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Investigating computational thinking skills based on different variables and determining the predictor variables

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This study aimed to determine how secondary school students' computational thinking skills changed according to gender, technology use i.e. mobile device ownership, technology competence, daily technology use periods, attitude towards science and attitude towards math. In addition, the relationships between these variables was determined in this study. The research, which was carried out with the participation of 722 secondary school students, was conducted with relational survey model. Convenience sampling method was used to determine the participants. Computational thinking scale, attitudes towards science scale and attitudes towards mathematics scale were used in the study as data collection tools. Descriptive statistics, independent samples t-test, single factor analysis of variance (ANOVA) and multiple regression analysis tests were used in this study. According to results, while computational thinking skills did not significantly differ according to gender; there was a significant difference in computational thinking skills according to mobile device ownership, technology competence, daily technology use periods, attitudes towards science and attitudes towards math. Three of the four models developed as a result of hierarchical regression analysis were found to be statistically significant. Accordingly, it can be argued that attitudes towards science, attitudes towards math and mobile device ownership are important predictors of computational thinking.

Introduction

Computational thinking (CT) is a concept that has been addressed in the context of computer sciences since the 1960s (Denning, 2009; Grover & Pea, 2013). Although it was perceived for many years as a skill that only computer scientists should have, Wing (2006) defines it as one that should be acquired by everyone. Similarly Benakli, Kostadinov, Satyanarayana and Singh (2017) and Wing (2014) emphasize that just as reading, writing and basic math skills, CT is a skill that should be possessed by everyone. Hsu, Chang and Hung (2018) consider CT as a universal skill that should be integrated in our daily lives. Researchers agree that CT is a 21st century skill that must be acquired by students at all levels of education from preschool to higher education (Barr & Stephenson, 2011; Grover & Pea, 2013; Shute, Sun, & Asbell-Clarke, 2017). Hence, many countries are observed to update their curricula to include CT skills (Angeli & Valanides, 2019; Barr & Stephenson, 2011; Garcia-Peñalvo & Mendes, 2018; Grover & Pea, 2013; Hsu et al., 2018; Roman-Gonzalez, Perez-Gonzalez, &

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Jimez-Fernandez, 2017). Researchers and educators all agree with the significance of CT and the necessity of providing students with CT skills. However, there is no consensus in regards to the best way to ensure that students acquire CT skills (Pérez-Marín, Hijón-Neira, Bacelo, & Pizarro, 2018; Shute et al., 2017). Denning (2017) attracts attention to the fact that it is highly crucial to know how to promote CT learning activities successfully. In fact, researchers make use of different methods and tools in order to equip students with CT skills. In this context, determining the variables that affect and predict CT can present important findings in terms of developing and assessing the CT skills of students. For this purpose, this study aimed to investigate how middle school students' CT skills differ according to gender, technology use, attitudes towards science and attitudes towards math and also to determine the relationships between these variables.

Theoretical Framework

Computational Thinking

Wing (2006) defined CT as problem solving, system design and understanding human behavior by using the concepts of computer sciences. According to Kong, Chiu and Lai (2018), it is imperative that students acquire CT skills in order to create a generation that can solve problems using creativity and technology. Wing (2006), who conducted important studies on CT, argues that it is not enough to teach students 3R skills (reading, writing and arithmetic) at early ages and CT skills should also be taught. Later in the academic realm, the significance of CT skills has been strengthened and a consensus has been reached that CT is an important skill that should be acquired by students (Pérez-Marín et al., 2018; Román-González, Pérez-González, Moreno-León, & Robles, 2018). Despite the consensus on its importance, no consensus has been reached on the definition of CT (Barr & Stephenson, 2011; Garcia-Peñalvo & Mendes, 2018; Grover & Pea, 2013; Kalelioglu, Gulbahar, & Kukul, 2016). Thusly it is witnessed that researchers have defined CT in different ways. Aho (2012) defined CT as formulating problems so that they can be solved with computational steps and algorithms. Korkmaz, Çakir and Özden (2017) stated that CT includes creativity, algorithmic thinking, collaboration, critical thinking, problem solving and communication skills. Wing (2014) remarked that CT indeed is thinking like a computer scientist when one encounters a problem. Shute et al. (2017) defined CT as a way of thinking and acting by using skills such as decomposition, abstraction, generalization, algorithmic design, debugging and iteration. Selby and Woollard (2013) addressed computational thinking as a combination of abstract thinking, thinking in segments, algorithmic thinking, evaluation, and generalization skills. Having said that, different CT definitions are found to emphasize certain common points. In their literature review, Kalelioğlu et al. (2016) found that CT studies include abstraction, problem solving and algorithmic thinking components the most. In their systematic review of CT-related research, Hsu et al. (2018), concluded that abstraction, algorithmic thinking, and automation are the most commonly used components in defining CT skill.

Gender and Computational Thinking

Gender is one of the variables that need to be addressed in regards to the acquisition and development of CT skills. Yildiz Durak and Saritepeci (2018) stated that gender can be important in the development of CT skill which is used as a concept related to computer sciences. As a matter of fact, studies were conducted in literature to investigate how CT skills differed according to gender. Yet it was found that these studies presented differing results. Whereas some research results highlighted that CT skills significantly varied according to gender (Atmatzidou & Demetriadis, 2016; Roman-Gonzalez et al., 2017), others concluded that there was no significant difference based on gender (Alsancak Sırakaya, 2019; Korucu, Gencturk, & Gundogdu, 2017; Yağcı, 2018). In their study, Yildiz Durak and Saritepeci (2018) indicated that gender is not a significant predictor of CT. Roman-Gonzalez et al. (2017) concluded that CT skills were higher in favor of male students. These different results can be interpreted in the way that more studies are needed to reveal the relationship between gender and CT.

Technology Use and Computational Thinking

Different methods are implemented to develop students' CT skills. Among these, technology-based methods and tools attract attention. Block-based programming, educational robotics, visual programming and developing games are frequently used in the development of students' CT skills. A fair number of studies have so far been conducted to reveal the relationship between CT and computer sciences (Grover, Pea, & Cooper, 2015; Repenning, 2012) and teaching programming (Kazimoglu, Kiernan, Bacon, & MacKinnon, 2011). Korkmaz et al. (2017) and Wing (2008) stated that CT is based on the concepts that are essential for computer sciences. To that end it can be argued that individuals' technology use may affect their CT skills. Korucu et al. (2017) pinpointed that students' CT skills did not differ according to the period of weekly internet use and their competence in using mobile devices, whereas they significantly altered according to their mobile device experiences. Korkmaz, Çakır, Özden, Oluk and Sarıoğlu (2015) articulated that students studying in technology-related departments (along with science and mathematics) developed significantly higher CT skills compared to students studying in other departments. Literature presents that there is not enough research to reveal the relationship between individuals' CT skills and technology use or how individuals' CT skills differ according to technology use. The present study is conducted with a view to determining how students' CT skills differed according to their mobile device ownership, technology competencies and daily period of technology use and aims to reveal the relationship between these variables.

Attitudes towards Science and Computational Thinking

Thanks to its components, CT is used in teaching within the scope of various fields. Science is one of the areas where it is extensively used. Previous studies show that CT is mostly used in physics (Farris & Sengupta, 2016; Sengupta, Kinnebrew, Basu, Biswas, & Clark, 2013) and biology (Basu, Kinnebrew, & Biswas, 2014; Swanson, Anton, Bain, Horn, & Wilensky, 2017) education. Sengupta et al. (2013) and Swanson et al. (2017), who conducted research on the integration of CT into science curriculum, reported that the CT-supported science curriculum yields successful results. Conducting a similar study, Basu et al. (2014) underpinned that science curriculum integrated with CT ensures significant gains in both CT and science. Libeskind-Hadas and Bush (2013) reported that biology education supported with CT and programming, a means of teaching they named BioComp, significantly enhanced learning efficiency and student interest in learning. Korkmaz et al. (2015) noted that students studying in science-related departments (along with mathematics and technology) had higher CT skills compared to students in other departments. Based on these explanations, it can be argued that CT and the field of science are related. Considering that attitude impacts student eagerness to the related course and achievement in it (Yilmaz, Altun, & Olkun, 2010), it can also be argued that students' CT skills will vary according to their science attitudes and there is the likelihood that a significant relationship between science attitude and CT exists.

Attitudes towards Mathematics and Computational Thinking

Examination of the previous studies shows that mathematics education is one of the areas where CT is used (Benakli et al., 2017; Snodgrass, Israel, & Reese, 2016; Weintrop et al., 2016). Rich and Yadav (2019), Sengupta et al. (2013) and Weintrop et al. (2016) uttered that CT can be integrated into the mathematics curriculum alongside some other areas. According to Benakli et al. (2017), hands-on computational activities that strengthen students' mathematics skills and their problem solving by using technology promote CT skills. Some researchers (Barr & Stephenson, 2011; Blikstein & Wilensky, 2009) emphasize that concepts included in CT skills such as algorithmic thinking, problem solving, critical thinking, and abstraction are key tools used in mathematics education. Korkmaz et al. (2015) asserted that students studying in departments related to mathematics (together with science and technology) had significantly higher CT skills than students studying in other departments. Based on these results, it can arguably be true that students' CT skills will differ according to their attitudes towards mathematics and there may be a significant relationship between attitudes towards mathematics and CT.

Research Hypotheses

In light of the theoretical foundations described above, it can be argued that gender, technology use, attitudes towards science and attitudes towards mathematics are important variables regarding students' CT skills. The research hypotheses developed in accordance with this view are given below:

(1) H1: Students' CT skills significantly differ according to gender.
(2) H2: Students' CT skills significantly differ according to ownership of mobile devices.
(3) H3: Students' CT skills significantly differ according to their technology competencies.
(4) H4: Students' CT skills significantly differ according to the period of daily technology use.
(5) H5: Students' CT skills significantly differ according to their attitudes towards science.
(6) H6: Students' CT skills significantly differ according to their attitudes towards mathematics.
(7) H7: There is a significant relationship between students' CT skills and their genders in favor of male students.
(8) H8: There is a significant relationship between students' CT skills and technology use.
(9) H9: There is a significant relationship between students' CT skills and their attitudes towards science.
(10) H10: There is a significant relationship between students' CT skills and attitudes towards mathematics.

Method

Research Model

This study aimed to investigate how middle school students' CT skills differed according to gender, technology use, attitudes towards science and attitudes towards math and to determine the relationships between these variables. Relational survey model was used for this purpose. The relational survey model intends to determine the change between two or more variables (Karasar, 2012).

Participants

Research participants consisted of 722 secondary school students. Convenience sampling method was used to determine the participants. Convenience sampling is a kind of non-probability sampling method in which researcher tries to reach the target number of samples starting from the respondents that can be reached relatively more easily in terms of cost, time, labor and accessibility (Büyüköztürk, Kılıç Çakmak, Akgün, Karadeniz, & Demirel, 2008). The participants who were classified with respect to their demographic characteristics are as follows: According to gender, 49.4% were females and 50.6% were males. Whilst 71.4% of the participants owned a mobile device, 28.6% did not have their own mobile devices. In terms of technology proficiency, 9.9% of the participants defined themselves as novice, 42.9% with medium proficiency and 47.2% as advanced users. As for the period of daily technology use, 67.4% of the participants declared that they used technology less than 1 hour a day, 24.1% between 1-4 hours a day, 6.8%, 4-8 hours a day, 1.7% more than 8 hours a day.

Data Collection Tools

Computational thinking scale, attitudes towards Science scale, attitudes towards mathematics scale were used in the study as data collection tools. The details of the data collection tools are given below:

Computational Thinking Scale: The scale developed by Korkmaz, Çakır and Özden (2015) was used to determine the CT skills of middle school students in this study. The scale with a total of 22 items includes 5 factors. Cronbach Alpha coefficient was calculated as .809 as a result of the analyses undertaken to determine the reliability of the scale. Cronbach Alpha coefficients for sub factors are as follows: Creativity .640; algorithmic thinking .762; collaboration .811; critical thinking .714 and problem solving as .867. Based on confirmatory factor analysis, Korkmaz, Çakır and Özden (2015) announced that the fit indices of the scale model were acceptable [$\chi 2$ (195, N=241)= 448,11628, p<.01, CMIN/DF=2,298 RMSEA= .074, S-RMR= .078, GFI= .89, AGFI= .84, CFI= .91, NNFI= .91, IFI= .90).

Attitudes towards Science Scale: The relevant factor of the STEM attitude scale developed by The Friday Institute for Educational Innovation and adapted to Turkish by Özcan and Koca (2019) was used to determine students' attitudes towards science. Based on the confirmatory factor analysis conducted by Özcan and Koca (2019), it was reported that the original factor structure of the scale was confirmed. Based on the reliability analysis, Cronbach Alpha coefficient was calculated as .87 for the science factor. The science factor in the 5-point Likert type scale consists of 9 items.

Attitudes towards Mathematics Scale: The relevant factor of the STEM attitude scale developed by The Friday Institute for Educational Innovation and adapted to Turkish by Özcan and Koca (2019) was used to determine students' attitudes towards math. The mathematics factor whose Cronbach Alpha coefficient was calculated as 0.86 based on the reliability analysis, consists of 8 items.

Data Analysis

Descriptive statistics, independent samples t-test, single factor analysis of variance (ANOVA) and multiple regression analysis tests were used in this study. So as to determine the normal distribution of variables, skewness, kurtosis coefficients were found, and graphic analyses were performed. It is concluded that Skewness and Kurtosis coefficients changed in the range of - \ + 1 and the graphs indicated normal distribution. Levene test was used to figure out which groups this difference originated from in the analyses where there was a significant difference as a result of the ANOVA test. Bearing in mind that the variances were not distributed homogeneously (p <.05) as a result of Levene test, Dunnett C test was used to determine the difference between the groups (Büyüköztürk, 2007).

Dependent and independent variables must be continuous variables measured in the least range scale in multiple regression analysis. Since the variables of gender and mobile device ownership used in the research were categorical, these variables were converted to artificial variables called "dummy variable" and re-coded (female = 0, male = 1; no = 0, yes = 1). Other assumptions of multiple regression analysis were also checked prior to the analysis. Scatter diagram was examined to determine the linear relationship between independent variables and the dependent variable. As a result of the examination, it was observed that there was a linear relationship between the variables. Additionally, multi-collinearity values (Tolerance, VIF) between independent variables were examined and it was determined that there was no multi-collinearity.

After determining that the assumptions required for multiple regression analysis were met, hierarchical regression analysis was performed. In hierarchical regression analysis, independent variables are included in the analysis in the order determined by the researcher and each variable is evaluated in regard to its contribution to the variance related to the dependent variable. In this study, the order in which the independent variables were included was determined according to the literature review. Thereupon participants' genders were included in the analysis for the first step. Participants' technology use and their attitudes towards science were included in the second and third steps of the analysis, respectively. Their attitudes towards mathematics was included in the fourth and the last step of the analysis.

Results

Results regarding Gender

Independent samples t-test was conducted to determine whether students' CT skills differed according to gender. Table 1 provides the test results.

Table 1. Change in CT skills based on gender

Gender	N	$\bar{X}$	Sd	df	t	p
Female	357	3.59	.66	719	-.977	.329
Male	364	3.63	.69			

Examination of Table 1 shows that while male students' CT skills mean scores ($\bar{X}$=3.63) were higher than female students' CT skills mean scores ($\bar{X}$=3.59), the difference was not significant ($t_{(719)}$= -.977, p>.05).

Results regarding Technology Use

Independent samples t-test was conducted to determine whether the students' CT skills differed according to their mobile device ownership (MDO) status. Table 2 presents the test results.

Table 2. Change in CT skills based on MDO

MDO	N	$\bar{X}$	Sd	df	t	p
Yes	511	3.67	.63	692	2.054	.040
No	183	3.59	.71			

According to Table 2, mean CT skill scores of students who owned mobile devices ($\bar{X}$=3.67) was significantly higher than the mean CT skill scores of students who did not own mobile devices ($\bar{X}$=3.59) ($t_{(692)}$= 2.054, p<.05).

One-factor analysis of variance was conducted for independent samples to determine whether the students' CT skills differed according to technology competence and period of daily technology use. Table 3 presents the test results.

Table 3. Change of CT skills based on technology competence and period of daily technology use

			N	X	Sd				N	X	Sd
Technology competence	1	Novices	63	3.34	.86	Period of daily technology use	1	< 1 hour	439	3.65	.61
	2	Medium	310	3.60	.61		2	1-4 hours	157	3.42	.75
	3	Advanced	341	3.68	.66		3	4-8 hours	44	3.78	.57
	4	Expert	8	3.40	1.15		4	8 hours <	11	3.36	1.40
		Total	722	3.61	.67			Total	651	3.60	.67

Variable	Source of variance	Sum of squares	df	Mean square	F	p	Significant difference
Technology competence	Between groups	6.646	3	2.215	4.970	.002	1 - 3
	In groups	320.072	718	.446			
	Total	326.718	721				
Period of daily technology use	Between groups	8.202	3	2.734	6.228	.000	2 - 1 2 - 3
	In groups	284.015	647	.439			
	Total	292.217	650				

Based on the analysis, it was concluded that students' perception of technology competence generated a significant difference in their mean CT skill scores ($F_{(3\text{-}721)}$= 4.970; p<.05). According to the Dunnett C test result, CT skills of students who perceived themselves at an advanced level in terms of technology competence were significantly higher than those of students who perceived them as novices. In a similar fashion, it was found that students' period of daily technology use generated a significant difference in their mean CT skill scores ($F_{(3\text{-}650)}$= 6.228; p<.05). According to the Dunnett C test result, students who used technology between 1-4 hours daily had significantly lower CT skills compared to students who used technology less than 1 hour a day or used technology between 4-8 hours.

Results regarding Attitudes towards Science and Mathematics

One-factor analysis of variance for independent samples was conducted to determine whether students' CT skills differed according to their attitudes towards science and mathematics. Table 4 presents the test results.

Table 4. Change of CT skills based on attitudes towards science and mathematics

			N	X	Sd				N	X	Sd
Science attitude	1	Low	67	3.43	.80	Mathematics attitude	1	Low	35	3.43	.61
	2	Medium	264	3.45	.73		2	Medium	410	3.50	.74
	3	High	391	3.75	.57		3	High	277	3.80	.53
		Total	722	3.61	.67			Total	722	3.61	.67

Variable	Source of variance	Sum of squares	df	Mean square	F	p	Significant difference
Science attitude	Between groups	16.347	2	8.173	18.934	.000	3 – 1 3 - 2
	In groups	310.371	719	.432			
	Total	326.718	721				
Mathematics attitude	Between groups	15.420	2	7.710	17.808	.000	3 – 1 3 - 2
	In groups	311.298	719	.433			
	Total	326.718	721				

According to Table 4, students' attitudes towards science generated a significant difference in their mean CT skill scores ($F_{(2\text{-}721)}$= 18.934; p<.05). According to the Dunnett C test result, CT skills of students with high science attitude levels were significantly higher than the CT skills of students with low and medium science attitude levels. Likewise it was concluded that students' mathematics attitudes caused a significant difference in their mean CT skill scores ($F_{(2\text{-}721)}$= 17.808; p<.05). According to the Dunnett C test result, CT skills of students with high mathematics attitude levels were higher compared to CT skills of students with low and medium mathematics attitude levels.

Results regarding the Variables that Predict Computational Thinking

Table 5 presents the descriptive statistics for all the variables. According to Table 5, there is a negative relationship between students' CT skills and their daily use of technology (DTU) (r = -. 07, p <.05). However, there is a positive relationship between CT skill and gender (r = .71, p <.05), mobile device ownership (MDO) (r = .18, p <.01), technology competence (TC) (r = .11, p <. 01), science attitude (SA) (r = .22, p <.001) and mathematics attitude (MA) (r = .24, p <.001).

Table 5. Means, standard deviations and correlations of the study variables

	M	SD	1	2	3	4	5	6	7
1.CT			--						
2.Gender	.52	.50	.71*	--					
3.MDO	.73	.45	.18***	.04	--				
4.TC	2.45	.70	.11**	.14***	.25***	--			
5. DTU	1.43	.69	-.07*	.12**	.05	.14***	--		
6.SA	3.68	.88	.22***	-.11**	.15***	.08*	-.10**	--	
7.MA	3.41	.62	.24***	-.11**	.18***	.06	-.08*	.52***	--

Note: Gender and mobile device ownership were dummy coded such that female=0 and male=1, no=0 and yes=1). *p<.05, **p<.01, ***p<.001

Hierarchical regression analysis was carried out to be able to determine the variables predicting students' CT skills. Gender was included in the analysis in the first block, technology use in the second block, attitudes towards science in the third block and attitudes towards mathematics in the fourth block. Hierarchical regression analysis results are given in Table 6.

Table 6. Hierarchical regression analysis results

Variable	B	SE B	β	t	R^2	ΔR^2	F	Sig
Model 1					**.005**	**.005**	**3.22**	**.073**
Gender	.09	.05	.07	1.79				
Model 2					**.048**	**.043**	**8.023**	**.000*** **
Gender	.09	.05	.07	1,705				
MDO	.25	.06	.16	4,110***				
TC	.07	.04	.07	1,689				
DTU	-.09	.04	-.09	-2,423*				
Model 3					**.085**	**.042**	**11.863**	**.000*** **
Gender	,119	,052	,089	2,302*				
MDO	,206	,059	,136	3,459**				
TC	,050	,038	,052	1,302				
DTU	-,072	,037	-,074	-1,923				
SA	,151	,030	,198	5,096***				
Model 4					**.101**	**.059**	**12.009**	**.000*** **
Gender	,130	,051	,098	2,544*				
MDO	,180	,059	,119	3,030**				
TC	,049	,038	,052	1,304				
DTU	-,067	,037	-,069	-1,805				
SA	,093	,034	,122	2,745**				
MA	,166	,048	,153	3,427**				

*p<.05, **p<.01, ***p<.001

According to Table 6, 0.5% of the total variance in students' CT skills was explained by gender, 4.8% by gender and technology use; 8.5% by gender, technology use and attitudes towards science and 10.1% by gender, technology use, attitudes towards science and attitudes towards mathematics. Accordingly, while Model 2, Model 3 and Model 4 predicted CT skills significantly ($p < .001$), Model 1 did not ($p > .05$).

With the previous 3 models, Model 4 explained 10.1% of the total variance in students' CT skills (R=.318, R2=10.1, p<.001). According to Regression coefficient (β) values, the relative order of importance of predictor variables on students' CT skills was as follows: attitudes towards mathematics, attitudes towards science, having a mobile device, gender, period of daily technology use and finally technology competence.

Gender explained 0.5% of the variance in CT skills. When the effect of gender was controlled, technology use additionally explained 4.3% of the variance. Model 3 which included attitudes towards science and Model 4 which included attitudes towards mathematics were found to contribute to explaining the total variance by 4.2% and 5.9%. Table **7** summarizes the acceptance or rejection status of the research hypotheses according to the analysis.

Table 7. Hypothesis acceptance/rejection

Hypothesis	**Acceptance/ rejection**
H1: Students' CT skills significantly differ according to gender.	Rejected
H2: Students' CT skills significantly differ according to ownership of mobile devices.	Accepted
H3: Students' CT skills significantly differ according to their technology competencies.	Accepted
H4: Students' CT skills significantly differ according to the period of daily technology use.	Accepted

H5: Students' CT skills significantly differ according to their attitudes towards science.	Accepted
H6: Students' CT skills significantly differ according to their attitudes towards mathematics.	Accepted
H7: There is a significant relationship between students' CT skills and their genders in favor of male students.	Rejected
H8: There is a significant relationship between students' CT skills and technology use.	Accepted
H9: There is a significant relationship between students' CT skills and their attitudes towards science.	Accepted
H10: There is a significant relationship between students' CT skills and attitudes towards mathematics.	Accepted

Discussion

This study aimed to determine the changes in secondary school students' CT skills according to different variables and to determine the relationships between these variables. Discussions and suggestions based on the study results are presented below.

Results of analyses show that students' CT skills did not differ by gender. Besides this, it was concluded that Model 1, which concentrated upon the relationship between CT skills and gender, was not statistically significant. According to these results, H1 and H7 were rejected. That being said, the relationship between CT and gender was found to be statistically significant only in Model 3 and Model 4. Thence it can be argued that male participants' CT skills were higher than female participants' CT skills, nonetheless the difference was small. These results are supported by other studies reporting that CT does not change according to gender (Alsancak Sırakaya, 2019; Korkmaz, Çakır, Özden, et al., 2015; Korucu et al., 2017; Oluk & Korkmaz, 2016; Yağcı, 2018). Similar to these, in their research with secondary school students, Yildiz Durak and Saritepeci (2018) concluded that gender was not a significant predictor of CT.

It was remarked that students' CT skills significantly differed based on mobile device ownership, technology competence and period of daily technology use. The findings revealed a significant relationship between technology use and CT skills. According to these results, H2, H3, H4 and H8 were accepted. The effect of technology use variables on CT skills can be enlisted in the following order of importance: mobile device ownership, period of daily technology use and lastly technology competence. Mobile device ownership was an important predictor of CT in Model 2, Model 3 and Model 4. The relationship between period of daily technology use and CT was negative solely in Model 2. Parallel to this, as the period of daily technology use increases, students' CT skills decrease. Different results were found in the studies presented in the literature though. In their study, Yildiz Durak and Sarıtepeci (2018) mentioned that the relationship between CT and the period of IT use and daily period of internet use was not significant. Oluk and Korkmaz (2016) underlined that CT skill did not differ according to daily computer use. Korucu et al. (2017) concluded that students' CT skills did not change according to their weekly internet use and their competence in using mobile devices, whereas they significantly differed according to their mobile device experiences. As can be seen, there are plenty of variables related to students' statuses with regard to technology use and their experiences pertaining to technology. These variables can be addressed more elaboratively in further studies.

Based on the study results, it was determined that students' CT skills significantly differed according to their attitudes towards science. Consistent with that, CT skills of students with high science attitude levels were significantly higher than the CT skills of students with medium or low science attitude levels. Based on the results of the hierarchical regression analysis, a significant positive relationship was detected between science attitude and CT. According to these results, H3 and H9 were supported. It was found that attitudes towards science, included in the third step of the hierarchical model, was the most important predictor of CT skills. The contribution of attitudes towards science in explaining the total variance in CT skills was calculated as 4.2%. These findings point to a result that attitudes towards science improve CT skills. Korkmaz et al. (2015b) accentuated that teaching programs implemented in science departments (along with mathematics and technology) may be contributing to students' CT skills more. While Yildiz Durak and Sarıtepeci (2018) underscored that science achievement was a significant predictor of CT reporting that the relationship between attitudes towards science and CT was not significant.

Research results indicate that attitudes towards mathematics can change CT skills. On that account, CT skills of students with high mathematics attitude levels were significantly higher than the CT skills of students with medium and low-level mathematics attitude levels. Uniformly, as a result of hierarchical regression analysis, a positive and significant relationship was diagnosed between attitudes towards mathematics and CT. According to these results, H6 and H10 were accepted. Attitudes towards mathematics, a variable included in Model 4, contributed 5.9% to the total variance. Attitudes towards mathematics appeared as the most important predictor of CT in this study. In the literature, the relationship between attitudes towards mathematics and CT was examined only by Yildiz Durak and Sarıtepeci (2018) who proclaimed that the relationship between CT and attitudes towards mathematics was not significant and attitudes towards mathematics did not significantly predict CT. Nevertheless, Yildiz Durak and Sarıtepeci (2018) expressed that mathematics achievement significantly predicted CT.

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