ON THE PREDICTORS OF COMPUTATIONAL THINKING SELF-EFFICACY

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ABSTRACT

Computational thinking (CT) is an important 21st-century skill. This paper aims at investigating predictors of CT self-efficacy among high-school students. The hypothesized predictors are grouped into three areas: (1) student characteristics, (2) home environment, and (3) learning opportunities. CT self-efficacy is measured with the Computational Thinking Scales (CTS) that comprises five dimensions: creativity, algorithmic thinking, cooperativity, critical thinking, and problem solving. N = 202 high-school students act as the sample, linear regression as the analysis method. The best prediction is possible for algorithmic thinking (R^2 = .511). For cooperativity, the explanatory power of our model it is weak (R^2 = .146). Across all five CTS dimensions, CT self-concept is the best predictor for CT self-efficacy.

KEYWORDS

Computational Thinking Scales, Gender and Home Environment, Cognitive Dispositions, Motivation, Learning Opportunities

1. INTRODUCTION

Computational thinking (CT) has emerged as a promising resource for solving problems across various subjects and work environments (Buitrago Flórez et al., 2017; D. Barr et al., 2011). Wing (2006, p. 33) conceptualized CT as “solving problems, designing systems, and understanding human behavior, by drawing on the concepts fundamental to computer science”. As a concept, CT may still be in its infancy (Shute et al., 2017; Tsarava et al., 2022). To contribute to a better understanding of CT, the purpose of our research is *prediction* (Newman et al., 2007), i.e., we test the association of CT with variables that might predict CT.

In previous work, we relied on a performance test to operationalize CT (Guggemos, 2021). Performance tests are often regarded as superior to self-assessment instruments. However, self-assessments are not by nature inferior to performance tests (Scherer et al., 2017). Rather, the validity of a measurement depends on its intended use (AERA et al., 2014). Self-assessment instruments tend to capture self-efficacy, which could be a good predictor for behavior (Scherer et al., 2017). Moreover, CT is a complex construct. Focusing solely on its cognitive nature may be an oversimplification (Kafai & Proctor, 2022). Román-González et al. (2019) argue that it is unlikely to capture a complex construct such as CT with a single measurement instrument.

Durak and Saritepeci (2018) utilized a cross-sectional sample of 156 students from grades 5 to 12 for investigating predictors of CT. To measure CT, Durak and Saritepeci (2018) relied on the Computational Thinking Scales (CTS) (Korkmaz et al., 2017). CTS is an established self-assessment instrument (Shute et al., 2017). Following ISTE (2015), it comprises five dimensions: creativity, algorithmic thinking, cooperativity, critical thinking, and problem solving. As multidimensionality implies, it may be problematic to aggregate the five dimensions using an overall (sum) score. This assertion is supported by (Guggemos et al., 2023). Using confirmatory factor analysis, they showed that a higher-order model with an overall CT-factor does not converge. Furthermore, the correlations among the five dimensions vary substantially; in some cases, they are not significantly different from zero, e.g., between algorithmic thinking and cooperativity. Durak and Saritepeci (2018) reported educational level (grade), mathematics and science class performances, and ways of thinking as significant predictors of CT. Building on this study, it is beneficial to also consider students’ CT motivation and family background because those factors may be important when investigating CT (del Olmo-Muñoz et al., 2020; Fraillon et al., 2019; Repenning et al., 2015).

Overall, investigating the association of each of the five CTS-dimensions with potential predictors may contribute to a better understanding of CT. Our research question is:

What are the predictors of high-school students' CT self-efficacy, i.e., creativity, algorithmic thinking, cooperativity, critical thinking, and problem solving, at the individual level?

To answer this research question, section 2 presents hypotheses on predictors of CT. These hypotheses are identical to those in (Guggemos, 2021). We focus on high school students and the individual level, i.e., we do not consider the classroom or school context.

2. THEORETICAL BACKGROUND AND HYPOTHESES

2.1 Conceptual Framework

The conceptual framework of the International Computer and Information Literacy Study 2018 (ICILS) structures our hypotheses (Fraillon et al., 2019). It distinguishes antecedents and processes. "Antecedents are exogenous factors that condition the ways in which (…) learning takes place" (Fraillon et al., 2019, p. 6). Antecedents comprise student variables, such as gender, and home environment variables, such as parents' socioeconomic status. "Processes are those factors that directly influence (…) learning" (Fraillon et al., 2019, p. 6). Such CT learning opportunities can be either formal or informal in nature (Grover & Pea, 2013; Wing, 2008).

2.2 Antecedents – Student

CT research has consistently underscored the significance of gender differences (Shute et al., 2017). Such differences in CT may be due to differences in self-efficacy and interest, which might be attributed to gender stereotypes (Master et al., 2016). The ICILS reports significantly higher CT scores for males in comparison to females for the overall sample. Román-González et al. (2017), using Spanish secondary students as a sample, found an increasing gender CT gap in favor of males as students age. Since our study is in the realm of high-school education, we expect: **H1.** The gender 'male' positively predicts CT.

CT is conceptualized as a problem-solving methodology across subjects (V. Barr & Stephenson, 2011; Wing, 2006). In light of this, it may be strongly related to reasoning skills (Ambrosio et al., 2015; Buitrago Flórez et al., 2017; Wüstenberg et al., 2012). Román-González et al. (2017) reported a medium correlation of CT with reasoning ability. We assume: **H2.** Reasoning skills positively predict CT.

According to Wing (2006, p. 33), CT may be an analytical ability, like "reading, writing, and arithmetic". In terms of mathematics skills, Wing (2008) claimed that CT and mathematical thinking share the same general way of approaching problems. Durak and Saritepeci (2018) reported higher CT levels for students with higher academic success in mathematics. Concerning language skills, V. Barr and Stephenson (2011) argued that CT concepts are also present in the language arts. In their literature review, Zhang and Nouri (2019) showed that reading is regularly regarded as a part of CT. Román-González et al. (2018) reported a medium positive correlation between CT and verbal ability. In sum, we hypothesize: **H3.** Mathematics skills positively predict CT; **H4.** Language skills positively predict CT.

The relationship between programming and CT is often thematized. Israel et al. (2015) regard the use of computers to model ideas and programming as an integral part of CT. Buitrago Flórez et al. (2017), as well as Lye and Koh (2014), argue that by means of programming, several core facets of CT can be addressed. Shute et al. (2017) concluded there is a close relationship between CT and programming skills due to similar underlying cognitive processes. Hsu et al. (2018) reported, based on their review of the literature, that programming is widely used to teach CT. We expect: **H5.** The ability to program positively predicts CT.

Many authors, including Wing (2006), emphasize that computer literacy is distinct from CT. However, the question remains whether computer literacy is conducive to CT or not. Since CT aims to represent a problem in such a way that a computer can solve it (Israel et al., 2015; Wing, 2006), knowledge about the capabilities of computers may be beneficial. Moreover, CT is often taught using computers and technology (Hsu et al., 2018). The ICILS also found a strongly positive correlation between information and computer literacy and CT. Against this background, we hypothesize: **H6.** Computer literacy positively predicts CT.

According to the expectancy-value model (EVM) by Wigfield and Eccles (2002), the expectation of success and subjective task value drive the level of achievement motivation. The expectation of success depends on the person's self-concept, which can be broadly defined as the perception of oneself (Shavelson et al., 1976). Drawing from this, CT self-concept could be defined as the perception about oneself in the area of CT. A core element of self-concept is the perceived competence (Bong & Skaalvik, 2003). As such, it may be closely related to self-efficacy. Indeed, domain specific self-concept and self-efficacy are often hard to separate (Bong & Skaalvik, 2003). The main difference might be the time orientation: self-concept is relatively stable whereas self-efficacy is malleable. In line with Retelsdorf et al. (2011), we rely on the self-concept and hypothesize: **H7.** CT self-concept positively predicts CT.

The second component of the EVM addresses the perceived task value. Following Wigfield and Eccles (2002), the individual perception of usefulness plays a central role. Students who regard CT as more important for their academic and personal success are expected to put more effort into CT learning. This is also expected from students who enjoy engaging in CT tasks and are interested in them, regardless of external incentives. The described elements of perceived task value are consistent with the self-determination theory (Ryan & Deci, 2000); they may be manifestations of self-determined motivation. We hypothesize: **H8.** 'Self-determined motivation' positively predicts CT.

2.3 Antecedents – Home Environment

Educational outcomes have often been linked to the home environment (Rutkowski & Rutkowski, 2013). An important aspect of home environment is 'Socioeconomic and Cultural Status' (SECS), which comprises parental income, parental education, parental occupation, and the availability of cultural goods at home. The rationale is that families with a higher SECS are able and willing to provide more favorable learning environments (Retelsdorf et al., 2011). In terms of empirical evidence, the ICILS consistently reported higher CT scores for students from families with a higher SECS. We hypothesize: **H9.** SECS positively predicts CT.

Another important aspect of home environment might be migration (OECD, 2015). Reasons for the lower performances of students from families with migration background could be due to language-related issues. The ICILS reported a significantly lower CT score for students from immigrant families in comparison to those from non-immigrant families. Hence, we hypothesize: **H10.** A migration background is negatively associated with CT.

2.4 Processes – Learning Opportunities

Both formal and informal learning opportunities may be necessary to foster CT (Grover & Pea, 2013; Wing, 2008). Although CT could be part of every subject, it is deeply rooted in computer science education (Grover & Pea, 2013) and draws on basic concepts of computer science (Wing, 2006). Hence, we regard computer science instruction as a formal learning opportunity for CT and hypothesize: **H11.** Computer science instruction positively predicts CT.

Besides formal learning opportunities, CT could also be fostered in informal settings, i.e., outside of school courses. Durak and Saritepeci (2018) hypothesized that the use of information and communication technology (ICT) and the internet has a positive influence on CT. However, both hypotheses were rejected. A reason for this could be that students use digital devices like smartphones to a great extent for leisure activities (Fraillon et al., 2019). These activities might not be conducive to CT. In light of this, the use of computers (PC and laptop) may be a better indicator for informal learning opportunities. We therefore hypothesize: **H12.** Duration of computer use positively predicts CT.

3. METHOD

3.1 Sample and Data Collection Process

Our sample comprises N = 202 students from the 11th (second last) grade of three 'Gymnasium Helveticum' (high schools) in German-speaking Switzerland. The students are nested in twelve classes. Data were collected using Questback Unipark. The class teachers supervised the students and ensured a suitable test environment. The allotted time was 90 minutes, but all students were allowed to finish their work. All students fully answered the questions. On average, the students were aged 17.23 years (SD = 0.85 years); 56% were female. They reported 2.89 hours (SD = 1.20 hours) of computer science instruction in the past. Of the student, 77% claimed to be able to program in languages such as Java or Python.

3.2 Measures

We operationalize CT self-efficacy using a validated short German version of CTS. The short version comprises three items for each of the five CTS dimensions. Table 1 reports sample items for all five dimensions of this short version. For all CTS items in the short version, refer to Guggemos et al. (2023).

Table 1. Sample items of the used CTS short version.

Creativity	“I believe that I can solve possible problems that may occur when I encounter a new situation.”
Algorithmic thinking	“I can mathematically express the solutions for the problems I face in daily life.”
Cooperativity	“I like solving problems related to a group project together with my friends in cooperative learning.”
Critical thinking	“I make use of a systematic method while comparing the options at hand and while reaching a decision.”
Problem solving	“I cannot apply the solutions I plan respectively and gradually.” (R)

Note. Items taken from Korkmaz et al. (2017, p. 565). Measured on a 7-point rating scale ranging from ‘not true at all’ to ‘entirely true’. R = reverse coding.

3.3 Data Analysis

We use linear regression to predict CT self-efficacy. Measurement error can bias the results. Therefore, we adopt the approach of Savalei (2019) to consider measurement error. We calculate sum scores for each of the five CT dimensions. Then we restrict the residual variance of these five dependent variables to an error variance corresponding to a reliability of .9. Such reliability might be a reasonable upper limit. This aligns with the actual observed values of α and ω, as presented in Table 2. We employ manifest variables for the independent variables (Retelsdorf et al., 2011). The analyses are performed with the package lavaan 0.6-9 (Rosseel, 2012).

4. RESULTS

4.1 Quality of Measurement Instrument – Dependent Variables

Table 2 displays the reliability as well as convergent validity of the five dimensions: α and $\omega > .7$, AVE > .5. Discriminant validity is also ensured as the heterotrait-monotrait ratio is smaller than 0.71. Overall, these figures indicate a decent quality of the measurement instrument (Hair et al., 2019).

Table 2. Validity and reliability assessment of the German CTS short version (N = 202)

						Manifest correlations, square root of AVE on diagonal				
Construct		M (SD)	α	ω	AVE	(1)	(2)	(3)	(4)	(5)
(1)	Creativity (3 items)	5.4 (1.2)	.87	.87	.75	.87				
(2)	Algorithmic thinking (3 items)	3.9 (1.7)	.90	.90	.73	**.28**	.85			
(3)	Cooperativity (3 items)	4.5 (1.6)	.89	.80	.70	.19	.13	.84		
(4)	Critical thinking (3 items	4.9 (1.2)	.80	.80	.57	**.59**	**.53**	**.19**	.75	
(5)	Problem solving (3 items)	5.3 (1.6)	.78	.78	.54	.17	-.00	-.14	.13	.73

Note. Items measured on a 7-point rating scale. λ = standardized loading, α = Cronbach’s alpha, ω = Revelle’s Omega Total, AVE = average variance extracted. Figures in bold represent correlations significant at the 5% level.

4.2 Quality of Measurement Instrument – Independent Variables

Table 3 summarizes the used variables and instruments for operationalizing the predictors. Sample items are provided. As can be seen, (where applicable) internal consistency reliability is achieved.

Table 3. Operationalization of predictors, assessment of reliability, and taken actions

Predictor	Instrument	Scale	Reliability	(Sample) item
Gender	self-report (Konsortium PISA.ch, 2018)	male = 1, female = 0	n/a	What is your gender?
Reasoning ability	6-items performance test (Heydasch et al., 2017)	binary, multiple-choice	ω = .76, α = .70 ✓	Preview available here: https://ww2.unipark.de/uc/HOT_preview/ospe.php?SES=39f1d2b152f885e494fd8ea5c6bd3fb6
Mathematical skills	self-report grade	1 (worst) – 6 (best)	n/a	What was your grade in Mathematics last school year?
Language skills	self-report grade	1 (worst) – 6 (best)	n/a	What was your grade in German last school year?
Ability to program	1-item self-evaluation	binary	n/a (single-item)	Are you able to program (e.g., Java or Python)?
Computer literacy	20-item performance test (Richter et al., 2010)	binary, multiple-choice	ω = .79, α = .76 ✓	You want to prevent other people from following your navigation behavior on the Internet. What measure contributes to this?
CT Self-concept	6-item self-evaluation (Köller et al., 2000)	rating 1 – 7	ω = .93, α = .88 ✓	Generally, solving that kind of tasks is easy for me. (Samples are provided)
Self-determined CT motivation	9-item self-evaluation (Prenzel et al., 1998)	rating 1 – 7	ω = .95, α = .93 ✓	Performing such tasks is fun for me (Samples are provided)
Parents' socioeconomic and cultural status (SECS)	self-report (Konsortium PISA.ch, 2018): scaled to M = 50, SD = 10	3 components: ISEI father, ISEI mother, no. books	n/a (formative measurement)	What does your mother do for a living? (open-ended question)
Migration background	self-report: at least one parent born outside of Switzerland (Retelsdorf et al., 2011)	yes = 1, no = 0	n/a	Were both your parents born in Switzerland? (reverse coding)
Past computer science instruction	self-report (Konsortium PISA.ch, 2018)	number of lessons	n/a	How many computer science lessons have you had in the past?
Duration of computer use	self-report (Konsortium PISA.ch, 2018)	rating 1 – 7 ranging from 0 – more than 6 hours/day	n/a	How long do you use the computer (PC or laptop) on a normal day?

Note. ISEI = International Socio-Economic Index of Occupational Status derived from parents' occupation (Ganzeboom et al., 1992). ω = Revelle's Omega Total, α = Cronbach's Alpha. ✓ = sufficient reliability. Self-report = fact is reported. Self-evaluation = (subjective) evaluation necessary. Rating scales 1 – 7 ranging from entire disagreement to entire agreement.

4.3 Regression Analysis

Table 4 depicts the results of the regression analysis.

Table 4. Linear regressions with the five CT self-efficacy dimensions as outcome variables (N = 202)

		CT dimensions									
		Creativity		Algorithmic Thinking		Cooperativity		Critical Thinking		Problem solving	
H	Predictor	Est.	s.e.[a]	Est.	s.e.[a]	Est.	s.e.[a]	Est.	s.e.[a]	Est.	s.e.[a]
1	Male gender	-0.19	0.15	0.27	0.19	-0.03	0.20	-0.17	0.14	0.10	0.16
2	Reasoning ability	-0.02	0.04	0.05	0.06	***-0.15***	***0.05***	-0.05	0.05	-0.04	0.05
3	Mathematical skills	***-0.19***	***0.09***	**0.57**	**0.12**	-0.04	0.15	-0.00	0.10	-0.00	0.13
4	Language skills	0.25	0.16	-0.21	0.15	-0.09	0.19	0.18	0.15	0.23	0.15
5	Ability to program	0.04	0.16	**0.53**	**0.18**	0.36	0.21	0.30	0.17	0.25	0.21
6	Computer literacy	0.01	0.02	-0.01	0.02	-0.01	0.03	0.02	0.02	0.03	0.02
7	CT self-concept	**0.30**	**0.08**	**0.28**	**0.10**	0.09	0.10	**0.47**	**0.08**	**0.23**	**0.10**
8	Self-determined CT motivation	0.08	0.07	**0.19**	**0.08**	0.05	0.08	**0.13**	**0.06**	***-0.22***	***0.09***
9	Parents' SECS	-0.00	0.01	0.01	0.01	0.02	0.01	**0.02**	**0.01**	-0.01	0.01
10	Migration background	-0.12	0.14	0.19	0.16	-0.12	0.17	-0.01	0.14	-0.13	0.16
11	Past computer science instruction	-0.08	0.07	-0.07	0.09	**0.23**	**0.11**	-0.14	0.08	0.10	0.09
12	Duration of computer use	-0.07	0.05	-0.09	0.06	-0.18	0.08	***-0.23***	***0.05***	-0.02	0.06
	R^2	.215		.511		.146		.467		.165	

Note. Figures in bold indicate significance at the 5% level; figures in italic indicate results contradicting the hypothesis.
[a] cluster robust standard error (cluster = class).

None of our hypothesis was fully supported. Hypotheses with mixed results are H1, H3, H5, H7, H8, H9, and H11. The hypotheses not supported by our evidence are H2, H4, H6, H10, and H12.

5. LIMITATIONS, DISCUSSION, AND IMPLICATIONS

5.1 Limitations

Our study is not without limitations. The associations reported cannot be interpreted as causal since omitted variables might account for the relationships. We attempted to mitigate this risk through a comprehensive review of variables that influence CT from a theoretical point of view. Our sample has a narrow scope, including only students from German-speaking Switzerland and specifically from one school type, the Gymnasium Helveticum. The dependent variable, CT, is measured using a short version of CTS. However, employing the full version could introduce problems related to discriminant validity (Guggemos et al., 2019).

5.2 Discussion

As Table 4 shows, the association between the CT predictors and CT self-efficacy varies considerably depending on the CTS dimension. Hence, our results may complement the work of Durak and Saritepeci (2018) who used CTS to form a single outcome variable. Contrary to our hypothesis, the male gender is not positively related to CT self-efficacy. This is consistent with the findings of Durak and Saritepeci (2018). Against this backdrop, the assertion that female students' lower CT can be attributed to lower self-efficacy may be doubtful. Across all five dimensions of CTS, CT self-concept appears to be the best predictor. This might not be surprising as self-concept and self-efficacy are closely related (Bong & Skaalvik, 2003). Self-determined motivation is also a significant predictor for algorithmic and critical thinking; this may point to the overall importance of motivation, as captured by the EVM, for predicting CT self-efficacy.

Other than in the ICILS, variables from the area *home environment* and *learning opportunities* can explain hardly any variance. The reason may be that the ICILS used a performance test instead of a self-assessment instrument to measure CT. Overall, the best prediction is possible for algorithmic thinking. The explained variance equals 51.1%, which may be a moderate proportion (Hair et al., 2019). For cooperativity, on the other hand, the explanatory power of the model is weak with an explained variance of only 14.6%.

There were also four findings contrary to our hypotheses that we will discuss in the following. Mathematics skills negatively predict creativity. The meta-analysis of Bicer et al. (2021) reports a positive association of general creativity and mathematical achievement (r = .39). However, the constructs in this meta-analysis are captured with performance tests. Students with higher mathematical skills may perceive their creativity as low although this might, in fact, not be the case. Further research may elaborate the nature of computational thinking creativity and develop test instruments for this construct. Developing such a domain specific concept may be promising. Bicer et al. (2021) showed that the association of mathematical achievement is higher with mathematical creativity (r = .53) than with general creativity (r = .39).

The association between reasoning ability and cooperativity is negative. Reasoning ability is a core facet of general intelligence. In light of this, the findings may be contrary to findings of more intelligent people are more capable of cooperating (Jones, 2008). Again, the reason for the negative association may lie in the nature of the CTS. Cooperativity in the sense of the CTS focus on the willingness to collaborate with friends and classmates. Intelligent students may deliberately choose who they work with. In a classroom setting, they may have had unfavorable experiences in the past, e.g., with group phenomenon such as free riding. This may have reduced their willingness to cooperate in such a setting. Further research may focus on the ability to cooperate in a broad context, i.e., not restricted to friends and classmates. The small correlation of cooperativity with the other four dimensions of CTS may also indicate a different nature of this construct.

Critical thinking is negatively associated with duration of computer use. However, McMahon (2009) reported a positive correlation between the length of time spent within technology-rich environments and the development of critical thinking skills. Again, our contrary finding could be attributed to the different nature of self-reports and performance tests as used by McMahon (2009). Another reason may be that students in their free time do not use computers for pedagogically meaningful purposes. Since free time is limited, heavy computer users might have less time for activities that are reportedly conducive to critical thinking, e.g., reading books and newspapers (Carr, 1988).

Problem solving is negatively associated with self-determined CT motivation. The reason may be the measurement of problem solving. Guggemos et al. (2023) argue that the operationalization of this dimension by CTS is problematic: all the items that capture problem solving are reversely coded. Hence, the factor problem solving may be a methodological artefact. At the content level, there is no obvious reason why self-determined CT motivation negatively predicts problem solving. Again, this finding might indicate the need to revise CTS.

5.3 Implications

Our work has three main implications: 1) Further elaboration on the CTS might help clarify the nature of the constructs and their operationalization. Specifically, the dimension *problem solving* could be problematic as it comprises only reversely coded items. 2) Aggregating the five CTS dimensions into a single CT-score seems problematic. Results vary significantly when each of the five dimensions is treated as a dependent variable. 3) Of all five CTS dimensions, algorithmic thinking may be at the core of CT self-efficacy, as the conceptually based predictors can explain the greatest proportion of variance.

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