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Level of computational thinking skills among first-year university students: Variation across gender, geographical background, academic discipline, and programming learning experience

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Abstract

This study explores the current status of computational thinking (CT) skills among first-year university students and examines whether any differences exist across genders, geographic backgrounds and academic disciplines with programming learning experience given the growing interest in computational thinking (CT) in recent years. It also investigates the correlations among the five sub-dimensions of CT. 375 Chinese undergraduates were selected through random sampling and completed a computational thinking skills questionnaire. Data were analyzed using quantitative methods, including descriptive statistics, independent samples t-tests, and Pearson correlation analysis. The following results were found: (1) The overall CT skills of the first-year students reached a moderate level. (2) Programming learning experience and academic discipline significantly influenced CT skills of undergraduates but no statistical difference was found across gender and geographic background. (3) There were significant and positive correlations among the five sub-dimensions of CT. The study reveals that differences in CT skills among first-year students are primarily associated with academic discipline and programming learning experience, emphasizing the need for targeted instructional strategies to support diverse learning backgrounds. The present study offers valuable insights into integrating CT into the university curriculum to benefit undergraduates across different academic disciplines.

Keywords: Academic discipline, Computational thinking, First-year university students, Geographical background, Programming learning experience, Instructional strategies.

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Contribution of this paper to the literature
This study revealed algorithmic thinking as the weakest dimension of computational thinking skills among first-year university students and highlighted that programming learning experience and academic discipline significantly influenced computational thinking skills. The findings provide empirical evidence for future focus on the reforming of curriculum to foster computational thinking skills. Moreover, the research proposed pathways of integrating CT skills into the curriculum that can benefit undergraduates from different disciplines.

1. Introduction

Computational thinking (CT) as a significant aspect of high-order thinking skills has received widespread attention from researchers and teachers in computer science since the 1960s (Grover & Pea, 2013). Its definitions also evolved with the technological advancements in recent decades. For instance, Wing (2006) defined CT as a series of thinking activities, namely, problem-solving, system design, and understanding about human behavior by using computer science principles. Later, he refined this definition emphasizing that CT is a problem-solving process with which information processing agents perform tasks efficiently and effectively (Wing, 2011). In addition, Aho (2012) illustrated that CT was conceptualized as the process of formulating problems as solvable through computational procedures and algorithms. The International Society for Technology in Education (ISTE, 2018) proposed a well-recognized definition that CT represents integrated abilities that encompass creativity, algorithmic thinking, critical thinking, problem-solving, and cooperativity, and this multidimensional perspective has been widely acknowledged by a variety of scholars and researchers based on these perspectives (Doleck, Bazelais, Lemay, Saxena, & Basnet, 2017; Korkmaz, Çakir, & Özden, 2017; Özgür, 2020; Varela, Rebollar, García, Bravo, & Bilbao, 2019).

CT skills are not exclusive to computer scientists but an essential competency that everyone should possess in the twenty-first century (Wing, 2006). Wing (2011) further highlighted CT as a core cognitive ability, comparable to other skills such as reading, writing, logical reasoning and mathematical thinking. Prior studies also emphasized the significance and urgency of developing CT skills across different disciplines because these skills could help students cope with the challenges in the digital age (Liu, Peng, & Srivastava, 2023; Özgür, 2020). In this regard, researchers and scholars advocated that more efforts should be devoted to integrating CT skills into the curriculum at all educational levels (Durak & Saritepeci, 2018; Li & Oon, 2024; Oluk & Korkmaz, 2016).

Existing studies on developing CT skills have mainly concentrated on primary or secondary schools (Alsancak, 2020; Chongo, Osman, & Nayan, 2020; Tang, Yin, Lin, Hadad, & Zhai, 2020) while relatively little attention has been paid to higher education contexts (Islami & Nikensari, 2023; Ranjeeth & Padayachee, 2024). In particular, studies focusing on Chinese university students, even freshmen remain scarce (Wang, Gao, & Chen, 2024; Xuchen Zhou, Zhang, Wang, & Chen, 2023). Previous studies have examined students' CT skill levels (Chongo et al., 2020; Kölemen, 2024), CT assessment methods, and the relationships between CT and influential factors such as gender (Alsancak, 2020; Durak & Saritepeci, 2018; Majeed, Jawad, & ALRikabi, 2022), grade level (Korkmaz & Bai, 2019; Tarigan, Paidi, Handoyo, Nuryani, & Dewi, 2024; Yağcı, 2018) and educational stage (Durak & Saritepeci, 2018; Kölemen, 2024). In addition, some empirical studies have explored practical approaches to developing CT skills (Lin et al., 2024; Xiaodan Zhou & Tsai, 2023).

There is still a considerable gap in knowing the CT skill levels of first-year university students and the factors that may influence them, such as geographical background, academic discipline, and programming learning experience. Although earlier studies have examined various aspects of CT. Addressing this gap is important, a deeper exploration of these areas can help teachers design more effective curricula, refine teaching strategies, and implement targeted interventions to foster the growth of CT skills in higher education.

This study aims to explore the following questions to address these research gaps:

1) What is the level of CT skills among first-year university students?
2) How do first-year university students' CT skills vary by gender, geographical background, academic discipline, and programming learning experience?
3) Is there any relationship among the five sub-dimensions of CT skills, including creativity, algorithmic thinking, cooperativity, critical thinking, and problem-solving?
4) What pedagogical strategies can be implemented to enhance university students' CT skills?

2. Research Methodology

2.1. Research Design

This study employed a quantitative approach to investigate the current status of CT skills among first-year university students and to examine how these abilities may differ across gender, geographical background, academic discipline and programming learning experience to address the above-mentioned questions. The data analysis was presented through both descriptive statistics and inferential statistics.

2.2. Participant Selection

This study recruited participants who were studying at Yuncheng University, located in northern China following random sampling. Approximately 4,000 students were registered as freshmen in the academic year 2024-2025, and their ages ranged from 17 to 20. According to the sample size calculation method proposed by Israel (1992), the research was supposed to recruit at least 364 participants to ensure a 95% confidence level with a 5% margin of error. Therefore, 400 freshmen were randomly selected to participate in this study. After excluding missing values, outliers and inconsistencies, 375 responses were valid. Table 1 provides an overview of their demographic information, including gender, geographical background, academic discipline, and programming learning experience.

Table 1. Demographic characteristics of participants.

Variables	Characteristics	N	%
Gender	Male	106	28.3
	Female	269	71.7
Geographical background	Rural area	277	73.9
	Urban area	98	26.1
Academic discipline	Humanities and social sciences	187	49.9
	Science and engineering	188	50.1
Programming learning experience	With a programming learning experience	79	21.1
	Without a programming learning experience	296	78.9
Total	375		

2.3. Instrument

A questionnaire was used as the instrument for this study. Specifically, the first section collected basic information of participants, such as gender, age, academic discipline and programming learning experience. The second section aimed to assess students' computational thinking abilities through the computational thinking scale (CTS), originally developed by Korkmaz et al. (2017). This five-point Likert scale comprises 21 items with five sub-dimensions including creativity, algorithmic thinking, cooperativity, critical thinking, and problem-solving (Korkmaz et al., 2017). Table 2 outlines the results of Cronbach's alpha for this scale and its five dimensions. According to Creswell (2009) Cronbach's alpha values between 0.7 and 0.9 represent good to excellent internal consistency. In other words, the scale adopted in this study demonstrated strong reliability.

Table 2. Reliability of the computational thinking scale.

Variables	Number of items	Cronbach's alpha
Computational thinking (CT)	21	0.942
Creativity	5	0.858
Algorithmic thinking	4	0.763
Cooperativity	4	0.896
Critical thinking	4	0.786
Problem-solving	4	0.821

2.4 Data Collection and Analysis

The CTS was distributed online through Questionnaire Star, a popular survey platform in China. In total, 400 first-year university students were invited to complete the questionnaire, and 382 responded, each taking approximately 10 minutes. After the data screening process, 375 valid responses were confirmed. As a result, the survey achieved a response rate of 95.5%, and 93.8% of the responses were deemed valid.

The collected data were then analyzed using the software SPSS 25.0. To illustrate, descriptive analysis was firstly used to display percentages, mean scores, and standard deviations. Then, the researcher used independent samples t-tests and Pearson correlation analysis to further address the research questions. Table 3 categorizes the high, moderate, and low levels based on the mean scores of overall CT skills.

Table 3. Mean score ranges for computational thinking skill levels.

Mean range	Interpretation
1.00-2.33	Low level of computational thinking
2.34-3.67	Moderate level of computational thinking
3.68-5.00	High level of computational thinking

3. Results

3.1. Level of Students' Computational Thinking Skills

Descriptive statistics were used to evaluate the level of CT skills among the first-year university students to answer the first research question. Table 4 presents the percentages, mean scores (mean), standard deviations (SD) of CT skills and the five CT sub-dimensions.

The results indicate that the overall CT skill level is moderate (M=3.59) with 47.8% of students demonstrating a high level while only 9.4% are classified at a low level. Among the five sub-dimensions, cooperativity exhibits the highest mean score (M = 3.74) whereas algorithmic thinking scores the lowest (M = 3.33). In terms of percentage distribution, the majority of students (55.9%) possess a high level of creativity while only 36.0% of learners reported a high level of algorithmic thinking.

Table 4. Descriptive statistics of first-year university students' computational thinking skills.

Dimensions	Item	Mean	SD	Min	Max	Percentage (%)		
						Low	Moderate	High
Computational thinking (CT)	21	3.59	0.52	2.04	5	9.4	42.8	47.8
Creativity	5	3.73	0.54	1.60	5	5.1	39.0	55.9
Algorithmic thinking	4	3.33	0.72	1	5	13.9	50.1	36.0
Cooperativity	4	3.74	0.64	1.25	5	10.3	37.4	52.3
Critical thinking	4	3.59	0.61	1	5	9.5	43.1	47.4
Problem-solving	4	3.56	0.64	1	5	9.3	45.3	45.3

3.2. Relationships between Computational Thinking Skills and Demographic Factors

The second research question was addressed using independent samples t-tests which examined how the CT skills differ across gender, geographical background, academic discipline, and programming learning experience.

Table 5 presents the statistical findings between students' CT skills and gender. The results indicate that the mean score of male students in overall CT (M = 3.65) is higher than that of their female peers (M = 3.56). When it comes to the five sub-dimensions, male students also reported higher mean values in creativity, algorithmic thinking, cooperativity, and problem-solving. It is noted that female students only demonstrated a slightly higher mean score in critical thinking compared to male learners. However, no statistically significant difference was found between the male and female students in overall CT ($p = 0.246$) or in any sub-dimension ($p > 0.05$).

Table 5. T-test results on the differences in computational thinking based on gender.

Dimensions	Male (N=106)		Female (N=269)		t	p
	Mean	SD	Mean	SD		
Computational thinking (CT)	3.65	0.53	3.56	0.51	1.162	0.246
Creativity	3.76	0.53	3.72	0.55	0.726	0.468
Algorithmic thinking	3.43	0.75	3.30	0.71	1.516	0.130
Cooperativity	3.82	0.63	3.72	0.64	1.359	0.175
Critical thinking	3.58	0.65	3.60	0.59	-0.101	0.920
Problem-solving	3.62	0.68	3.54	0.63	1.133	0.258

According to Table 6, students from urban areas have slightly higher mean scores in overall CT and all its sub-dimensions compared to their rural counterparts. Besides, no significant difference was found between geographical backgrounds and overall CT or any sub-dimension. Creativity ($p = 0.059$) and algorithmic thinking ($p = 0.059$) approaches marginal significance suggesting a potential trend that may warrant further investigation. Thus, geographical background does not exert a significant impact on students' CT skills.

Table 6. T-test results on differences in computational thinking based on geographical background.

Dimensions	Rural area (N=277)		Urban area (N=98)		t	p
	Mean	SD	Mean	SD		
Computational thinking (CT)	3.53	0.52	3.62	0.52	1.534	0.126
Creativity	3.72	0.55	3.76	0.53	1.893	0.059
Algorithmic thinking	3.22	0.71	3.38	0.72	1.895	0.059
Cooperativity	3.65	0.70	3.78	0.61	1.655	0.099
Critical thinking	3.59	0.58	3.60	0.62	0.199	0.843
Problem-solving	3.53	0.69	3.58	0.63	0.656	0.512

According to Table 7, the overall CT scores of science and engineering disciplines students are significantly higher than those of humanities and social science students. Furthermore, significant differences are observed in CT skills according to academic discipline, particularly in algorithmic thinking ($p < 0.001$) and problem-solving ($p = 0.005$). However, cooperativity ($p = 0.420$) and critical thinking ($p = 0.177$) show no statistically significant differences. Creativity shows a marginal difference ($p = 0.049$) with science and engineering students scoring slightly higher. Overall, these findings indicate that academic discipline has a significant effect on CT, particularly in the dimensions of problem-solving and algorithmic thinking.

Table 7. T-test results on differences in computational thinking based on academic discipline.

Dimensions	Humanities and social science (N=187)		Science and engineering (N=188)		t	p
	Mean	SD	Mean	SD		
Computational thinking (CT)	3.52	0.50	3.67	0.53	-2.746	0.006
Creativity	3.71	0.52	3.75	0.56	-0.691	0.049
Algorithmic thinking	3.15	0.73	3.52	0.66	-5.092	0.000
Cooperativity	3.72	0.62	3.77	0.65	-0.808	0.420
Critical thinking	3.55	0.62	3.63	0.59	-1.354	0.177
Problem-solving	3.47	0.65	3.66	0.63	-2.846	0.005

According to Table 8, students with prior programming learning experience demonstrate significantly higher overall CT scores ($p = 0.001$) compared to those without such experience. They score significantly higher in algorithmic thinking ($p < 0.001$), problem-solving ($p = 0.001$), creativity ($p = 0.003$), and critical thinking ($p = 0.019$). Nevertheless, no significant difference is found in cooperativity ($p = 0.222$). These findings suggest that prior programming experience positively influences CT skills, particularly in algorithmic thinking, problem-solving, and creativity.

Table 8. T-test results on differences in computational thinking based on programming learning experience.

Dimensions	With a programming learning experience (N=79)		Without a programming learning experience (N=296)		t	p
	Mean	SD	Mean	SD		
Computational thinking (CT)	3.77	0.55	3.54	0.50	3.349	0.001
Creativity	3.89	0.55	3.69	0.53	2.970	0.003
Algorithmic thinking	3.60	0.66	3.27	0.72	3.734	0.000
Cooperativity	3.82	0.71	3.72	0.62	1.224	0.222
Critical thinking	3.73	0.61	3.56	0.60	2.364	0.019
Problem-solving	3.78	0.67	3.51	0.63	3.372	0.001

3.3. Correlation among the Five Sub-Dimensions of CT

Table 9 presents the Pearson correlation coefficient among the five sub-dimensions of CT. All correlations are statistically significant ($p < 0.01$) indicating strong interrelationships. Problem-solving exhibits the strongest relationships with critical thinking and algorithmic thinking suggesting its strong association with logical reasoning and structured problem-solving approaches. Additionally, creativity shows a moderate relationship with algorithmic thinking and problem-solving while cooperativity shows relatively weaker correlations with the other sub-dimensions, particularly with algorithmic thinking ($r = 0.461$).

Table 9. Correlation among the five sub-dimensions of computational thinking

Dimensions	Creativity	Algorithmic thinking	Cooperativity	Critical thinking	Problem-solving
Creativity	1				
Algorithmic thinking	0.522**	1			
Cooperativity	0.527**	0.461**	1		
Critical thinking	0.592**	0.630**	0.547**	1	
Problem-solving	0.633**	0.717**	0.576**	0.774**	1

Note: **$p < 0.01$ (1% level of significance).

4. Discussion

The aim of this study is to assess the level of CT skills among first-year university students and explore their relationships with key demographic factors, including gender, geographical background, academic discipline, and programming learning experience.

The findings revealed that CT skills among first-year university students are generally at a moderate level. The result is consistent with previous studies conducted by Yağcı (2018); Korkmaz and Bai (2019); Chongo et al. (2020) and Liu (2023). However, Majeed et al. (2022) and Kölemen (2024) draw a different conclusion. They argued that university students' CT skills are generally high. The study found the following descending order of students' performance: cooperativity, creativity, critical thinking, problem-solving, and algorithmic thinking in examining the sub-dimensions of CT. The ranking aligns with the findings of Chongo et al. (2020); Xu (2022) and Jin (2023) who similarly found algorithmic thinking to be the weakest dimension. In contrast, Korkmaz and Bai (2019) recognized creativity as the strongest dimension while problem-solving and algorithmic thinking were relatively weak. Most studies consistently identified algorithmic thinking as the greatest challenge students face when developing CT skills, especially in higher education despite variations in the specific rankings. These findings signal more focus on the cultivation of algorithmic thinking when teachers intend to reform instructional strategies to enhance CT skills.

Male students reported higher levels of CT skills than their female peers but no significant difference existed across genders, either in overall CT ability or five sub-dimensions. Such findings corroborated previous studies by Chongo et al. (2020); Alsancak (2020); Majeed et al. (2022) and Tarigan et al. (2024) who also found no significant relationship between students' CT skills and gender. Nevertheless, Atmatzidou and Demetriadis (2016); Korkmaz and Bai (2019) and Kölemen (2024) reported significant gender differences in CT competence across different educational stages. These contradictory results require further studies to explore any other potential factor that may mediate the relationship between gender and CT skills.

Furthermore, urban students achieved higher CT scores than their rural counterparts but differences in regional background did not yield any statistical significance in either overall CT ability or the five sub-dimensions based on statistical results. Similarly, Tanti, Kurniawan, Kuswanto, Utami, and Wardhana (2020) concluded that although urban students had higher critical thinking skills than rural students, no direct correlation existed between CT ability and geographic background. Li and Oon (2024); Fu and Hashim (2024) and Li et al. (2025) elucidated the potential impact of geographical disparities on CT skills, particularly in science, technology, engineering or math education. These studies illustrated that rural students were more likely to encounter considerable challenges in developing CT due to limited access to advanced technological infrastructure, teacher-centered instructional approaches, and insufficient hands-on learning opportunities.

When it comes to different academic disciplines, science and engineering students had significantly higher CT skills than their peers in humanities and social sciences, and a significant relationship was found between overall CT skills and academic disciplines, particularly in the dimensions of algorithmic thinking, problem- solving and creativity. These results correspond with prior studies such as Dehbozorgi and Roopaei (2024); Ravan and Huang (2024) and Cannady et al. (2025) who examined specialized learning modules focused on CT. These modules led to better CT performance among students in these fields, especially problem-solving and creativity skills. Similarly, Khenner (2024) and Kölemen (2024) also reported that students' CT skills significantly differed based on academic discipline. Recent studies suggest a growing focus on integrating CT into humanities and social sciences curricula (Bonilla-Castañeda, Villalba-Condori, Cardona-Reyes, Acra-Despradel, & Turner-Lam, 2024; Christensen, 2023). Govender (2022) observed that students in humanities and social sciences rarely have access to systematic training in algorithmic and computational methods compared to their peers majoring in science and engineering despite these advancements. This finding demonstrates the necessity of incorporating interdisciplinary teaching strategies into CT education (Bonilla-Castañeda et al., 2024).

Students with programming learning experience possessed better CT skills compared to their peers without such experience. Significant relationships were also observed between programming learning experience and four sub-dimensions ($p<0.05$) except for cooperativity ($p = 0.222$). These results align with quantitative findings reported in earlier studies by Oluk and Korkmaz (2016); Hsu, Chang, and Hung (2018); Jong and Jeuring (2020); Özgür (2020); Saritepeci (2020); Govender (2022); Osztián, Kátai, and Osztián (2022); Choi and Choi (2024) and Cannady et al. (2025). These studies not only concluded that prior programming experience positively predicted the mastery of CT skills but also asserted the process of programming as a useful means to foster CT skills. Ranjeeth and Padayachee (2024) reported a moderate yet significant relationship between programming learning experience and the problem-solving dimension, suggesting that programming instruction may be particularly effective in strengthening specific aspects of CT. However, the cultivation of CT skills with its five sub-dimensions cannot merely rely on programming learning. Türker and Pala (2020) suggested diverse instructional strategies to help students gain CT skills in addition to the necessary training with programming courses. Jong and Jeuring (2020) also emphasized that non-programming tasks related to the humanities and social sciences also empowered learners with CT skills through hands-on programming activities. Integrated instructional approaches are recommended to comprehensively support the improvement of CT skills, especially for students with limited programming experience.

Finally, the present study reports significant and positive relationships among the five sub-dimensions of CT skills, illustrating that a higher level of one single dimension could result in the enhancement of other dimensions. This finding conforms to empirical studies by Korkmaz and Bai (2019) and Putri, Tanjung, and Siregar (2024) who similarly reported significant and positive correlations among CT sub-dimensions. It also reveals the interconnected characteristics of CT components and their overlapping effect on the cognitive development of learners. However, other researchers have argued that these relationships may not be universally applicable or conceptually straightforward and contended that certain factors can influence the relationships between CT sub-dimensions (Grover & Pea, 2013; Lye & Koh, 2014; Román-González, Pérez-González, & Jiménez-Fernández, 2017). For example, sub-dimensions of CT skills could be influenced by task types, the learning context, individual cognitive styles, and other specific conditions in relation to educational experiments. In other words, the relationships among CT dimensions are more complex and context-dependent rather than a simple linear positive correlation. Consequently, these findings provide valuable insights into the instructional design aimed at enhancing CT skills and more targeted instructional strategies are required to support the development of different dimensions with specific characteristics.

The present study offers several implications for educational practices. Teachers in the tertiary schools should adopt systematic strategies to cultivate students' CT skills, with targeted instructional interventions to bridge the gap between students with or without programming learning experience. For example, innovative teaching approaches, such as problem-based learning, project-based learning or collaborative learning can be integrated into programming courses such as C, Python or Scratch (Cannady et al., 2025; Choi & Choi, 2024) so that learners could strengthen their CT skills with an emphasis on algorithmic thinking and problem-solving abilities (Islami & Nikensari, 2023; Wang et al., 2024). Moreover, students from different academic disciplines are encouraged to raise their awareness of developing CT skills during their first or second year of study. Regular learning activities can be organized with better integration of core CT concepts and competencies into a wide range of curricula to help students adapt to the evolving demands of the digital era (Bonilla-Castañeda et al., 2024; Ravan & Huang, 2024). Finally, a comprehensive CT assessment system is essential and crucial for educators to systematically track and evaluate the progression of students' CT skills over time (Tang et al., 2020). Recent intelligence tools are also recommended in assessment systems to support the personalized and adaptive learning of students because teachers and students can receive instant feedback about their weak points and individualized support to foster overall CT skills.

5. Conclusion

This study investigates the current status of CT skills among first-year university students and examines whether any difference in CT skills exists across genders, geographical backgrounds, academic disciplines, and programming learning experiences. A total of 375 students were surveyed through random sampling and the data were analyzed with the method of independent samples t-tests and correlational analysis. The findings are as follows: (1) This study demonstrated a moderate level of overall CT skills with particularly high level in creativity and cooperativity while algorithmic thinking scored the lowest. (2) Programming learning experience and academic discipline significantly influenced students' computational thinking, but no statistical difference existed across gender and geographic background. (3) There were significant and positive relationships among the five sub-dimensions of CT. The research provides valuable insights into the pathways of incorporating CT skills into the curriculum system in order to further enhance the undergraduates' CT skills across disciplines.

However, the study is not free from limitations. First, the study relied on a quantitative analysis method, which was insufficient for delving into the process of developing CT skills. Second, the sample of this study was restricted to first-year students at only one university which would limit the findings applicable to other contexts. Third, this study might disregard other factors related to CT skills although it scrutinized the effects of variables such as gender, geographic background, academic discipline, and programming learning experience. Therefore, future studies can be carried out to include a more diverse sample, collect both quantitative and qualitative data, and examine other factors in relation to CT skills. Educational interventions are also recommended to assess the effect of innovative instructional approaches on developing CT skills at different educational levels.

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