Jiang, B. et al. (Eds.) (2025). Proceedings of the 33rd International Conference on Computers in Education. Asia-Pacific Society for Computers in Education

Computational Thinking (CT) Proficiency among Malaysian Teacher Trainees: A Cross-Institutional Analysis in the Central Zone

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Abstract: Computational Thinking (CT) has become an essential competency in 21st-century education, equipping individuals with structured problem-solving skills necessary for a technology-driven world. In Malaysia, the Ministry of Education has integrated CT into the national curriculum, however, research indicates varying extent of CT proficiency among teacher trainees, raising concerns about their preparedness to implement CT in classrooms. This study examines the extent of CT proficiency among teacher trainees in the Central Zone of Teacher Training Institutes or known locally as Institut Pendidikan Guru Malaysia (IPGM), focusing on their competency in abstraction, decomposition, pattern recognition, algorithmic thinking, logical reasoning, and evaluation. A quantitative approach was employed, using a validated multiple-choice instrument to assess CT proficiency among 448 teacher trainees. Descriptive and One-way ANOVA analyses were conducted to determine CT competency and the effect of institutional background towards CT proficiency among teacher trainees. The findings indicate that teacher trainees exhibit strong competencies in evaluation, decomposition, and algorithmic thinking, but face challenges in logical reasoning and pattern recognition. ANOVA analysis result confirmed significant differences across institutions. These disparities may reflect differences in institutional practices, instructional strategies, or student support systems. The study provides insights into CT integration in teacher education and offers recommendations for curriculum improvements to better equip teacher trainees with computational problem-solving skills.

Keywords: Computational thinking, teacher trainee, Institut Pendidikan Guru Malaysia, proficiency, development

1. Introduction

Computational Thinking (CT) has become a cornerstone of 21st-century education, gaining recognition worldwide as an essential skill for solving problems, designing systems, and understanding human behavior through the lens of computing (Wing, 2006). Rooted in computer science, CT involves a structured way of thinking that enables individuals to break down complex problems, recognize patterns, develop step-by-step solutions (algorithms), and apply logical reasoning and evaluation. Increasingly, however, CT is also framed not only as a set of discrete skills but as a mindset or epistemic stance, a way of approaching problems that includes dispositions such as persistence, adaptability, and reflective judgment (Grover & Pea, 2013; Brennan & Resnick, 2012). This broader view positions CT as both a procedural competence and a cognitive orientation toward systematic modeling, iterative refinement, and critical evaluation. As digital technologies continue to evolve rapidly and reshape our lives through the Fourth Industrial Revolution (IR 4.0), many countries have made CT a key part of their education systems. The goal is clear: to prepare students for a future where technology and innovation play a central role (Istenic, 2020).

In Malaysia, the Ministry of Education (MOE) has taken proactive steps by embedding CT into the national educational curriculum at the primary and secondary school levels [Kurikulum Standard Sekolah Rendah (KSSR) and Kurikulum Standard Sekolah Menengah (KSSM)]. These curricula aim to cultivate problem-solving skills among students by focusing on core CT components such as abstraction, decomposition, pattern recognition, algorithmic thinking, logical reasoning, and evaluation (MOE, 2017). However, despite these forward-thinking policies, research reveals inconsistencies in how well teacher trainees grasp and apply CT. These disparities often stem from differences in curriculum design, teaching methods, and access to technological tools (Wing, 2011; Kang et al., 2022). As the bridge between policy and classroom practice, teacher trainees play a crucial role in shaping how CT is taught. Their own proficiency in CT directly influences how effectively they can integrate these concepts into various subjects and learning experiences. Unfortunately, studies show that many teacher trainees still struggle with specific CT components, particularly decomposition and pattern recognition, both vital for tackling real-world problems in educational settings (Ung et al., 2021).

Importantly, the value of CT in teacher education extends beyond technical know-how. It nurtures critical thinking, creativity, and adaptability, qualities essential for success in today's digital economy (Yadav et al., 2017). Theoretical perspectives such as constructivism and constructionism (Papert, 1980) emphasize that CT thrives when learners actively create, test, and refine solutions, while Bloom’s taxonomy situates CT within higher-order thinking skills such as analysis, evaluation, and creation (Shute et al., 2017). These frameworks inform this study’s research design and interpretation, as they guide how CT proficiency is operationalized and how findings will be linked to policy implications. It is also important to acknowledge that CT proficiency is multidimensional. While multiple-choice instruments can provide valid, large-scale measures of foundational CT knowledge and reasoning, they do not fully capture open-ended, design-based applications, iterative debugging, or reflective evaluation. Therefore, in this study, test scores will be interpreted as indicators of foundational proficiency, with the recognition that comprehensive CT assessment would require additional performance-based and reflective measures.

This study aims to assess how teacher trainees in the Central Zone of IPGM apply CT in educational settings. It will explore their extent of proficiency and examine how their academic backgrounds and institutions may influence their abilities. Ultimately, the findings will offer valuable insights into the effectiveness of current training models and help guide improvements. By providing evidence-based recommendations, this study hopes to support the ongoing effort to equip future educators with the tools they need to foster computational problem-solving in classrooms, an effort that aligns with both national goals and global educational priorities. The research questions guiding this investigation are: What is the extent of CT proficiency among teacher trainees in Institut Pendidikan Guru Malaysia (Central Zone)? Do the mean overall scores differ significantly across the five selected teacher training institutions (Central Zone)?

2. Literature Review

Research on CT in education has evolved from conceptual discussions to empirical investigations examining how it can be integrated into teaching and learning across diverse contexts. Globally, studies highlight the value of CT as both a set of cognitive tools and a mindset that supports analytical reasoning and structured problem-solving in multiple disciplines (Grover & Pea, 2013; Brennan & Resnick, 2012; Kafai & Burke, 2014). Countries such as the United States, the United Kingdom, and Finland have incorporated CT into national curricula using cross-disciplinary strategies, including coding, robotics, and algorithmic reasoning, to cultivate transferable problem-solving skills among students (Yadav & Berthelsen, 2021). The success of these initiatives has been linked to teacher preparation programs that deliberately embed CT in pedagogical training, ensuring educators can translate CT principles into classroom practice (Barr & Stephenson, 2011; Mon et al., 2020).

In Malaysia, CT is embedded in the Kurikulum Standard Sekolah Rendah (KSSR) and Kurikulum Standard Sekolah Menengah (KSSM) to promote core competencies such as abstraction, decomposition, pattern recognition, algorithmic thinking, logical reasoning, and evaluation (MOE, 2017). Despite these curricular commitments, empirical studies report uneven levels of CT proficiency among teacher trainees due to inconsistent training quality, varying access to digital tools, and differing pedagogical approaches (Kamaruddin et al., 2021).

Yadav et al. (2017) note that without intentional integration of CT concepts into teacher education, pre-service teachers often struggle to apply these skills effectively. These findings echo global concerns that CT integration remains uneven across subject domains, with STEM fields receiving more systematic attention than non-STEM areas (Weintrop et al., 2016; Yadav et al., 2014). CT's six core components (decomposition, pattern recognition, abstraction, algorithmic thinking, logical reasoning, and evaluation) are interdependent and each presents distinct instructional challenges. Decomposition, or breaking complex problems into smaller units, is a common area of difficulty due to cognitive overload (Grover & Pea, 2018). In Malaysia, scaffolding has been employed to improve decomposition skills (MOE, 2017), yet mastery remains inconsistent. Pattern recognition can facilitate predictive thinking and decision-making but is not always easily transferred between disciplines, especially without visual or interactive aids (Yusoff et al., 2021). Abstraction, the ability to focus on relevant details while ignoring the non-essential, is a priority in computational modelling and algorithm design, but educators require more targeted training to teach it effectively (Ung et al., 2021). Algorithmic thinking is often taught through programming languages like Scratch or Python, along with flowcharts and pseudocode (Grover & Pea, 2013), while logical reasoning and evaluation are nurtured through structured tasks and reflective activities (Denning, 2017; Shute et al., 2017). Pedagogical strategies grounded in constructivism (Papert, 1980) and Problem-Based Learning (PBL) have been shown to effectively develop CT skills by immersing learners in authentic, real-world problems requiring systematic analysis and iterative refinement (Weintrop et al., 2016).

These approaches align CT with higher-order thinking skills in Bloom's taxonomy, particularly in the domains of analysis, evaluation, and creation (Shute et al., 2017). Studies also highlight the potential of CT in non-STEM contexts, such as language and social sciences, where decomposition supports discourse analysis, pattern recognition aids in identifying thematic structures, and algorithmic thinking underpins writing strategies (Kafai & Burke, 2014; Yadav et al., 2014). However, persistent misconceptions that CT is exclusively technical hinder its adoption in these areas. Assessment of CT proficiency has relied on varied instruments, including multiple-choice tests, performance-based tasks, and self-report surveys. Multiple-choice assessments, such as the Computational Thinking Performance Test (CTPT) (Román-González et al., 2017) and the competent Computational Thinking test (cCTt) (El-Hamamsy et al., 2022), are valued for their efficiency, objectivity, and scalability (Weese & Feldhausen, 2017). When supported by strong psychometric evidence, these tools can validly measure CT's core components but may overlook design-based and reflective dimensions (Brennan & Resnick, 2012; Shute et al., 2017). In Malaysia, there is limited research on validated CT instruments for teacher trainees, and few studies have examined concurrent validity or the relationship between measured CT proficiency and teaching readiness. Taken together, the literature demonstrates both the global momentum for CT integration and the specific challenges facing Malaysian teacher education. While frameworks, competencies, and pedagogical strategies are well-documented, gaps remain in empirical evidence on how teacher trainees develop and apply CT in authentic teaching contexts. Addressing these gaps particularly through context-specific assessment tools and targeted professional development will be essential for equipping future educators to foster computational problem-solving across disciplines.

3. Methodology

This study employed a quantitative research design to examine the extent of CT among teacher trainees at IPGM in the Central Zone. The quantitative approach was chosen for its ability to produce objective and statistically analyzable data, allowing for the identification of trends and relationships among variables. As emphasized by Creswell (2018) and Fraenkel and Wallen (2019), this method also supports broader generalization of findings and enhances the study's replicability and precision. To assess CT skills, a multiple-choice questionnaire (MCQ) was specifically developed for this research. The instrument was constructed to reflect six core components of CT: abstraction, decomposition, pattern recognition, algorithmic thinking, logical reasoning, and evaluation. The initial item pool was generated based on a comprehensive review of existing CT frameworks and assessment literature, including the works of Wing (2006) and Shute et al. (2017). Each question was designed around real-world problem-solving scenarios to encourage higher-order thinking and application of CT concepts.

The content validation of the instrument was conducted using the Delphi method, involving a panel of 3 experts with extensive experience in computational thinking, educational technology, and assessment. The validation process consisted of three iterative rounds. In the first round, experts reviewed each item for clarity, relevance, and alignment with CT components, and qualitative feedback was collected to inform revisions. In the second round, items were rated using a four-point Likert scale to assess relevance and clarity, with items scoring below the threshold Content Validity Index (CVI) of .80 being revised or removed. The final round achieved expert consensus, and the overall CVI across all items reached .93, indicating strong content validity and expert agreement. Following content validation, a pilot study was conducted with 60 teacher trainees from a different IPGM campus to test the instrument's psychometric properties. Item analyses were performed using classical test theory. Items with difficulty indices (p-values) between .30 and .90 were retained, ensuring a balanced level of challenge. Discrimination indices (D-values) were calculated, and items with values of .52 considered acceptable for distinguishing between high and low performers. Additionally, distractor analysis was conducted to evaluate the plausibility of incorrect answer choices, with non-functioning distractors being revised. The internal consistency of the instrument was measured using the Kuder-Richardson Formula 20 (KR-20), yielding a reliability coefficient of.84, which reflects high internal consistency. The final instrument comprised 30 refined items, with an even distribution across the six CT components.

The study sample consisted of 448 teacher trainees from IPGM campuses located in the Central Zone of Malaysia. The sample size was determined using Cochran's formula for large populations to ensure sufficient statistical power (Cochran, 1977). To capture the diversity of the trainee population, stratified sampling was employed based on academic programs and academic levels. This sampling strategy enhanced the representativeness of the sample and reduced sampling bias, particularly important in educational research where background and training can influence CT proficiency. Data collection was carried out through face-to-face administration of the MCQ across selected IPGM campuses. This method allowed the researchers to provide immediate clarification, reduce the likelihood of misinterpretation, and ensure the integrity of responses. Moreover, it minimized the risk of technical issues and disengagement commonly associated with online data collection. The in-person format contributed to a high response rate and improved the overall quality and completeness of the dataset. Trained enumerators facilitated the data collection process to maintain consistency and adherence to ethical standards.

The collected data were analyzed using IBM SPSS Statistics Version 28. Descriptive statistics, including means, standard deviations, and frequencies, were used to summarize overall CT performance. To determine whether significant differences existed in CT scores across groups, a One-Way Analysis of Variance (ANOVA) was conducted. The groups were defined by institution. Where significant differences were observed, post hoc test was applied to identify specific group differences while controlling for Type I error. This approach aligned with recommended procedures for robust statistical testing, as outlined by Scheffé (1999) and Pallant (2020). Despite its methodological strengths, the study acknowledges several limitations. Although stratified sampling enhanced internal validity, the geographic scope was limited to the Central Zone, potentially restricting the generalizability of the findings to other regions of Malaysia. Furthermore, while face-to-face data collection yielded high-quality data, it was time-intensive and required substantial logistical resources. Future research could address these limitations by expanding the geographic scope and incorporating qualitative methods, such as interviews or open-ended responses. Such approaches would provide deeper insights into how teacher trainees conceptualize and apply CT within diverse educational contexts.

4. Result

This study examines the extent of CT among 448 teacher trainees in IPGM, Central Zone, analyzing gender distribution, institutional representation, and course specialization. The sample comprises 143 males (31.9%) and 305 females (68.1%), reflecting the typical gender ratio in Malaysian teacher education. Respondents are from five IPGM Kampus, with the largest group from IPGK Pendidikan Islam (35.9%), followed by IPGK Ilmu Khas (18.5%), IPGK Ipoh (18.1%), IPGK Bahasa Melayu (16.3%), and IPGK Bahasa Antarabangsa (11.2%), ensuring diverse representation. The Malay Language specialization (31%) is the most common, followed by TESL (16.1%), Physical Education (11.2%), Islamic Education (9.4%), and Home Science (9.4%). Other fields include Special Education, Mathematics, Biology, Arabic Language, Music, and Early Childhood Education, showcasing the multidisciplinary nature of teacher training. The demographic diversity provides valuable insights into the integration of CT across various disciplines. Table 1 shows demographic profile of respondents in the study.

Table 1. *Demographic Profile of Respondents in The Study.*

Items	Details	Frequencies	Percentage (%)
Gender	Male	143	31.9
	Female	305	68.1
Institution	IPGK Pendidikan Islam	161	35.9
	IPGK Ilmu Khas	83	18.5
	IPGK Bahasa Antarabangsa	50	11.2
	IPGK Bahasa Melayu	73	16.3
	IPGK Ipoh	81	18.1
Main Course of Study	Malay Language	139	31
	Teaching English as a Second Language (TESL)	72	16.1
	Islamic Education	42	9.4
	Home Science	42	9.4
	Physical Education	50	11.2
	Special Education	11	2.5
	Mathematics	15	3.3
	Biology	11	2.5
	Arabic Language	25	5.6
	Music	16	3.6
	Early Childhood Education	25	5.6

4.1 Extent of CT proficiency among teacher trainees in Institut Pendidikan Guru Malaysia (Central Zone).

Table 2 presents the average percentage of correct and wrong responses for six components of CT among teacher trainees in Institut Pendidikan Guru Malaysia (Central Zone). The results indicate varying levels of competency in CT components. Evaluation recorded the highest correct percentage (72.32%), while Logical Reasoning had the lowest (55.13%). Pattern Recognition also showed a relatively lower performance, with 38.84% wrong responses.

Table 2. *Average Percentage of Correct and Wrong Responses.*

Components of CT	Average Percentage (%)	
	Correct	Wrong
Abstraction	65.18	34.82
Decomposition	68.08	31.92
Pattern Recognition	61.16	38.84
Algorithm	69.64	30.36
Logical Reasoning	55.13	44.87
Evaluation	72.32	27.68

4.2 Mean Overall Scores (One-way ANOVA)

One-way ANOVA was conducted to examine the differences in overall achievement scores across five educational institutions (IPGKPI, IPGKIK, IPGKBA, IPGKBM, and IPGKI). The analysis includes tests of homogeneity of variances, ANOVA, robust tests of mean equality, and post-hoc multiple comparisons using Tamhane's T2 and Games-Howell procedures, in line with Scheffe (1999) methodological rigor for post-hoc analysis.

4.2.1 Test of Homogeneity of Variance

The assumption of homogeneity of variances was evaluated using Levene's test. The results were statistically significant across all test types as shown in Table 3. Given the significance level ($p < .05$), the assumption of equal variances is violated. Therefore, robust tests and multiple comparisons suitable for unequal variances were applied.

Table 3. *Levene's Test Result.*

Test Type	Levene Statistic	df1	df2	Sig.
Based on Mean	3.065	4	443	.016
Based on Median	3.101	4	443	.016
Based on Median (adj. df)	3.101	4	436	.016
Based on Trimmed Mean	3.177	4	443	.014

4.2.2 One-Way ANOVA

The ANOVA indicated statistically significant differences in overall scores between institutions as shown in Table 4. The significant F-statistic ($p < .05$) suggests that not all group means are equal. However, since homogeneity of variance was violated, robust tests were also considered.

Table 4. *One-way ANOVA Result*

Source	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2560.585	4	640.146	5.487	.000
Within Groups	51686.931	443	116.675		
Total	54247.516	447			

4.2.3 Robust Tests of Equality of Means

Robust procedures (Welch and Brown-Forsythe) confirmed significant differences in means as shown in Table 5. Both tests yielded p-values less than .05, further validating the presence of statistically significant differences between groups, even when adjusting for heterogeneity.

Table 5*: Welch and Brown-Forsythe Result*

Source	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2560.585	4	640.146	5.487	.000
Within Groups	51686.931	443	116.675		
Total	54247.516	447			

4.2.4 Post-Hoc Multiple Comparisons

Due to unequal variances, Tamhane's T2 and Games-Howell post-hoc tests were employed. Both tests are conservative and appropriate for heteroscedastic data. Significant pairwise differences ($p < .05$) are highlighted. The results of Tamhane's T2 post-hoc analysis revealed significant differences between certain institutional pairs. Specifically, students from IPGKIK scored significantly higher than those from IPGKPI, with a mean difference of -6.637 ($p = .000$). This indicates that the mean overall achievement score for IPGKIK was substantially greater than that for IPGKPI. Additionally, the comparison between IPGKIK and IPGKBM showed a significant mean difference of 5.825 ($p = .006$), suggesting that students from IPGKBM outperformed those from IPGKIK in overall scores. The Games-Howell procedure, which similarly adjusts for unequal variances and sample sizes, corroborated these findings. The same pairwise differences were found to be statistically significant: IPGKPI versus IPGKIK (mean difference = -6.637, $p = .000$) and IPGKIK versus IPGKBM (mean difference = 5.825, $p = .006$). The consistency of results across both post-hoc methods lends strong support to the reliability of these observed differences.

5. Discussion

The findings provide critical insights into CT proficiency among IPGM teacher trainees in the Central Zone, revealing notable variations across components and institutions. Strength in the Evaluation component aligns with Shute et al. (2017), who link evaluative thinking to reflective practices such as peer feedback, self-assessment, and classroom reflections, fostering metacognitive awareness. This supports constructivist principles (Papert, 1980) and higher-order thinking in Bloom's Taxonomy, consistent with international findings where reflective pedagogies enhance self-directed learning (Mon et al., 2020). Strong performance was also observed in Algorithmic Thinking and Decomposition, echoing national (MOE, 2017) and international research (Grover & Pea, 2013) that link scaffolded activities (flowcharts, pseudocode, Scratch/Python) to structured reasoning. The integration of decomposition in KSSR and KSSM (MOE, 2017) appears effective, though possible surface-level mastery may limit transferability to abstraction (Ung et al., 2021). Weaker performance in Logical Reasoning and Pattern Recognition mirrors prior findings on their abstract demands (Weintrop et al., 2016; Denning, 2017).

These skills identifying structures across problems and supporting systematic decision-making require explicit, context-rich instruction (Yadav et al., 2017). Practical strategies include comparative case analysis, "odd one out" pattern drills, visual analogy mapping, structured debates, and discipline-specific thematic mapping. In STEM subjects, logic puzzles and conditional flowchart exercises can strengthen reasoning processes, while in non-STEM contexts, literary structure analysis and historical cause–effect mapping can enhance pattern recognition. Variations across institutions reflect systemic factors such as curriculum design, pedagogical practices, resource availability, institutional philosophy, and exposure to CT-integrated subjects echoing Kamaruddin et al. (2021) and Yusoff et al. (2021), who note that even within a centralized framework, institutional culture and educator expertise significantly shape CT outcomes. Methodologically, reliance on a multiple-choice instrument, while efficient and objective, may limit the capture of authentic CT application. Prior studies have shown that open-ended or design-based assessments such as programming projects, computational modeling, and simulation-based problem-solving often reveal deeper reasoning processes and creativity not visible in MCQ formats (Román-González et al., 2017; Grover & Pea, 2013). Differences in outcomes between these formats are often linked to curricular emphasis, pedagogical scaffolding, available resources, and institutional priorities.

A mixed-methods approach combining MCQs with performance-based tasks and artefact analysis would provide a richer, context-sensitive profile of CT proficiency. These results reaffirm CT's multidisciplinary relevance beyond STEM (Grover & Pea, 2013; Kafai & Burke, 2014). In language education, decomposition and pattern recognition support narrative analysis, while algorithmic thinking can structure writing processes. In social sciences, logical reasoning can be fostered through structured debate, and thematic mapping can develop pattern recognition in history or sociology. Addressing persistent misconceptions that CT is STEM-exclusive (Yadav et al., 2014; Weintrop et al., 2016) requires targeted professional development, cross-disciplinary collaboration, and curriculum exemplars that integrate CT into diverse subject areas. Theoretically, these findings support a holistic conceptualization of CT as a universal problem-solving framework (Wing, 2011) grounded in constructivist learning theories (Papert, 1980). Embedding CT in teacher education demands systemic support, targeted training, and authentic assessment to move beyond surface exposure toward deep, reflective integration. The Malaysian case mirrors global challenges, underscoring the need to adapt best practices to local contexts while ensuring equitable CT skill development across institutions and disciplines.

6. Conclusion

The analysis of CT competencies indicates that trainees excel in Evaluation, Algorithmic Thinking, and Decomposition but face persistent challenges in Logical Reasoning and Pattern Recognition, reflecting strengths in structured and reflective thinking alongside a need for enhanced support in abstract and analytical skills. Institutional variations suggest that differences in teaching strategies, support systems, and program designs significantly shape CT outcomes, underscoring the importance of a standardized yet adaptable integration framework that extends beyond STEM into disciplines such as language education. Targeted professional development for teacher educators is essential to cultivate CT not merely as a set of discrete skills but as a broader cognitive stance toward problem-solving, learning, and design. While the study offers valuable comparative insights, its cross-sectional, single-method design constrains interpretive depth; incorporating interviews, classroom observations, and trainee reflections could provide richer contextual understanding of how CT is developed and applied. Future research should adopt mixed-methods designs to capture CT in authentic teaching contexts, implement longitudinal and intervention-based approaches to monitor skill progression, and rigorously validate CT assessment tools for cultural and curricular relevance within the Malaysian educational landscape.

Acknowledgements

This study is supported by the Fundamental Research Grant Scheme (FRGS) of the Malaysian Ministry of Higher Education (FRGS/1/2023/SSI07/UPM/01/1). The assistance of the Research Management Center (RMC) of Universiti Putra Malaysia in coordinating and distributing fund for this research is greatly appreciated.

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