

The Effect of Gender, Grade, Time and Chronotype on Computational Thinking: Longitudinal Study

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Abstract. Problem-solving and critical thinking are associated with 21st century skills and have gained popularity as computational thinking skills in recent decades. Having such skills has become a must for all ages/grade levels. This study was conducted to examine the effects of grade level, gender, chronotype, and time on computational thinking skills. To this end, the study was designed to follow a longitudinal research model. Participants were 436 secondary school students. Computational thinking test scores were collected from the students at certain time intervals. Results indicate that computational thinking skills are independent of gender, time, and chronotype but differ significantly depending on grade level. The interaction between grade level and time of testing also has a significant impact on computational thinking skills. The difference in grade level can be interpreted as taking an information technologies course increases computational thinking. The results suggest that such courses should be promoted to children at a young age. The joint effect of gender, grade level, and chronotype were not statistically significant and it is recommended to conduct future studies to investigate this result.

Keywords: Computational thinking, chronotype, time of day, gender, grade.

1. Introduction

Technology pushing us to name societies and time in various ways has a significant effect on the transformation and formation of the desired and expected characteristics of people. What is meant here is the changing roles, characteristics, and competencies of people along with advances in technology. With the century we are in, the 21st century

skills have become a concept that we often hear, and the importance of which is often underscored. This concept is intended to define the skills that we should equip our kids with when preparing them for the future of the world (Sing, 1991). There are studies (Ananiadou and Claro, 2009; Trilling and Fadel, 2009; Dede, 2010; Lai and Viering, 2012; Göksün and Kurt, 2017) highlighting the importance of these skills particularly in educational settings.

Studies on the 21st century skills vary and present different approaches on how these skills are sorted and classified (Wagner, 2014; Dicerbo, 2014; Kylonen, 2012; Lai and Viering, 2012; Trilling and Fadel, 2009). Wagner (2014) identified these skills of the new century as critical thinking and problem-solving, accessing and analyzing information, inter-system and interpersonal collaboration and leadership, entrepreneurship and initiative, quick wit and adaptability, effective verbal and written communication, and curiosity and imagination. Trilling and Fadel (2009) briefly described them as information curiosity, fluency in media use, and technology-based learning. Computation (information processing) and problem-solving skills are at the forefront of the 21st century skills. This situation directs us to the concept called computational thinking.

In that same vein, Bundy (2007) claimed if you would like to understand the 21st century, you need to understand information processing. Today, teaching student computational thinking is regarded as a way to offer them essential life skills, and the ideas behind computational thinking have the ability to impact the education of students of all ages around the world (Henderson, Cortina, Hazzan, and Wing, 2007). Because computational thinking is at the heart of all STEM practices (Henderson, Cortina, Hazzan, and Wing, 2007), information processing should be encouraged at the K-12 level (Grover and Pea, 2013). In other words, the way we can understand the era we are in and have the skills required to adjust to it seems to be possible only through information processing. Therefore, it is important to emphasize information processing and computational thinking skills in educational processes.

Computational thinking has been defined as a fundamental skill for everyone, not just for computer scientists by Wing (2006) who coined the term first. While the initial definitions of computational thinking are more general, the concept and components of computational thinking have been examined and explained in more detail in the studies carried out in the years to come.

1.1. *Computational Thinking*

Computational thinking influences research in almost all disciplines, in both the physical and social sciences (Bundy, 2007). It deals with defining information- processing disciplines and provides us with an alternative way of packaging, presenting, understanding, and studying information (Henderson, Cortina, Hazzan, and Wing, 2007). Many definitions of computational thinking can be found. Wing's (2006) research on and definitions of computational thinking have contributed to the understanding of this concept and its dissemination as a subject of research. According to Wing's initial studies, compu-

tational thinking is based on the strengths and limitations of computational processes, regardless of whether they are carried out by a person or a machine (Wing, 2006). The essence of computational thinking is an abstraction (Wing, 2008). Abstraction, in this context, is defining certain patterns, generalizing from specific instances and is the key to dealing with complexity (Wing, 2011). Wing (2011) stated in his revised definition that computational thinking refers to thought processes involved in the formulation of problems and their solutions so that the solutions are represented in a way that can be effectively carried out by an agent processing information.

Although several studies focus on problem-solving skills in general, different definitions of computational thinking can be found. Computational thinking was defined by Bundy (2007) as one's being able to generate different pathways using the mental activities required for the problems one encounters. Denning (2009) has argued that computational thinking was referred to as algorithmic thinking in the 1950s and 1960s, but today it has been expanded to include thinking with many levels of abstraction, using mathematics to develop algorithms, and looking at how well a solution can be reached. While computational thinking is associated with algorithmic thinking and computer science, it is identified to be more detailed than algorithmic thinking and to have a broader impact than computer science (Üzümcü and Bay, 2011).

Furber (2012) proposed a concise definition of computational thinking as the process of recognizing aspects of computing in the surrounding world and the process of applying tools and techniques from computer science to understand and reason both natural and artificial systems and processes (Angeli *et al.*, 2016). Computational thinking is a set of thinking skills, and it involves defining, understanding, and solving problems, reasoning at multiple levels of abstraction, understanding and applying automation, and analyzing the appropriateness of the abstractions made (Lee *et al.*, 2011). Royal Society (2012) emphasized that computational thinking is the process of understanding and justifying both natural and artificial systems and processes by recognizing the aspects of computing and applying computer science instruments and techniques. It is a thinking strategy to manage the thinking process necessary to solve a problem (Barr, Harrison, and Conery, 2011).

There are various views on the elements and characteristics that constitute the concept of computational thinking. Lee *et al.* (2011) identified the components of computational thinking as abstraction, automation, and analysis, and described their use in problem-solving as computational thinking. In another definition, the components of computational thinking were described as abstraction, decomposition, algorithmic design, evaluation, and generalization (Selby and Woollard, 2013). Weintrop *et al.* (2014) determined the following items as the sub-dimensions of computational thinking: (1) data and information skills, (2) modeling and simulations skills, (3) computational problem-solving skills, and (4) systems thinking skills.

In its 2015 guidelines, the International Society for Technology in Education (ISTE) listed the characteristics of computational thinking as follows:

- Formulating problems in a way that enables us to use a computer and other tools to help solve them.
- Logically organizing and analyzing data.

- Representing data through abstractions, such as models and simulations.
- Automating solutions through algorithmic thinking (a series of ordered steps).
- Identifying, analyzing, and implementing possible solutions with the goal of achieving the most efficient and effective combination of steps and resources.
- Generalizing and transferring this problem-solving process to a wide variety of problems (ISTE, 2015: 13).

ISTE has also suggested that a set of tendencies or attitudes that are the primary elements of computational thinking support and improve these skills. These can be listed as follows: confidence in dealing with complexity, persistence in working with difficult problems, tolerance for ambiguity, the ability to deal with open-ended problems, and the ability to communicate and work with others to achieve a common goal or solution (ISTE, 2015).

It is important to acquire computational thinking skills, which represent an important set of skills as twenty-first century skills for the new generation of learners. For this reason, teaching computational thinking skills and researching the factors affecting these skills are important. The first factor that comes to mind is gender as the attitudes and performances of girls and boys in even simple reading and writing tasks differ (Merisuo-Storm, 2006). Research on comparing the development of CT skills between genders in K-12 robotics activities are relatively sparse (Yadav *et al.*, 2011; Atmatzidou and Demetriadis, 2016). Recently Angeli and Validenes (2020) stated that gender was a significant variable in the study in which they developed the computational thinking skills of young children at pre-school level. Based on meta-analysis studies it was stated that the CT seems to be moderately gender-biased as its items have a large visuospatial load that could be favoring males (Román-González *et al.*, 2018).

One of the variables examined besides gender in computational thinking skills is age or grade. Atmatzidou and Demetriadis (2016) stated in their studies that computational thinking is independent of gender and age. There are studies examining the effects of gender and age or grade on computational thinking skills in early childhood (Sullivan and Bers, 2013; Bers, Flannery, Kazakoff and Sullivan, 2014), in primary school (Rijke, Bollen, Eysink and Tolboom, 2018), in middle school (Kalas and Tomcsányiová, 2009; Ardito, Czerkawski and Scollins, 2020), and among students at different grade levels (Tomcsányiová and Kabátová, 2013).

Chronotype is another factor that affects success and performance. Studies conducted in different countries and at different grade levels show that chronotype is related to academic achievement (Borisenkov *et al.*, 2010; Preckel *et al.*, 2011; Arbabi *et al.*, 2015; Rahafar *et al.*, 2016; Kolomeichuk *et al.*, 2016; Enright and Refinetti, 2017; Rahafar *et al.*, 2017; Mirghani, 2017).

1.2. Chronotype

Chronotype, or morningness-eveningness, is related to individual differences in the sleep-wake rhythm, preferred bed and rise times, as well as peak times for mental and physical activity (Adan *et al.*, 2012). Humans differ significantly in their chronotypes,

and a chronotype is sometimes regarded as a personality-like trait (Randler *et al.*, 2017a). Morning people achieve their best performance in the morning, have no problems in getting out of bed, but become tired in the evening very early. In contrast, evening types have problems with getting up, need more time to have their senses clear, but can work in the afternoon and even at night (Adan *et al.*, 2012). Further, men are usually more evening-oriented than women (Randler and Engelke, 2019). Chronotype transforms from childhood, when children are usually morning oriented, to puberty, when people are typically evening oriented (Randler *et al.*, 2017b). This trait is related to many psychological and physiological aspects (for an overview, see Adan *et al.*, 2012), but also to school performance. In most studies, school achievement was negatively related to chronotype, so morning students received higher grades (Tonetti *et al.*, 2015). This was the case among 4th-grade primary school children (Arbabi *et al.*, 2017), middle school children (Kolomeichuck *et al.*, 2016), and also in school graduation exams (Randler and Frech, 2006). Just recently, a study showed an influence of chronotype on motivational aspects of university students during the pandemic, also suggesting that morning students cope better with this environment (in combination with other individual difference traits, such as personality; see Staller *et al.*, 2021). In an experimental study, 9th graders enrolled in a chemistry classroom (lab) performed better and were motivated more strongly when the lab course took place from 15:00 onwards compared to 9:00 (Itzek-Greulich *et al.*, 2017).

There are no studies in the literature that examine computational thinking skills in relation to gender, grade level, time of day, and chronotype altogether. Therefore, the aim of this study is to examine the effect of gender, grade level, chronotype, and time of day on computational thinking skills. For this purpose, students' computational thinking performances were measured at different times, and effects of gender, grade level, and chronotype were examined.

2. Method

2.1. Model

This study was carried out as a longitudinal survey. In longitudinal survey models, a trait is measured repeatedly over multiple times without interfering with students. In this study, the Computational Thinking Test scores of middle school students were measured at 9:00 in the morning for the first week as the first measurement, and at 3:00 p.m. after two weeks as the second measurement.

2.2. Participants

The participants of the study consisted of a total of 436 students who were studying in three different secondary schools located in one of Turkey's metropolitan areas and accessible based on the convenience sampling method. Although questionnaires were

distributed to a total of 600 students in these target schools, when questionnaires from students who did not participate in the first- or second-time administration were excluded, 456 students remained. Among these students, 436 usable cases remained when the data of students who did not complete the gender, grade, age, chronotype or Computational Thinking Test in the measurement instrument were removed. Of the students participating in the study, 224 (51.4%) were female and 212 (48.6%) were male. And of them, 104 (23.9%) were sixth grade, 119 (27.3%) were seventh grade, and 213 (48.9%) were eighth grade students. The students were 10 to 15 years old and had an average age of 12.78 (± 1.03).

2.2. Instruments

Two tests were used together as a single measurement instrument in the study: the Computational Thinking Test and the Composite Scale of Morningness (CSM). They are described below. The instrument also included demographic questions about age, gender, grade level, and bedtime.

2.2.1. Computational Thinking Test

The Computational Thinking Test was developed by Román-González (2015) and adapted to Turkish by Uysal and Horzum (2018). Within the scope of this study, 14 out of 28 questions were considered by experts to be appropriate for the secondary school level and included in the measurement instrument. This test, consisting of 14 questions, was administered to a total of 132 students studying in a secondary school as a pilot study prior to the actual study. Of the responses, 114 were identified to be suitable for use, so item analyses were carried out based on these responses. Item discrimination and item difficulty indices of the 14 items based on the item analyses are presented in Table 1.

The average item difficulty index of the test was 0.56, and the average item discrimination index was 0.40. The mean test score was 7.4, and the standard deviation

Table 1
Item analysis results of the Computational Thinking Test

Item No	Difficulty Index	Distinctiveness	Item No	Difficulty Index	Distinctiveness	Item No	Difficulty Index	Distinctiveness
1	0.94	0.39	2	0.77	0.43	3	0.64	0.39
4	0.76	0.30	5	0.73	0.49	6	0.54	0.49
7	0.75	0.51	8	0.30	0.32	9	0.32	0.37
10	0.55	0.48	11	0.24	0.30	12	0.25	0.40
13	<u>0.48</u>	<u>0.31</u>	14	<u>0.56</u>	<u>0.35</u>			

*Difficulty index

was 2.56. The difficulty index was taken as very easy ($p > 0,90$), easy ($0,89 > p > 0,60$), somewhat easy ($0,59 > p > 0,35$), and difficult ($p < 0,34$). These values indicate that 1 item was very easy, 5 items were easy, 4 items were somewhat easy, and 4 items were difficult. In this respect, the overall item difficulty index of the test can be said to be at a medium level. Again, when evaluated out of 14 points, the average test score is 7.4, which proves that it is at a moderate level. The test also turned out to be a good test for discrimination. In addition, the KR20 value of the test was 0.61. This value can be argued to be an acceptable value for the reliability of the test.

2.2.2. Composite Scale of Morningness (CSM)

The CSM used to measure the students' day and night preferences in the study was developed by Smith, Reilly, and Midkiff (1989) and adapted to Turkish by Önder, Beşoluk, and Horzum (2013). The scale consisted of 13 Likert-type items, 3 of which had 5-point options, and 10 had 4-point options. One may score between 13 and 55 points on the scale, and an increase in the score on the scale indicates an increase in the preference for morningness. Önder *et al.* (2013) reported the internal consistency coefficient of the scale as 0.73. In the present study, the internal consistency coefficient of the scale was 0.81.

2.2.3. Data Collection and Analysis

Permission was obtained from the Directorate of National Education for the study, and the surveys were administered to volunteer students one week at 9:00 a.m. and two weeks later at 3:00 p.m. face-to-face, two weeks in between. The data collected were entered into the SPSS package program. A mixed between/within-subjects ANCOVA was conducted to assess the impact of grade level and chronotype on computational thinking at the first and second measurements. The pre/post computational thinking test scores constituted the within-subjects factor, the grade and chronotype constituted the between-subjects factor variables. Gender was a control variable.

3. Results

Computational Thinking Test scores of the students ranged from 1 to 14 ($X \pm SD = 8.12 \pm 2.70$; $X \pm SD = 8.56 \pm 2.85$) at the first and second measurements, respectively, indicating a significant increase at the second without controlling any variables ($t = -1.99$). With regard to chronotypes, the scores of the students ranged from 18 to 50 ($X \pm SD$; 33.99 ± 6.05). When the chronotype scores were categorized, 123 (28.2%) students were morning type, 205 (47.0%) were neither type, and 108 (24.8%) were evening type. Mean and standard deviation values for the Computational Thinking Test scores across grade levels and chronotypes at the first and second measurements are presented in Table 2.

Table 2
Mean scores and standard deviations of students' Computational Thinking Test scores across grade levels and chronotypes at the first and second measurements

Time	Sixth	Seventh	Grade Eighth	Morning	Chronotype	
					Neither	Evening
9:00	7.32 ± 2.45	8.06 ± 2.89	8.54 ± 2.63	8.81 ± 2.83	8.25 ± 2.77	7.72 ± 2.53
15:00	7.05 ± 2.78	8.55 ± 2.87	9.30 ± 2.57	8.24 ± 2.73	8.42 ± 2.80	8.54 ± 2.96

3.1. Effects of Grade and Chronotype on First/Second Measurement of Computational Thinking Test Scores

A mixed between/within-subjects ANCOVA was conducted to assess the impact of grade level and chronotype on the Computational Thinking Test scores at the first and second measurements. First and second measurements were the within-subjects factor, the grade level and chronotype were the between-subjects factor, and gender was the covariate. ANCOVA results are given in Table 3.

Table 3 shows that there was not a significant main effect with regard to the first and second measurements ($F(1,436) = 0.56, p > 0.05$). This finding indicates that there was no statistically significant difference between the first measurement of Computational Thinking Test Scores at 9:00 a.m. ($X \pm SD = 8.12 \pm 2.70$) and the second measurement at 3 p.m. two weeks later ($X \pm SD = 8.56 \pm 2.85$). This finding suggests that there were students who gave an average of 8 correct answers out of 14 questions in both

Table 3
ANCOVA results table

Source	Sum of Squares	df	Mean Square	F	p
Between-Subjects	4981.06	435			
Gender	5.82	1	5.82	0.55	.46
Grade	412.81	2	206.40	19.63	.00
Chronotype	60.28	2	30.14	2.87	.06
Grade × Chronotype	24.08	4	6.02	0.57	.68
Error	4480.07	426	10.52		
Within-Subjects	1674.19	436			
Time	2.10	1	2.10	0.56	.46
Time × Gender	0.57	1	0.57	0.15	.70
Time × Grade	27.99	2	13.99	3.71	.03
Time × Chronotype	20.25	2	10.12	2.68	.07
Time × Grade × Chronotype	14.79	4	3.70	0.98	.42
Error (Time)	1608.50	426	3.78		
Total	6655.25	871			

*Note: Time refers to computational thinking measurements (1 and 2).

measurements, and this was not influenced by the measurement time or the repetitive measurement alone.

The two-way interaction of the first/second measurement of Computational Thinking Test \times gender was not significant ($F_{(1,436)} = 0.15, p > 0.05$), but the two-way interaction of the first/second measurement of Computational Thinking Test \times grade was significant ($F_{(2,436)} = 3.71, p < 0.05$). The significant two-way interaction indicates that the first and second measurements of the Computational Thinking Test scores varied as a function of the grade level. Further investigation of this interaction was analyzed using a Bonferroni adjustment while holding the alpha level at 0.05. The results are shown in Fig. 1.

At the first measurement of the Computational Thinking Test, the eighth-grade students had significantly higher scores than the sixth-grade students (Fig. 1). At the second measurement, the eighth- and seventh-grade students had significantly higher scores than the sixth-grade students. There was no significant difference in any other comparisons. The eighth- and seventh-grade students had significantly higher Computational Thinking Test scores at the second measurement in comparison to the first measurement, but not the sixth-grade students. All these findings show that the Computational Thinking Test scores of students who did not take the sixth-grade information technology course were lower than those of students who took the course. In this regard, the scores demonstrate the importance of teaching the information technology course and computational thinking skills at an earlier age.

The other two-way interaction (first/second measurement of computational thinking test \times chronotype) was not significant ($F_{(2,436)} = 2.68, p > 0.05$) but as it was very close to being a significant difference, a decision was made to examine the source of the dif-

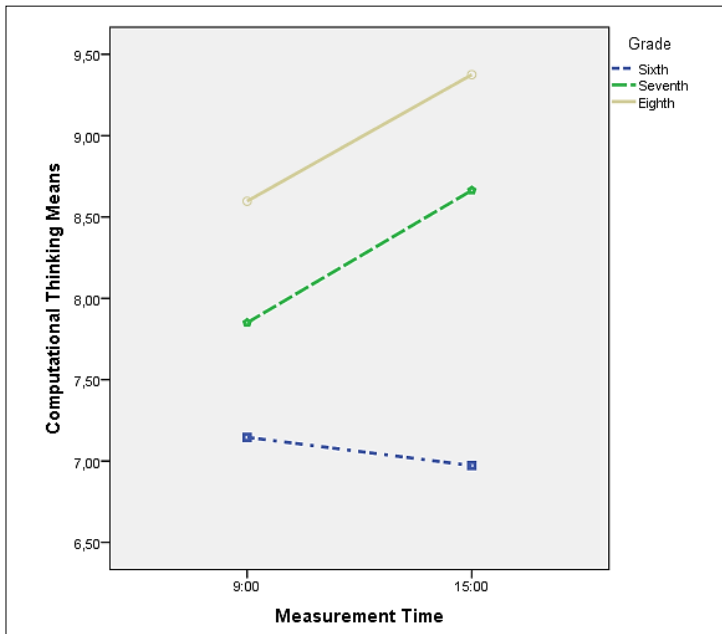


Fig. 1. Computational Thinking Test scores and grade plot of the two-way interaction.

ference. Further investigation of this interaction was analyzed using a Bonferroni adjustment while holding the alpha level at 0.05.

The students of the evening type were found to have higher scores in the measurements taken at 3:00 p.m. when their first and second measurements were compared. Moreover, the students of the morning type were found to have higher scores in the measurements taken at 9:00 a.m. There was no difference between the two measurements of the students of neither type. This finding shows the value of planning courses according to chronotypes in practices demanding mental abilities, such as computational thinking. There was no significant difference in comparisons between chronotypes in the first and second administrations of the Computational Thinking Test. Furthermore, the three-way interaction (Grade \times Chronotype \times First/Second Measurement of Computational Thinking) was not significant ($F_{(4, 436)} = 0.98, p = 0.42$).

4. Discussion

The purpose of this study is to investigate the influence of gender, school level, chronotype, and time on computational thinking skills. To that end, a mixed-design ANCOVA (between/within-subjects) was conducted to evaluate the influence of grade level and chronotype on Computational Thinking Test scores at the first and second times of measurement. The results of the ANCOVA analysis show that there is a significant difference between grade levels and that the two-way interaction between the first/second measurement of Computational Thinking Test and grade level is significant ($F_{(2,436)} = 3.71, p < 0.05$). While the sixth grade students who participated in the study did not take a computational thinking course, the seventh- and eighth-grade students did. This difference can be taken as evidence that the information technology course enhances students' computational thinking skills. There are studies in the literature that support this finding (Seo and Kim 2016; Brackmann, Román-González, Robles, Moreno-León, Casali, and Barone 2017; Nouri, Zhang, Mannila, and Norén 2020). Therefore, it is important to offer students training on Computational Thinking.

Results show that although Computational Thinking test scores differ between measurement times, this difference is not statistically significant. Eighth- and seventh- grade students scored higher on the Computational Thinking Test at the second measurement than at the first measurement, whereas the sixth grade students scored lower. In fact, many studies in the literature indicate that there are different time periods during which people are mentally active in the morning and evening. Chronotype is known to affect not only physical but also cognitive performance (Facer-Childs, Boiling, and Balanos, 2018). Preckel *et al.* (2011) emphasized that there is a negative relationship between morningness and cognitive abilities. Logical reasoning, reaction time, numerical memory, visual memory, and prospective memory skills related to computational thinking skills are also related to morningness (Kyle *et al.*, 2017). On the other hand, Nowack and Van Der Meer (2018) found that morning-type people have more cognitive resources at the most favorable times of the day that they can apply to more challenging conditions to perform better than evening-type people. However, their study was on adults. In our

study, since computational thinking is a subject that requires mental activity, a significant difference between morning and afternoon measures was expected for the morning- and evening-type students. Unlike other studies, no statistically significant difference was found between morning and afternoon measurements in the present study. This fact suggests that there is no statistically significant relationship between chronotype and computational thinking. Grade levels may have masked this expected difference. The participants in this study were sixth grade students who received no training on computational thinking and seventh and eighth-grade students who received training on computational thinking at the end of the 6th grade. As shown in Table 3 although there is no significant difference, the p-value of 0.07 is quite close to the significant level. For this reason, conducting a study in which all participants are individuals who have taken a course on computational thinking could lead to different results.

Males are more negatively impacted by technology use, such as technology addiction, gambling addiction, and cyberbullying, than females, according to numerous studies in the literature (Ünal, 2020; Wang, Sheng, and Wang, 2019). In the present study, although a significant difference was expected between males and females, no significant difference was found. Obviously, this result is different from the results of studies on gender differences in the literature (Atmatzidou and Demetriadis, 2016; Angeli and Valanides, 2020). The reason for this situation can be explained by the fact that the current study conducted is different from previous studies in terms of the class of the students participating in the research or in terms of computational thinking skills training. Previous research has suggested that the timing of performance has an impact on the outcome (Enright and Refinetti, 2017; Facer-Childs, Boiling, and Balanos, 2018; Nowack and Van Der Meer, 2018). As predicted, this study showed that evening-type students performed better at 3:00 p.m. than at 9:00 a.m., whereas morning-type students performed better at 9:00 a.m. than at 3:00 p.m. However, this observed difference between the times was not statistically significant.

Finally, it should be noted that the joint effect of gender, class, and chronotype was not statistically significant. Future research may be able to shed light on why there is no such interaction, despite popular belief.

5. Conclusion

As a conclusion Computational Thinking Test scores of students who did not take the sixth-grade information technology course were lower than those of students who took the course. In this regard, the scores demonstrate the importance of teaching the information technology course and computational thinking skills at an earlier age.

6. Limitations

In this study, the difference between the 7th, 8th and 6th grades represent that courses on subjects such as computational thinking, coding, and algorithmic thinking significantly

affect students' computational thinking skills. Therefore, such courses should be promoted to children at a young age.

The effects of time of day were investigated using test results from the same students at 09:00 a.m. and 03:00 p.m. This time frame is very close to the Turkish school day. Computational thinking performance can be examined over more time intervals or on different student groups as a between-groups factor. The effective hours of different practices of computational thinking can be examined through empirical studies, and policies can be developed for the teaching of computational thinking skills. Similar studies on high school and university students, as well as adult learners, can be conducted to examine computational thinking performance across age groups and determine appropriate study hours.

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