ISTE). (2015). *Computational thinking leadership toolkit first edition.* Retrieved from https://cdn.iste.org/www-root/ct-documents/ct-leadershipt-toolkit.pdf?sfvrsn=4

Jajuri, T., Hashim, S., Ali, M. N., & Abdullah, S. M. S. (2019). The implementation of Science, Technology, Engineering and Mathematics (STEM) activities and its effect on student's academic resilience. *Asia Pacific Journal of Educators and Education*, *34*, 153–166. https://doi.org/10.21315/apjee2019.34.8

Juškevičienė, A., Dagienė, V., & Dolgopolovas, V. (2021). Integrated activities in STEM environment: Methodology and implementation practice. *Computer Applications in Engineering Education*, *29*(1), 209–228. https://doi.org/https://doi.org/10.1002/cae.22324

Kalelioglu, F., Gulbahar, Y., & Kukul, V. (2016). A framework for computational thinking based on a systematic research review. *Modern Computing*, *4*(3), 583–596.

Katai, Z. (2015). The challenge of promoting algorithmic thinking of both sciences and humanities oriented learners. *Journal of Computer Assisted Learning*, *31*(4), 287–299. https://doi.org/https://doi.org/10.1111/jcal.12070

Khine, M. S. (2018). Strategies for developing computational thinking. In M. S. Khine (Ed.), *Computational thinking in the STEM disciplines* (pp. 3–9). Springer. https://doi.org/10.1007/978-3-319-93566-9_1

Kong, S.-C., Chiu, M. M., & Lai, M. (2018). A study of primary school students' interest, ellaboration attitude, and programming empowerment in computational thinking education. *Computers & Education*, *127*, 178–189. https://doi.org/10.1016/j.compedu.2018.08.026

Korkmaz, Ö., Çakir, R., & Özden, M. Y. (2017). A validity and reliability study of the Computational Thinking Scales (CTS). *Computers in Human Behavior*, *72*, 558–569. https://doi.org/10.1016/j.chb.2017.01.005

Labusch, A., Eickelmann, B., & Vennemann, M. (2019). Computational thinking processes and their congruence with problem-solving and information processing. In S.-C. Kong, & H. Abelson (Eds.), *Computational thinking education* (pp. 65–78). Singapore: Springer. https://doi.org/10.1007/978-981-13-6528-7_5

Lamb, R., Firestone, J., Schmitter-Edgecombe, M., & Hand, B. (2018). A computational model of student cognitive processes while solving a critical thinking problem in science. *The Journal of Educational Research*, *112*(2), 243–254. https://doi.org/10.1080/00220671.2018.1514357

Lee, I., & Malyn-Smith, J. (2020). Computational thinking integration patterns along the framework defining computational thinking from a disciplinary perspective. *Journal of Science Education and Technology*, *29*(1), 9–18. https://doi.org/10.1007/s10956-019-09802-x

Lei, H., Chiu, M. M., Li, F., Wang, X., & Geng, Y. jing. (2020). Computational thinking and academic achievement: A meta-analysis among students. *Children and Youth Services Review*, *118*(June), 105439. https://doi.org/10.1016/j.childyouth.2020.105439

Li, Y., Schoenfeld, A. H., diSessa, A. A., Graesser, A. C., Benson, L. C., English, L. D., & Duschl, R. A. (2019). On thinking and STEM education. *Journal for STEM Education Research*, *2*(1), 1–13. https://doi.org/10.1007/s41979-019-00014-x

Li, Y., Schoenfeld, A. H., diSessa, A. A., Graesser, A. C., Benson, L. C., English, L. D., & Duschl, R. A. (2020). On computational thinking and STEM education. *Journal for STEM Education Research*, *3*(2), 147–166. https://doi.org/10.1007/s41979-020-00044-w

Matriculation Division. (2018). *Curriculum specification for chemistry*. Ministry of Education Malaysia.

Ministry of Education Malaysia (MOE). (2013). *Malaysia education blueprint 2013–2025.* Putrajaya: Ministry of Education Malaysia.

Moore, T. J., Guzey, S. S., & Brown, A. (2014). Greenhouse design to increase habitable land: An engineering unit. *Science Scope*, *37*(4), 51–57. https://doi.org/10.2505/4/ss14_037_07_51

Moore, T. J., Johnson, C., Peters-Burton, E., & Guzey, S. (Eds.) (2021). The need for a STEM road map. In *STEM Road Map 2.0: A framework for integrated STEM education* (pp. 3–12). Routledge. https://doi.org/10.4324/9781003034902-2

Moore, T. J., Stohlmann, M. S., Wang, H. H., Tank, K. M., Glancy, A. W., & Roehrig, G. H. (2014). Implementation and integration of engineering in K-12 STEM education. In S. Purzer, J. Strobel, & M. E. Cardella (Eds.), *Engineering in pre-college settings: Synthesizing research, policy, and practices* (pp. 35–60). Purdue University Press. https://doi.org/10.2307/j.ctt6wq7bh.7

Nunnally, J., & Bernstein, I. (1994). *Psychological methods*. New York: McGraw-Hill.

Polit, D.E., & Beck, C.T. (2006) *Essentials of nursing research* (6th ed.). Philadelphia: Lippincott Williams & Wilkins.

Repenning, A., Basawapatna, A. R., & Escherle, N. A. (2017). Principles of computational thinking tools. In P. J. Rich, & C. B. Hodges (Eds.), *Emerging research, practice, and policy on computational thinking* (pp. 291–305). Springer International Publishing. https://doi.org/10.1007/978-3-319-52691-1_18

Riley, D. D., & Hunt, K. A. (2014). *Computational thinking for the modern problem solver*. CRC press. https://doi.org/10.1201/b16688

Schwab, K. (2016). *The fourth industrial revolution.* Crown Publishing Group.

Schwab, K. (2018). *Shaping the fourth industrial revolution*. Crown Publishing Group.

Selby, C. C., & Woollard, J. (2014). Refining an understanding of computational thinking. Working paper, University of Southampton. Retrieved from https://eprints.soton.ac.uk/372410/1/372410UnderstdCT.pdf

Sengupta, P., Kinnebrew, J. S., Basu, S., Biswas, G., & Clark, D. (2013). Integrating computational thinking with K-12 science education using agent-based computation: A theoretical framework. *Education and Information Technologies*, *18*(2), 351–380. https://doi.org/10.1007/s10639-012-9240-x

Shaughnessy, J. M. (2013). Mathematics in a STEM context. *Mathematics Teaching in the Middle School*, *18*(6), 324. http://www.jstor.org/stable/10.5951/mathteacmiddscho.18.6.0324

Shute, V. J., Sun, C., & Asbell-Clarke, J. (2017). Demystifying computational thinking. *Educational Research Review*, *22*, 142–158. https://doi.org/10.1016/j.edurev.2017.09.003

Sırakaya, M., Sırakaya, D. A., & Korkmaz, Ö. (2020). The impact of STEM attitude and thinking style on computational thinking determined via structural equation modeling. *Journal of Science Education and Technology*, *29*(4), 561–572. https://doi.org/10.1007/s10956-020-09836-6

Snalune, P. (2015). The benefits of computational thinking. *ITNOW*, *57*(4), 58–59. https://doi.org/10.1093/itnow/bwv111

Sullivan, F. R., & Wilson, N. C. (2015). Playful talk: Negotiating opportunities to learn in collaborative groups. *Journal of the Learning Sciences*, *24*(1), 5–52. https://doi.org/10.1080/10508406.2013.839945

Tang, X., Yin, Y., Lin, Q., Hadad, R., & Zhai, X. (2020). Assessing computational thinking: A systematic review of empirical studies. *Computers & Education*, *148*, 103798. https://doi.org/https://doi.org/10.1016/j.compedu.2019.103798

Vasquez, J. A., Comer, M., & Snieder, C. (2013). *STEM Lesson essentials, Grade 3-8: Integrating Science, Technology, Engineering and Mathematics* (1st ed.). Heinemann Educational Books.

Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining computational thinking for mathematics and science classrooms. *Journal of Science Education and Technology*, *25*(1), 127–147. https://doi.org/10.1007/s10956-015-9581-5

Wilensky, U., & Reisman, K. (2006). Thinking like a wolf, a sheep, or a firefly: Learning biology through constructing and testing computational theories—an embodied modeling approach. *Cognition and Instruction*, *24*(2), 171–209. https://doi.org/10.1207/s1532690xci2402_1

Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, *49*(3), 33–35. https://doi.org/10.1145/1999747.1999811

Wing, J. M. (2010). *Computational thinking: What and why?* Retrieved from http://www.cs.cmu.edu/~CompThink/papers/TheLinkWing.pdf

Wing, J. M. (2014). *Computational thinking benefits society*. 40th Anniversary Blog of Social Issues in Computing. Retrieved from http://socialissues.cs.toronto.edu/index.html%3Fp=279.html

Yadav, A., Stephenson, C., & Hong, H. (2017). Computational thinking for teacher education. *Communication of the ACM*, *60*(4), 55–62. https://doi.org/10.1145/2994591

Yağcı, M. (2019). A valid and reliable tool for examining computational thinking skills. *Education and Information Technologies*, *24*(1), 929–951. https://doi.org/10.1007/s10639-018-9801-8

Yuen, T., Boecking, M., Stone, J., Tiger, E. P., Gomez, A., Guillen, A., & Arreguin, A. (2014). Group tasks, activities, dynamics, and interactions in collaborative robotics projects with elementary and middle school children. *Journal of STEM Education*, *15*(1), 39–45. https://www.jstem.org/jstem/index.php/JSTEM/article/download/1853/1585