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REGULAR ARTICLE

Demographic and Educational Correlation of High School Students' Computational Thinking Skills: Evidence from Four Chinese Schools

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Abstract Computational Thinking (CT) is a vital skill for digital citizens in the twenty-first Century. Investigating CT skills and their relationships with demographic and educational factors serve as the basis of CT skills cultivation. However, there is limited research focusing on high school students and inconsistent results regarding the relationship between students' CT skills and their demographic factors. To fill these gaps, this study explored demographic and educational factors that correlate with high school students' CT skills in Chinese educational settings. We adopted a cross-sectional research design and employed Computational Thinking Scale (CTS) for K-12 students to measure the CT skills of 1043 students from four urban high schools in northern and southern China. According to the Mann–Whitney *U* test and the Kruskal–Wallis test, male students outperformed female students in four sub-dimensions of CT skills. Additionally, tenth graders (average age of 16) scored significantly higher in two sub-dimensions of CT skills compared to eleventh graders (average age of 17). While no significant differences in CT skills were found between students from northern and southern China. Furthermore, students' academic performance in total and their academic performance in English, math, and Information Technology were positively related to their CT skills. We compared our results with previous literature, discussed possible reasons for our findings, and recommended that collaborative, interdisciplinary, problem-based learning experiences that are oriented toward problem-solving should be implemented, especially for female students, to foster high school students' CT skills.

Keywords Computational thinking (CT) · Computational thinking skills · Academic achievement · High school · Assessment

Introduction

Computational Thinking (CT) is regarded as a vital thinking skill for digital citizens in the twenty-first Century, given the dramatic impact of the computer and the Internet on human beings' living and work. Considering the importance of CT, scholars have spent great efforts in measuring students' CT skills (Coban & Korkmaz, 2021; Hava & KoyunluÜnlü, 2021; Kastner-Hauler et al., 2022) and developing learning tools and materials to better arm students with this core skill (Angeli & Giannakos, 2020; Kuo & Hsu, 2020; Saritepeci, 2020). The design and development of learning experiences and materials should be based on students' zone of proximal development to ensure the validity and efficiency of instruction (Basawapatna, 2013; Margolis, 2020). In other words, the level of students' CT skills and the possible factors that would influence it serve as the basis of further CT education.

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High school is an essential juncture for the development of thinking skills (Carlgren, 2013), as well as for the cultivation of practical skills relevant to daily life and professional endeavors, all of which ultimately shape their choices of academic majors and career aspirations (Claiborne et al., 2020). To prompt and nudge high school students' CT skills to a higher level, educators require measuring high school students' current level of CT skills and designing proper instruction accordingly. However, further studies are still needed to understand high school students' CT skills level. Although increasing studies explore students' CT skills and correlated variables in K-12 education, there is a lack of understanding of high school students' CT skills, compared to elementary and middle schools (Tang et al., 2020). Further, among current studies, there was an inconsistent result regarding the relationship between students' CT skills and their demographic factors, such as gender, grade, and region. Furthermore, unclear relationships existed between students' academic performances (e.g., in English, Information Technology (IT), and math) and their CT skills. (Sun et al., 2022).

To fill these gaps, this study investigated high school students' CT skills and explored their relationships with demographic factors (gender, grade, and region) and academic achievements in general and in three subjects related to CT (i.e., English, math, and IT). Findings from our work can be used as evidence for further research to assess CT skills and their correlations and to support high school educators in designing CT-related courses.

Literature Review

CT's Definition and Assessment

Jeannette M. Wing (2006) first coined CT as "solving problems, designing systems, and understanding human behaviors, by drawing on the concepts fundamental to computer science." With continuous exploration, CT has also been recognized as a critical competence and a high-order thinking skill that students need when learning all kinds of subjects (Tang et al., 2020). According to the International Society for Technology in Education (ISTE) CT leadership toolkit (2015), CT extends and refocuses human creativity and critical thinking when individuals utilize computers to improve their problem-solving capacity. Based on ISTE (2015), Korkmaz et al. (2017) further interpreted that CT reflected six sub-dimensions, i.e., creativity, algorithmic thinking, critical thinking, problem-solving, establishing communication, and establishing cooperation. These six dimensions were widely applied by educational researchers (Li & Chen, 2020; Polat et al., 2021; Zhao et al., 2022). On one hand, these six dimensions correlate with the revised Bloom's taxonomy, which presents a framework of educational objectives beyond a particular course or curriculum, including remembering, understanding, applying, analyzing, evaluating, and creating (Krathwohl, 2002). Take the dimension of algorithmic thinking as an example, it includes comprehending, applying, evaluating, and producing the algorithms (Korkmaz et al., 2017), covering the revised Bloom's taxonomy and providing a framework for educators to scaffold teenagers to develop algorithm thinking (Sarawagi, 2014). On the other hand, according to Piaget's Cognitive Development theory, children older than 11 years old are involved in the formal operational stage. During this stage, children begin to reflect on abstract concepts and logical thoughts, deductive reasoning, systematic arrangement, as well as to apply general principles to solve a specific problem (Ghazi et al., 2014). This implies that CT's definition of ISTE (2015) and interpretation of Korkmaz et al. (2017) are suitable for our research age group, i.e., teenagers in high school aged 16–17.

Under ISTE's definition, assessment tools focus more on students' transfer of their CT skills to different types of problems, i.e., their ability to tackle general problem-solving scenarios. In alignment with this focus on general problem-solving contexts, the Computational Thinking Scale (CTS) was developed by Korkmaz et al. (2017). CTS contained 29 items and five sub-dimensions: creativity, algorithmic thinking, critical thinking, problem-solving ability, and cooperation ability. Creativity was listed as a sub-dimension of CTS because of Cropley's (1997) general principles about cultivating children's creativity (Korkmaz et al., 2017) and the fact that creativity covers critical problem-solving, contributing to CT (Israel-Fishelson et al., 2021). Stem from Brown's (2015) theory and definition, algorithm thinking represents the ability to comprehend, apply, evaluate, and produce algorithms. It was concluded in CTS because individuals need to solve a problem by proceeding in sequence. The dimension of critical thinking, defined based on Halpern's (1996) theory, was also included in CTS as critical thinking is a prerequisite of CT (Buckley, 2012). CT also represents a distinctive fusion of thinking skills that, when applied collectively, form a potent approach to problem-solving (Barr et al., 2011; Selby & Woollard, 2013). Therefore, when considering the programming process as a central problem-solving procedure, problem-solving ability (skills) is indispensable within CTS. Finally, CTS includes cooperation ability because it is inevitable for individuals in the twenty-first century to cooperate to solve complex problems (Korkmaz et al., 2017).

After scrutinizing the related paper and developing a theoretical framework, Korkmaz et al. (2017) formed an item pool, including "How Creative Are You?" creativity scale (Aksoy, 2004), "Problem-Solving Scale" scale, "Cooperative Learning Attitude Scale" (Taylan, 1990), "The Scale of California Critical Thinking Tendency" (Kökdemir & Dönmez, 2003), and "Logical-Mathematical Thinking" scale (Yesil & Korkmaz, 2010). Items measuring communication skills and algorithm thinking were developed based on expert opinions, interviews with undergraduate students, and experts' revisions. In the end, CTS was finalized by a pilot survey on 13 students and proved to be validated by 726 students' survey data.

Later, Korkmaz and Bai (2019) applied CTS to measure K-12 students' CT skills and revised it according to survey data from 1,015 Chinese high school students to modify CTS for this age group. The revised CTS encompassed the same five sub-dimensions, underpinned by the same theoretical framework as the CTS. Since intra-personal skills (e.g., communication, collaboration, or questioning) and students' perceptions of CT skills were easier to measure through the self-reported Likert scale (Lu et al., 2022), this study employed revised CTS to measure students' CT skills.

Students' Demographics and CT Skills

Studies have explored the possible relationship between CT skills and demographic factors, such as gender, grade, and region, while the conclusions were contradictory. For gender, some studies have found that boys and girls differed in CT performance (Polat et al., 2021; Román-González et al., 2017). For example, Jiang and Li (2021) measured 336 Chinese fifth graders' CT skills by CTS before and after five-week Scratch learning, discovering that boys' general CT skills were significantly higher than girls' in both tests. In confirming whether gender differences in CT contributed to pedagogical designs for CT (Angeli& Giannakos, 2020), our study aimed to further confirm the gender differences in CT skills.

Whether CT skills differ among students from different grades has not reached consistency. Some studies concluded that students in higher grades had higher levels of CT perceptions, while some studies had different findings. For example, Durak and Saritepeci (2018) reported Ankara's students' CTS and found that the increase in the level of education, from secondary school (fifth to eighth grades) to high school (ninth to twelfth grades), had paralleled with CT skills in general. However, using similar instruments (i.e., CTS), Korkmaz and Bai (2019) surveyed 1015 tenth graders and eleventh graders in two schools in Ningxia Province and Jiangxi Province, China, discovering that only CT's sub-dimensions (i.e., critical thinking and problem-solving) are negatively related to grades. Further studies are needed to explore the relationship between students' CT skills and their grades.

Furthermore, students from different regions may have different CT skills levels. This is because educational outcomes are related to the regional educational environment, including educational policies and socio-economic development status (González-Betancor & López-Puig, 2020). For example, both Polat et al. (2021) and Jiang and Li (2021) applied CTS to measure the CT skills of fifth and sixth graders (i.e., 10–12 years old). Polat et al. measured the CT skills of 328 Istanbul students studying in a private school and got an average score of 3.44 in CTS; while Jiang & Li investigated 336 Chinese rural primary school (in Zhejiang Province) students' CTS and got an average score of 3.20 before five-week Scratch learning and 3.92 after the lessons. This comparative result indicated that students from different regions had diverse CT skills. Indeed, disparities in CT skills of primary school teachers in rural settings and urban settings have been substantiated: rural teachers reported significantly lower levels of CT skills compared to their urban counterparts (Kale et al., 2018). Some research attributed these regional differences to the digital divide, which encompasses different physical access, motivational access, skills access, and usage access for using technologies (Celik, 2023; Karpinski et al., 2021). For example, a survey involving 865 Turkish higher education students revealed that the digital divide had a positive effect on computational thinking skills, i.e., reduction of the digital divide positively impacts CT skills (Celik, 2023). Socio-economic, racial stereotyping, and cultural background add to on digital divide, limiting K-12 students' access to advanced interaction with computer science and technology, efforts in learning computational thinking, and development of CT skills (Czerkawski & Lyman, 2015; Kale et al., 2018). Moreover, Hava & KoyunluÜnlü (2021) investigated students with low socio-economic levels in four public middle schools in Turkey and found students' CT skills would significantly impact their STEM career interests and attitudes toward inquiry. Limited research has examined regional differences among K-12 students. Thus, our study aims to explore whether disparities in CT skills emerge based on geographic location.

Student's Academic Achievement and CT Skills

CT consisted of such skills as algorithmic processing and critical thinking, which aided students' understanding of domain knowledge, like math, science, and language (Grover & Pea, 2013). These skills would help students perform better in school and obtain more academic achievement (Polat et al., 2021). Thus, it is helpful to correlate student's academic achievements to CT skills. CT skills were found positively related to mathematical thinking and IT basic skills, like programming (Sun et al., 2022). Specifically, academic success in math was positively related to CT skills (Durak & Saritepeci, 2018; Polat et al., 2021). While the correlation degree between academic achievement in IT and CT skills was unclear. Furthermore, for English as a Foreign Language (EFL) students, CT skills might also be associated with their English academic achievement. This was because EFL students with better English levels could better comprehend programming language, use computer programming (i.e., vocabulary, syntax, and symbols), and find their programming errors (Pudyastuti & Palandi, 2014). As this study's participants are Chinese (EFL) students, we investigate their academic achievement in total and in math, IT, and English.

High school is a critical stage for students to develop thinking skills, as well as to learn fundamental knowledge of specific academic fields (Grover et al., 2014). High school students' academic performances in different fields might influence their major selection in universities (Sadler et al., 2012). Tang et al. (2020) systematically reviewed 96 journal articles and analyzed current CT assessments' educational context, assessment construct, assessment type, and reliability and validity evidence. They summarized that few studies examined high school students' CT skills, compared to elementary school. Thus, exploring the relationship between CT skills and high school student's academic achievements would help us better understand this issue.

Research Purposes and Hypotheses

This study aimed to investigate Chinese high school students' CT skills and their relationship with demographic factors (gender, grade, and region) and educational factors (academic achievements in total and three related subjects). The study identified CT as a general problem-solving skill. Based on ISTE's theoretical framework and developed assessment tools, revised CTS for high school students, CT skills included five dimensions: creativity, algorithmic thinking, critical thinking, problem-solving ability, and cooperation (Korkmaz & Bai, 2019). Under this framework, the overarching research purposes were two-fold: (1) to measure the CT skills level in sample schools and (2) to find out the correlation between high school students' CT skills and demographic factors, as well as their academic performance. Specifically, this study addresses the following hypotheses:

Hypotheses Regarding Students' CT Skills and Demographic Factors

Hypothesis 1a Male students' CT skills are significantly higher than those of female students.

Hypothesis 1b Eleventh graders' CT skills are significantly higher than those of tenth graders.

Hypothesis 1c Students' CT skills significantly vary between different regions.

Hypotheses Regarding Students' CT Skills and Academic Achievement

Hypothesis 2a Academic performance in total positively influences CT skills.

Hypothesis 2b Academic performance in math positively influences CT skills.

Hypothesis 2c Academic performance in IT positively influences CT skills.

Hypothesis 2d Academic performance in English positively influences CT skills.

Methodology

Participants

The survey was a cross-sectional survey. Data were collected from four experimental high schools in southern and northern regions of China (School A, B, C, and D, detailed information is shown in Table 1) of a national project, whose aim was to improve K-12 school students' CT through AI-related educational programs. Specifically, project communities reached out to Chinese secondary schools using convenience sampling and personal connections to invite

Table 1 Description of sample schools

School	Region and Location	Sample size	Region	Feature
A	Downtown area of Beijing	480	Northern	Affiliated school of Chinese top University
B	Urban area of Hangzhou	80	Southern	Model schools of AI education
C	Urban area of Hangzhou	181	Southern	Model school for first-class ordinary high schools
D	Urban area of Ningbo	302	Southern	Experimental schools of modern educational technology in China

collaboration on this project. Four schools in the southern and northern regions of China responded and were selected as experimental schools. Thus, we started with these four schools and planned to extend to more public schools in future. The survey was a preliminary test of students' CT skills before introducing AI-related educational programs and experiments. We administered the online questionnaire to all students in both tenth and eleventh grades across the four selected schools, 1,198 students in total. After careful review, 155 students' data were excluded due to reasons, such as survey abandonment or failure to submit the questionnaire online. Therefore, 1043 valid responses were utilized for subsequent analysis. With a commendable response rate of 87.06%, the likelihood of non-response bias impacting the outcomes was deemed minimal, demonstrating a satisfactory level of representativeness within the studied population (Armstrong & Overton, 1977).

Chinese high school students usually take IT courses in the first two years (i.e., tenth grade and eleventh grade) and prepare for the National College Entrance Examination (NCEE) in the twelfth grade (Farley & Yang, 2020; Jiang et al., 2023; Sun et al., 2021). Considering that the twelfth graders were not enrolled in the IT course and thus unable to measure academic performance in this course, we narrowed our selection to the tenth graders and eleventh graders. Convenience sampling was applied when delivering the questionnaires to each school.

Instrument

Our questionnaire contained three parts: (1) students' demographic information; (2) students' academic performance in the relevant subjects in total and in three relevant subjects (English, math, and IT); (3) students' CT skills, including creativity, algorithmic thinking, cooperative ability, critical thinking, and problem-solving.

Students' demographic information contained gender, grade, and region. Plus, this study adopted a self-reported academic performance approach, in which the academic performance was divided into four groups: top 25% (Group 1), 25%-50% (Group 2), 50%-75% (Group 3), and bottom 25% (Group 4). Students were asked to indicate one group they belonged to according to their academic performance in class. We adopted this self-reported approach from previous work (Kohyama, 2017; Li & Ranieri, 2013; Ratelle & Duchesne, 2014). This approach guaranteed anonymity and prevented students from answering questionnaires under the pressure of teachers' control (Li & Ranieri, 2013). This measurement may also weaken the requirement for consistent standards of performance assessment among schools, as self-reported data focus more on investigating how well students perceived themselves in specific subjects (Li & Ranieri, 2013). Though self-reported measures were subjective, researchers have found relatively strong correlations between students' self-reports academic performance and actual grades among high school students (Ratelle & Duchesne, 2014; Teye & Peaslee, 2015), especially for students with high ability and good grade point averages (Kuncel et al., 2005). Therefore, although self-reported academic achievements might need cautious and additional discussion when interpreting data, they could be considered reliable and valid (Kuncel et al., 2005; Sticca et al., 2017).

For the measurement of CT skills, the revised CTS created by Korkmaz and Bai (2019) was adopted and adapted. The scale contained five dimensions and 22 items (as mentioned in Sect. "CT's definition and assessment"). Answers were scored on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

Data Collection and Analysis

Before the investigation, permission was taken from all the school principals and relevant institutions. No financial incentives were paid to participants. All participants were informed about the purpose of the survey and their personal information was de-identified. The online Chinese questionnaire was delivered in October 2021. 1043 students from tenth and eleventh grades in four high schools completed the survey. Among them, 583 (55.90%) were male students and 460 (44.10%) were female students. 576 (55.23%) were from tenth grade (15–16 years old) and 467 (44.77%) were from eleventh grade (16–17 years old). In terms of location, 480 (46.02%) were from Beijing, 261(25.02%) were from Hangzhou, and 302 (28.95%) were from Ningbo. All data were analyzed in SPSS 26 and AMOS 25. The study applied confirmatory factor analysis (CFA), descriptive analysis, and causal-comparative methods (i.e., Mann–Whitney U test and the Kruskal–Wallis test). We refer to previous studies and APA guide to report our statistical results (APA, 2020; Boykin et al., 2019; Zainuddin, et al., 2020).

Results

Validation of Instrument

Factorial validity was checked for the research instrument. The KMO value acquired in this study (0.93) was greater than the values recommended (Watkins, 2018). BST was significant ($\chi2 = 19{,}057.254$; $df = 231$, $p \leq 0.001$), demonstrating that the measure was suitable for factor analysis (Field, 2009). Initial EFA with Eigenvalues for 22 items revealed a five-factor structure. Cronbach's Alpha was tested to define the reliability of the subscales in the whole sample and was 0.84, 0.90, 0.92, 0.90, and 0.93, respectively. The values were suitable and acceptable ratios for this measure (Heale

& Twycross, 2015). CFA was used to evaluate the measurement model while keeping the same factor and items (Table 2), indicating that all fit indices values were suitable for using this instrument factor model to measure the study aspects (Tabachnick & Fidell, 2001).

Students' CT Skills

The average score of the students' CT skills was 3.8. Students scored highest in the dimension of creativity ($M = 4.0$, $SD = 0.74$), followed by the cooperation ability ($M = 3.87$, $SD = 0.83$) and critical thinking ($M = 3.8$, $SD = 0.80$). Notably, the lowest score was in the problem-solving ($M = 3.6$, $SD = 0.88$). Shapiro–Wilk test is a formal and widely applied normality test, which provides an omnibus indicator of non-normality judged over all the sample sizes used (Das & Imon, 2016; Razali & Wah, 2011; Yazici & Yolacan, 2007). Thus, although Skewness (Range 0.04–0.72) and Kurtosis (0.14–1.13) values indicated the data was normally distributed, we considered Shapiro–Wilk test results, i.e., the score of CT did not follow a normal distribution (Table 3). Correspondingly, this study applied the Mann–Whitney *U* test and the Kruskal–Wallis test to examine the median differences between gender, grade, school region, and academic performance (Jabar, 2023; Zhang & Zhang, 2009). For comparisons between participants' CT skills of the two groups (i.e., gender, grade and school region), we applied the Mann–Whitney U test; for comparison among four academic performance groups, we applied the Kruskal–Wallis test (Tao et al., 2022; Yang & Cao, 2021) and further reported pairwise comparisons to better explain the results.

Students' CT Skills and Demographic Factors

As shown in Table 4, students' CT skills differed significantly according to gender, $z = -5.47$, $p < 0.001$. Therefore,

Table 2 Confirmatory factor analysis of the revised CTS

Fit statistics	χ^2/df	RMSEA	RMR	CFI	GFI	AGFI	TLI	NFI
Model fit value	4.737	.058	.030	.964	.929	.907	.957	.955
acceptable fit	≤5.000	≤.080	≤.050	.950	.900	.900	.950	.900

χ2 chi-square; *df* degree of freedom; *RMSE* root mean square error of approximation; *RMR* root mean square residual; *CFI* comparative fit index; *GFI* goodness of fit index; *AGFI* adjusted goodness of fit index; *TLI* Tucker–Lewis index; *NFI* normed fit index

Table 3 Descriptive statistics of revised CTS and its sub-dimensions

	M	SD	Skewness		Kurtosis		Shapiro–Wilk
			Statistic	Std. Error	Statistic	Std. Error	*p*
Creativity	4.0	0.74	−0.48	0.08	0.93	0.15	< .001
Algorithmic thinking	3.6	0.84	0.09	0.08	−0.21	0.15	< .001
Cooperative ability	3.9	0.83	−0.43	0.08	0.26	0.15	< .001
Critical thinking	3.8	0.80	−0.25	0.08	0.14	0.15	< .001
Problem-solving	3.6	0.88	−0.72	0.08	1.13	0.15	< .001
Total	3.8	0.61	0.04	0.08	0.32	0.15	< .001

Table 4 CT skills' differences among students with different demographic backgrounds

	N	Total M (SD)	Creativity M (SD)	Algorithmic thinking M (SD)	Cooperative ability M (SD)	Critical thinking M (SD)	Problem-solving M (SD)
Gender							
Male	583	3.8 (0.66)	4.0 (0.80)	3.8 (0.87)	4.0 (.86)	3.9 (0.83)	3.5 (1.03)
Female	460	3.7 (0.53)	3.9 (0.66)	3.4 (0.74)	3.8 (.78)	3.7 (0.75)	3.6 (0.65)
Region							
Northern China	480	3.8 (0.65)	4.0 (0.78)	3.6 (0.86)	3.9 (.85)	3.8 (0.83)	3.5 (0.90)
Southern China	563	3.7 (0.58)	3.9 (0.70)	3.6 (0.83)	3.8 (.80)	3.8 (0.78)	3.6 (0.87)
Grade							
Tenth Grader	576	3.8 (0.63)	4.0 (0.75)	3.6 (.84)	3.9 (0.85)	3.9 (0.82)	3.6 (0.89)
Eleventh Grader	467	3.7 (0.59)	3.9 (0.72)	3.6 (.84)	3.8 (0.80)	3.8 (0.79)	3.6 (0.88)

hypothesis 1a was accepted. Further comparisons showed that male and female students scored significantly differently in creativity ($z=-2.71$, $p=0.007<0.050$), algorithm thinking ($z=-7.79$, $p<0.001$), cooperative ability ($z=-4.12$, $p<0.001$), and critical thinking ($z=-5.70$, $p<0.001$). When comparing the median and mean scores, male students scored significantly higher than female students in four sub-dimensions (creativity, algorithmic thinking, cooperative learning, and critical thinking).

Students from different regions did not score significantly differently in CT skills, $z=-1.46$, $p=0.143>0.050$, so hypothesis 1c was rejected. Also, there was no significant difference in the three sub-dimensions of students' CT skills between the two regions: algorithm thinking ($z=-1.14$, $p=0.254>0.050$), critical thinking ($z=-0.57$, $p=0.566>0.050$), and problem-solving ($z=-0.70$, $p=0.483>0.050$). The differences were in creativity ($z=-2.02$, $p=0.044<0.050$) and cooperative ability ($z=-2.28$, $p=0.023<0.050$). When comparing the median and mean scores, students from northern China scored significantly higher than those from southern China in creativity and cooperative ability.

Tenth graders' CT skills significantly differed from eleventh graders' CT skills, $z=-2.13$, $p=0.034<0.050$. Therefore, hypothesis 1b was rejected. The tenth graders scored significantly higher than the eleventh graders in creativity ($z=-2.13$, $p=0.033<0.050$) and cooperative ability ($z=-3.20$, $p=0.001<0.050$). There were no significant differences between tenth graders and eleventh graders in algorithm thinking ($z=-1.09$, $p=0.275>0.050$), critical thinking ($z=-1.64$, $p=0.101>0.050$), and problem-solving ($z=-0.06$, $p=0.956>0.050$).

Students' CT Skills and Academic Achievement

As shown in Table 5, the students' CT skills scored significantly differently according to their academic performance in total, $H(3)=44.13$, $p<0.001$. Thus, hypothesis 2a was accepted. There were significant differences in creativity ($H(3)=24.15$, $p<0.001$), algorithm thinking ($H(3)=38.87$, $p<0.001$), critical thinking ($H(3)=45.49$, $p<0.001$), and problem-solving ($H(3)=34.59$, $p<0.001$). Pairwise comparison showed there were no significant differences among students with different academic achievements in cooperative ability, ($H(3)=5.82$, $p=0.121>0.050$). For creativity, Group 1 scored significantly higher than Group 2 ($p=0.044<0.050$), Group 3 ($p=0.005<0.050$), and Group 4 ($p<0.001$). For algorithm thinking, Group 1 scored significantly higher than Group 2 ($p=0.012<0.050$), Group 3 ($p<0.001$), and Group 4 ($p<0.001$). For critical thinking, Group 1 scored significantly higher than Group 2 ($p=0.039<0.050$), Group 3 ($p<0.001$), and Group 4 ($p<0.001$). For problem-solving, Group 4 scored

Table 5 CT skills differences among students with different academic performances

	N	Total M (SD)	Creativity M (SD)	Algorithmic thinking M (SD)	Cooperative ability M (SD)	Critical thinking M (SD)	Problem-solving M (SD)
Academic achievement in total							
Group 1	303	3.9 (0.61)	4.1 (0.71)	3.8 (0.85)	3.9 (0.83)	4.0 (0.78)	3.7 (1.03)
Group 2	313	3.8 (0.54)	4.0 (0.65)	3.6 (0.74)	3.9 (0.80)	3.9 (0.73)	3.6 (0.76)
Group 3	224	3.7 (0.56)	3.9 (0.67)	3.4 (0.78)	3.8 (0.79)	3.7 (0.73)	3.6 (0.74)
Group 4	203	3.6 (0.71)	3.8 (0.93)	3.4 (0.95)	3.8 (0.89)	3.6 (0.93)	3.3 (0.93)
Academic achievement in math							
Group 1	350	3.9 (0.58)	4.1 (0.69)	3.9 (0.77)	4.0 (0.81)	4.1 (0.73)	3.7 (0.96)
Group 2	244	3.8 (0.57)	4.0 (0.67)	3.6 (0.75)	3.9 (0.85)	3.8 (0.76)	3.6 (0.84)
Group 3	243	3.7 (0.54)	3.9 (0.69)	3.4 (0.78)	3.9 (0.76)	3.7 (0.72)	3.5 (0.75)
Group 4	206	3.5 (0.71)	3.8 (0.90)	3.3 (0.94)	3.7 (0.89)	3.5 (0.94)	3.3 (0.90)
Academic achievement in IT							
Group 1	297	4.0 (0.61)	4.1 (0.75)	3.9 (0.83)	4.0 (0.83)	4.1 (0.81)	3.7 (1.00)
Group 2	286	3.8 (0.54)	4.0 (0.65)	3.6 (0.72)	3.9 (0.76)	3.8 (0.67)	3.6 (0.78)
Group 3	234	3.6 (0.58)	3.9 (0.69)	3.4 (0.80)	3.8 (0.81)	3.6 (0.79)	3.5 (0.72)
Group 4	226	3.6 (0.66)	3.9 (0.85)	3.5 (0.93)	3.8 (0.90)	3.6 (0.86)	3.3 (0.92)
Academic achievement in English							
Group 1	333	3.8 (0.58)	4.0 (0.70)	3.6 (0.82)	3.9 (0.82)	3.8 (0.79)	3.6 (0.87)
Group 2	240	3.8 (0.58)	4.0 (0.67)	3.7 (0.80)	3.9 (0.87)	3.9 (0.78)	3.6 (0.89)
Group 3	201	3.8 (0.59)	4.0 (0.69)	3.5 (0.77)	3.9 (0.75)	3.8 (0.77)	3.6 (0.78)
Group 4	269	3.7 (0.69)	3.8 (0.87)	3.6 (0.94)	3.8 (0.87)	3.7 (0.87)	3.4 (0.95)

significantly lower than Group 1 ($p < 0.001$), Group 2 ($p < 0.001$), and Group 3 ($p = 0.006 < 0.050$).

Students' CT skills scored significantly differently according to their academic performance in math ($H(3) = 68.80$, $p < 0.001$) and hypothesis 2c was accepted. All sub-dimensions of CT skills differed significantly among student groups with different academic achievements in math: creativity ($H(3) = 19.33$, $p < 0.001$), algorithm thinking ($H(3) = 99.18$, $p < 0.001$), cooperative ability ($H(3) = 13.23$, $p = 0.004 < 0.050$), critical thinking ($H(3) = 59.70$, $p < 0.001$), and problem-solving ($H(3) = 32.73$, $p < 0.001$). Pairwise comparison showed Group 1 scored significantly higher than Group 2 ($p = 0.001 < 0.050$), Group 3 ($p < 0.001$), and Group 4 ($p < 0.001$) in CT skills. For algorithm thinking and critical thinking, Group 1 scored significantly higher than Group 2 ($p < 0.001$), Group 3 ($p < 0.001$), and Group 4 ($p < 0.001$). For problem-solving, Group 1 scored significantly higher than Group 3 ($p = 0.005 < 0.050$) and Group 4 ($p < 0.001$).

Students' CT skills scored significantly differently according to their academic performance in IT ($H(3) = 66.81$, $p < 0.001$). Thus, hypothesis 2d was accepted. All sub-dimensions of CT skills differed significantly among academic achievement in IT: creativity ($H(3) = 16.11$, $p = 0.001 < 0.050$), algorithm thinking ($H(3) = 69.32$, $p < 0.001$), cooperative ability ($H(3) = 12.81$, $p = 0.005 < 0.050$), critical thinking ($H(3) = 60.25$, $p < 0.001$), and problem-solving ($H(3) = 63.76$, $p < 0.001$). Pairwise comparisons of CT skills showed that Group 1 scored significantly higher than Group 2 ($p = 0.001 < 0.050$), Group 3 ($p < 0.001$), and Group 4 ($p < 0.001$) and Group 2 scored significantly higher than Group 3 ($p = 0.015 < 0.050$), and Group 4 ($p = 0.002 < 0.050$). For creativity, Group 1 scored significantly higher than Group 3 ($p = 0.006 < 0.050$) and Group 4 ($p = 0.003 < 0.050$). For algorithm thinking, Group 1 scored significantly higher than Group 2 ($p < 0.001$), Group 3 ($p < 0.001$), and Group 4 ($p < 0.001$). For cooperative ability, Group 1 scored significantly higher than Group 3 ($p = 0.029 < 0.050$), and Group 4 ($p = 0.008 < 0.050$). For critical thinking, Group 1 scored significantly higher than Group 2 ($p = 0.001 < 0.050$), Group 3 ($p < 0.001$), and Group 4 ($p < 0.001$). Noticeably, in problem-solving, there was a gap between the top 50% and bottom 50% of students in IT courses. Both Group 1 and Group 2 outperformed Group 4 in problem-solving dimension.

Students' CT skills scored significantly differently according to their academic performance in English ($H(3) = 7.73$, $p = 0.052 > 0.050$). Thus, hypothesis 2b was rejected. While two sub-dimensions of CT skills differed significantly among student groups with different academic achievements in English: creativity ($H(3) = 11.14$, $p = 0.011 < 0.050$) and problem-solving ($H(3) = 12.16$, $p = 0.007 < 0.050$). Pairwise comparison showed that Group 4 scored significantly lower than Group 1 ($p = 0.012 < 0.050$) and Group 2 ($p = 0.049 < 0.050$) in creativity.

Discussion

Contextualizing our findings within the existing literature, we discuss demographic factors (gender, grade, and region) and educational correlations (academic achievements in total and three related subjects) of CT skills. We further discuss the implications of these findings for cultivating CT skills in high school education, including (1) although our participants' CT skills are relatively higher than those reported in existing research, they still scored relatively low on problem-solving dimension, suggesting the need for problem-solving oriented learning design. (2) Through analyzing the differences in CT skills between demographic factors, we suggest that problem-based collaborative learning experiences need to be further meticulously designed to foster students' CT skills, especially for female students. (3) Regarding academic achievements, we argue that the cultivation of CT skills requires interdisciplinary learning experiences in math, English, and ICT; further efforts are needed to adjust the existing curriculum to embed CT skills education.

Firstly, we found that the CT skills of our participants were relatively high compared to the existing literature using the same measurement tool (revised CTS) (Guggemos et al., 2019; Korkmaz & Bai, 2019; Yağcı, 2018). For example, Korkmaz and Bai (2019) applied revised CTS to measure the CT skills of 1015 tenth and eleventh graders in high schools in Ningxia Province and Jiangxi Province, China, obtaining an average CT skills score of 3.58. Students in the current research scored higher in CT skills than in Korkmaz and Bai's study. One possible explanation for our higher CT skills is that our schools were situated in three prosperous areas in China; while Korkmaz and Bai (2019) opted for students from two comparatively less affluent municipalities in China, which exhibit a relatively lower level of socio-economic development. For example, in 2021, the three cities' GDP per capita was double that of the two regions (National Bureau of Statistics, 2020). This implied the existence of regional differences in high school students' CT skills. The detailed comparison between our research and Korkmaz & Bai's research might align with the argument that socio-economic factors may result in a digital divide, which consequently leads to varying levels of CT skills (Celik, 2023; Czerkawski & Lyman, 2015; Kale et al., 2018). Moreover, this study found that students' scores in problem-solving dimension were relatively low, which was similar to previous findings on Chinese high school students (Korkmaz & Bai, 2019). This finding confirmed the necessity of current Chinese educational reform that emphasizes the cultivation of students' problem-solving skills (Hu et al., 2021). For example, ICT teachers can try to transform from traditional teaching into problem-based learning (PBL), where they can guide students in applying appropriate problem-solving strategies, so as to improve their problem-solving skills (Lin et al., 2020).

Secondly, the study found that gender and grade were significantly correlated with students' CT skills. Male students scored significantly higher than female students in four sub-dimensions of revised CTS students, consistent with some of previous studies (Korkmaz & Bai, 2019; Polat et al., 2021; Román-González et al., 2017). Indeed, gender inequity has been regarded as an important issue in cultivating CT skills and related competencies worldwide, from early childhood to career development. Students' gender stereotypes and attitudes toward STEM may influence their motivation for learning computers and developing computational thinking skills (Master et al., 2023). Male students might perceive themselves as more advanced in technology competence, resulting in higher self-perception about their CT skills than female students (Polat et al., 2021). If this is the case, our findings implicate an urgent need for projects and curricula specially designed to reduce gender stereotypes, encourage positive attitudes toward programming, and enhance CT skills among female high school students. For instance, research has shown that problem-solving learning strategies in STEM education that foster female students' enthusiasm can equally enhance CT skills of both female and male students (Paucar-Curasma et al., 2023).

The study also found significant differences in CT skills of students from different grades. The tenth graders scored significantly higher than the eleventh graders in two sub-dimensions (creativity and cooperative learning). The results were consistent with previous research by Korkmaz and Bai (2019). This may be explained partly by the Chinese educational reform. Chinese high schools emphasize more on students' core literacy development rather than focusing only on the rate of admission (Ministry of Education of the People's Republic of China, 2022a). Chinese educators have brought a revolutionary educational curriculum to the younger grades to ensure students' core literacy development, including creativity and cooperative learning (Buitrago Flórez et al., 2017). For example, tenth-grade students may be more likely to engage in group work activities, which may promote their cooperative learning. Plus, NCEE leads a more exam-oriented education for higher-grade students, which may encourage more competition rather than cooperation, resulting in lower cooperative learning skills (Li, 2020). The different CT skills between grades indicates the importance of integrating CT into the curriculum that focuses on core literacy development within a collaborative learning atmosphere, which has been proven to effectively promote students' CT skills (Chowdhury et al., 2018; Lai & Wong, 2022).

The study found that students' CT skills in total had no significant difference between schools from Northern China (School A) and schools from Southern China (School B, C, D), while there were some regional differences in two sub-dimensions (creativity and cooperative ability). One possible explanation is that all schools are top schools located in Chinese prosperous areas, where students may have access to better educational resources and support. However, Beijing, as the capital of China, has more advantages in providing better teaching and learning environments for both teachers and K-12 students. For example, Beijing's expenditure on education per capita (Beijing: 5200.04 Yuan/person) is much higher than that of Hangzhou (3369.63 Yuan/person) and Ningbo (2861.73 Yuan/person) (National Bureau of Statistics, 2020). Our result may shed light on previous research, which found that regional differences in resources, environment, and experienced teachers would influence the quality and continuity of education (Ozbal & Karakutuk, 2020). However, due to the limitations of sample selection, we should be particularly cautious in interpreting these differences.

Thirdly, the study confirmed the close relationship between students' CT skills and their academic performances in English, math, and IT, in line with previous studies' findings (Lei et al., 2020; Weintrop et al., 2016). The result showed that student's academic achievement in English correlated to students' CT skills in two sub-dimensions (creativity and problem-solving). This finding may support the positive relationship between students' academic achievement in English and their programming skills (Qian & Lehman, 2016). Indeed, familiarity with English is an important prerequisite for students to learn programming skills (Ruby & Krsmanovic, 2017). Teachers may develop tools and scaffoldings to help English-as-foreign-language students become familiar with programming-related English expressions, so as to help them learn programming. Meanwhile, integrating CT skills into English curriculum design may benefit both their CT skills development and their language learning (Hsu & Liang, 2021; Nesiba et al., 2015; Parsazadeh et al., 2021; Weng & Wong, 2017). For example, Parsazadeh et al. (2021) applied the 'present, practice, and produce' method to integrate CT into the English curriculum for fifty-two elementary school students in Taiwan. The results showed that this design not only improved their problem-solving skills (a sub-dimension of CT skills) in digital storytelling but also increased their extrinsic and intrinsic motivation toward learning English, as well as their English proficiency.

Additionally, students' academic performance in math and IT positively impacts students' CT scores and all its five sub-dimensions, parallel to the literature (Durak & Saritepeci, 2018; Polat et al., 2021). The results were understandable because mathematical thinking overlapped CT in problem-solving, modeling, data analysis and interpretation, and statistics and probability (Shute et al., 2017). In Chinese high schools, the math curriculum contains function applications, statistics, common logic terms, counting principles, etc. High school students would learn skills about abstracting, modeling, and solving problems, which are sub-dimensions of CT skills. Math is the foundation of Computer Science (CS) and programming because variables in CS cover the uses of those in math (Bråting & Kilhamn, 2021). Therefore, how to embed CT skills education in the mathematics curriculum to improve students' CT skills is of great significance and has been widely explored (Barcelos et al., 2018; Weintrop et al., 2016). For example, Israel and Lash (2020) analyzed teachers' lesson plans in a public elementary school to summarize strategies to integrate CS and CT skills training into primary math classes, highlighting multiple levels of complexity among different grades, an emphasis on math, and three types of interdisciplinary lessons according to levels of integration, teaching sequencing, looping, and conditional logic. In high schools, the similar integration of CT and math could be further explored.

Currently, Chinese IT courses include knowledge related to databases, programming, artificial intelligence, etc. (Ministry of Education of the People's Republic of China, 2022a, 2022b). These contents offer students opportunities to practice CT skills. For example, programming is a vital tool for supporting CT cognitive tasks, such as logical thinking and problem-solving (Tikva & Tambouris, 2021). However, the study's findings indicated that students' academic achievement in IT had a less significant impact on their CT skills than in math, consistent with previous studies (e.g., Polat et al., 2021). This may be because, compared with math and other traditional subjects, the IT course is a novel subject with fewer class hours (Ministry of Education of the People's Republic of China, 2022a, 2022b). Consequently, teachers and students might spend less time on it. Given the importance of CT skills, teaching them within traditional disciplines of school curriculum including English, math, and ICT is imperative to improve CT skills (Valovičová et al., 2020; Yeni et al., 2023). For example, Hsu et al. (2022) integrated programming learning and language learning and designed an educational robot-integrated pair programming board game for primary school students and demonstrated its benefits in promoting learners' CT competencies, language learning, and CT skills, as well as reducing their language learning anxiety. A similar interdisciplinary learning approach could contribute to a more comprehensive enhancement of CT skills in high schools.

Limitations and Future Research

There are still some limitations in the study. Firstly, this study chose a validated questionnaire developed by Korkmaz and Bai. (2019) to measure high school students' CT skills. A continuous effort has been made to define the CT framework and CT assessment tools. Further research may combine diverse assessment tools to better reveal students' CT skills and perceptions. Comparison of various tools may also contribute to better choosing CT assessment tools in future studies. Secondly, although we endeavored to include as many schools as possible, the sample schools were selected based on our research project and convenience sampling, resulting in participants being only from schools in the southern and northern regions of China. Our sample selection may limit their ability to fully represent the broader spectrum of typical public high schools in China. In future research, we plan to broaden the scope by incorporating larger sample sizes from diverse schools across various regions, facilitating meaningful comparisons with our obtained results. Finally, our findings found interestingly that economic, socio, and cultural contexts might potentially be relevant to students' CT skills. As our study did not focus on comparative analysis among economic, socio, and cultural factors, future studies can better understand how such factors impact students' CT skills by comparing and analyzing different CT curriculum designs, CT teaching strategies, and economic, and social and cultural contexts.

Conclusion

This empirical study explored the demographic and educational correlation of high school students' CT skills by investigating four Chinese high schools. This study proved that students' demographic dimensions (gender and grade) significantly correlated with their CT skills. There were no significant differences in CT skills among students from northern China and southern China. At the same time, the study found that student's academic achievement in total, and different subjects (i.e., English, math, and IT) were positively related to their CT skills. The results shed light on the necessity of adopting different CT education instructional strategies for students with different demographic backgrounds and learning capabilities. To enhance students' CT skills, we propose implementing collaborative, interdisciplinary, problem-based learning experiences that are oriented toward problem-solving, particularly for female students. Moreover, CT-related knowledge and skills should be embedded in multiple subjects' curricula can also contribute to the improvement of students' CT skills.

Data availability Data will be made available on request.

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