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Research Article

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Scratch, computational thinking, and grit: At the beginning, during, and after the COVID-19 Pandemic

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Abstract

The Covid-19 pandemic has deeply affected the whole world. In order to continue education during the pandemic, emergency distance education applications were utilized. The purpose of the research is to evaluate how block-based programming affects computational thinking (CT) and grit at the beginning, during and after pandemic. The study used a quasi-experimental pretest-posttest design. This sample was divided into three groups based on the stage of the COVID-19 Pandemic at which they were enrolled in a programming course: before the pandemic, during the pandemic, and after the pandemic. The participants are 104 teacher candidates in the Faculty of Education of a Turkish state university. As a result of the research, it is observed that block-based coding instruction has a significant difference between the pre-test and post-test scores of computational thinking in the pre-pandemic and pandemic groups. The difference in this case has a moderate effect size. There was no significant difference between the pretest and posttest scores of the post-pandemic group. Comparing the groups revealed that the pre-pandemic and during pandemic groups had significantly higher median scores in computational thinking skills than the post-pandemic group. According to these results, it can be argued that the negative effects of the pandemic were seen in the post-pandemic group. The results of the short grit scale emphasize the importance of non-cognitive factors in distance education in the context of the consistency of interest dimension. Moreover, it indicates a significant and positive relationship between grit and computational thinking skills.

Keywords: Scratch, Computational thinking, Grit, Pandemic

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Scratch, bilgi işlemsel düşünme ve azim: Pandemi öncesi, pandemi süreci ve pandemi sonrası

Özet

Covid-19 pandemisi tüm dünyayı derinden etkilemiştir. Pandemi sürecinde eğitim-öğretimin devam edebilmesi için acil uzaktan eğitim uygulamaları işe koşulmuştur. Araştırmanın amacı, blok tabanlı programlamanın pandemi başlangıcında, pandemi süresince ve pandemi sonrasında bilgi işlemsel düşünmeyi ve azmi nasıl etkilediğini belirlemektir. Çalışmada yarı deneysel desenlerden ön test-son test kontrol gruplu yöntem kullanılmıştır. Örneklem, Türkiye'deki bir devlet üniversitesinin Eğitim Fakültesi'nde öğrenim gören 104 öğretmen adayıdır. Araştırma sonucunda blok tabanlı kodlama eğitiminin, pandemi öncesi ve pandemi süreci gruplarında bilgi işlemsel düşünme ön test ve son test puanları arasında anlamlı bir farka neden olduğu görülmektedir. Söz konusu fark orta düzeyde bir etki büyüklüğüne sahiptir. Pandemi sonrası grubun ön test ve son test puanları arasında anlamlı bir fark bulunmamıştır. Gruplar arası fark incelendiğinde, pandemi öncesi ve pandemi sırasındaki grupların bilgi işlemsel düşünme becerilerinde pandemi sonrası gruba göre anlamlı derecede daha yüksek medyan değerlerine sahip olduğu görülmüştür. Bu sonuçlara göre pandeminin olumsuz etkilerinin pandemi sonrası grupta görüldüğü söylenebilir. Azim ölçeği sonuçları, ilginin tutarlılığı boyutu bağlamında uzaktan eğitimde bilişsel olmayan faktörlerin önemini vurgulamaktadır. Ayrıca azim ve bilgi işlemsel düşünme becerileri arasında anlamlı ve pozitif bir ilişkiyi işaret etmektedir.

Anahtar Kelimeler: Scratch, Bilgi işlemsel düşünme, Azim, Pandemi

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1. Introduction

Advances in science and technology change the type, size and characteristics of the problems people face. Therefore, new methods and skills of problem solving are needed to solve contemporary challenges. According to World Economic Forum's Future of Jobs Report (2020), abilities such as critical thinking and analysis, problem-solving, active learning, resilience, stress tolerance, and flexibility will become increasingly valuable to employers in the future. The same survey suggests that the vocations that will be in higher demand in the future include those associated with information and communication technologies (ICT), such as software and application developer, robotics engineer, and artificial intelligence and machine learning specialist. Further, jobs altered by ICT, such as process automation specialist, digital transformation specialist, and digital marketing and strategy specialist, may also become more important. Considering this impending change, it is inevitable that transformation will also occur in the education systems tasked with fostering the employees of the future. Training in ICT, cognitive, and non-cognitive skills, all of which will play a significant role in future industry, is at the heart of such a transition.

Programming is the fundamental basic component of all digital solutions, software, and systems that we use. Thus, to comprehensively understand the digital world, fundamental knowledge of programming is needed. Programming represents a means of innovating, problem-solving, and applying ideas in the digital world (Nouri et al., 2020), and relates to a variety of thinking and knowledge areas (Durak and Guyer, 2019). Programing is also valued for its relationship with computational thinking (CT) which is emphasized by many researchers. CT was introduced by Papert (1980) and popularized by Wing (2006). CT is using an approach to solving problems, developing systems and understanding human behaviour that draws on concepts essential to computing (Wing, 2006). CT is an essential skill for all individuals, not just computer scientists (Wing, 2008). In addition to coding and CT, non-cognitive abilities have a significant influence on one's problem-solving skills. Zhao et all (2021) states that grit, self-efficacy of group learning and patterns of adaptive learning are important factors in programming education of different groups of learners. In addition, the Coronavirus Disease 2019 (COVID-19) Pandemic, has altered the learning-teaching processes and psychological states of individuals. Although the rapid deployment of e-learning systems during the pandemic helped prevent disruption to education systems, it remains necessary to examine variations in the effectiveness of learning and teaching during the pandemic when compared to the pre- and post-pandemic periods.

2. Literature Review

2.1. Computational Thinking

Wing (2006) is credited with popularizing the concept of CT; however, signs of its development can be traced to as early as the 1950s (Denning, 2017). One of the most significant pillars in the creation of the CT concept was Papert's (1980) book. In addition, the book particularly focused on children and the nature of thinking. Thus, it can be asserted that CT has quite an extensive theoretical foundation. According to Wing (2006), CT includes problem-solving, system-designing, and human-behavior-understanding processes that make use of fundamental computer science concepts. Furthermore, Aho (2012) defines CT as mental processes that entail the application of computational stages to generate problem-solving procedures.

The International Society for Technology in Education (ISTE) and the Computer Science Teachers Association (CSTA) are two key bodies to have investigated CT in depth. According to these bodies, CT defined as a problem-solving process that includes the following actions:

- Formulating problems in such a way that a computer and other tools can be used to
- Systematically organizing and evaluating data in a rational manner.
- Describing data using abstractions.
- Automating solutions.
- Describing data using abstractions.
- Generalizing the technique of problem-solving and applying it to a wide range of problems.
- Additionally, the aforementioned actions should be supported by particular attitudes:
- Confidence in the face of adversity.
- Persistence in resolving challenging issues.
- Tolerance of ambiguity.
- Capability to address open-ended challenges and collaborate with others to attain a common objective or solution.

The ISTE's and CSTA's definitions of CT indicate that cognitive skills alone are insufficient for problem-solving; particular attitudes that assist cognitive abilities play a vital role in the learning process. Additionally, the problem-solving mental processes applied in CT may be applicable to many other subjects (Barr and Stephenson, 2011; Ching et al., 2017; Hsu and Baldwin, 2018). According to Barr and Stephenson (2011), this is because numerous specialties require problem-solving, logical, or algorithmic thinking. Consequently, Barr and Stephenson believe that the community of computer science educators may play an important role in the future widespread development of algorithmic problem-solving practices and inter-disciplinary CT applications. In addition, Mishra and Yadav (2013) state that, with CT, it is possible to transcend typical human-computer interactions, while Voogt et al. (2015) believe that, with CT, not only do students become technology consumers, but also experience an boost in their creativity. Ching et al. (2018) recommend using a graphical programming interface rather than the syntax of programming languages to enable students to focus on computing concepts. As underlined by Voogt et al. (2015), this proposal is significant because it can help create familiarity with the fundamental concepts of CT among teachers of subjects other than computer science. Another key point highlighted by Voogt et al. (2015) is that real-world scenarios assist the comprehension of the fundamental concepts of CT: while teaching algorithms, teachers should start with examples from daily life such as the steps involved in brushing one's teeth or the steps of an experiment (Yadav et al., 2017).

2.2. Grit

When establishing the elements that explain success, researchers tend to focus on, in addition to intelligence quotient and other cognitive criteria, non-cognitive qualities such as perseverance, locus of control, conscientiousness, and self-control (Nichols, 2017). Duckworth and Yeager (2015) assert that non-cognitive skills support goal-directed effort, good social connections, and decision-making. In this context, the present research considers the influence of the variable grit, which has been a focus of numerous studies. Duckworth et al. (2007) define grit as perseverance and passion for long-term goals. To demonstrate grit, one must work diligently at difficult activities, sustaining his/her level of effort and interest regardless of setbacks. The achievement-oriented parts of conscientiousness and grit overlap; however, grit emphasizes long-term resilience: a gritty person not only completes the work at hand, but also pursues a certain objective over the course of several years. Persons with a need for achievement continue to work regardless of the difficulty of their goals, whereas individuals with grit prioritize long-term goals and do not abandon them if they do not receive favorable feedback (Duckworth et al., 2007).

According to Bowman et al. (2015), during one’s college years’ grit can influence a variety of academic and non-academic outcomes, with the perseverance of effort (PE) component of grit being a more accurate predictor of the effect in question than the consistency of interest (CI) dimension. Similarly, Weisskirch (2018) suggested that PE is a component that favorably influences one’s grade point average at universities. Further, according to Hwang et al. (2018), who considered students of the Open University, perseverance is a significant predictor of academic adjustment and degree of accomplishment while, according to Wolters and Hussain (2014), PE is a significant predictor of all aspects of self-regulated learning.

Importantly, the PE dimension has been prominently noted in studies that have observed positive results regarding the determination variable. This circumstance requires consideration of the criticisms regarding the grit variable. According to Crede (2018), grit is largely a repackaging of conscientiousness, while, according to Crede et al. (2017), grit, consisting of PE and CI dimensions, has not been confirmed to be a high-level construct. Another criticism is brought by Fosnacht et al. (2019), who conducted confirmatory factor analysis of the Short Grit Scale using data from the 2016 National Survey of Student Engagement. According to the results of the analysis, acceptable fit values were reached for the Short Grit Scale after an item from the PE dimension was excluded from the analysis; however, they do not recommend its use for important decisions due to the lack of good fit indices. Nevertheless, they state that its use in educational research is acceptable.

The Covid-19 pandemic has deeply affected the whole world and emergency distance education practices have been put into use in order to continue education during the pandemic. However, it should be evaluated how the education and instruction carried out in such an extraordinary situation affects the cognitive and non-cognitive skills of pre-service teachers. In this context, the aim of the study was to determine how block-based programming affected computational thinking and grit at the beginning, during and after the pandemic. In line with this purpose, the following questions were analyzed.

RQ1: Is there a significant difference in pretest-posttest scores for CT and grit across the three different learning environments?

RQ2: Do the three different learning environments have a significant effect on students' CT skills?

RQ3: Do the three different learning environments have a significant effect on students' grit?

RQ4: Is there a significant relationship between CT and grit?

3. Methodology

The 3.1. Research Design

In the present research, a pretest-posttest quasi-experimental design was used to determine the effect of computer programming on individuals' CT and grit levels. The research was conducted at a state university in Türkiye. The research commenced in 2020, when distance education became prevalent as a result of the COVID-19 Pandemic, and was completed in 2022, when in-person education had largely returned. In the spring term of 2019–2020, the first six weeks of the courses were taught face-to-face, and the remaining nine weeks were remote; for the spring term of 2020–2021, distance education alone was used; while for the spring term of 2021–2022 face-to-face education returned.

3.2. Participants

The participants were mathematics teacher candidates studying at a Turkish state university's faculty of education. The research sample consisted of prospective mathematics teachers because they are the only teacher training program to include the Algorithm and Introduction to Programming course in the curriculum. Therefore, the study's findings will be meaningful for teacher education. The research was conducted among students of the Algorithm and Introduction to Programming course, of whom a total of 104 participated in this study.

Of the participants, 44 were examined during their engagement in blended learning, 37 were examined during their engagement in distance education, and 23 were examined during their engagement in face-to-face learning. The gender distribution was 79 women to 23 men. The age range of the groups was 19–25 years.

3.3. Data Collection and Analysis

The CT scale developed by Korkmaz et al. (2017) and the Short Grit Scale developed by Duckworth and Quinn (2009) and adapted into Turkish by Sarıçam et al. (2016) were used as data-collection tools for this research. The Cronbach's alpha coefficient for the Short Grit scale was determined to be .83 for the overall scale, .80 for the sub-dimension of consistency of interest, and .71 for the sub-dimension of perseverance of effort. The test-retest reliability coefficient for the overall scale was 0.69. The item-total correlations were ranged from .33 to .65. The Cronbach Alpha reliability coefficient for the CT scale is 0.822. However, it is seen that the split-half correlations for the components range from 0.406 to 0.713. The Spearman-Brown values range from 0.578 to 0.832, the Guttmann Split-Half values range from 0.578 to 0.832. The CT scale comprises the sub-dimensions of creativity, algorithmic thinking, cooperation, critical thinking, and problem-solving, while the Short Grit Scale comprises the consistency of interest (CI) and perseverance of effort (PE) dimensions.

In the analysis of the data, in accordance with the recommendations of Crede (2018) and Steinmayr et al. (2018), the sub-dimensions separately rather than merely collecting the total score for the PE scale, in addition, due to the lack of normal distribution in the data, as indicated by the Kolmogorov-Smirnov normality test ($p<.05$), nonparametric tests were chosen for data analysis.

3.4. Procedure

For the first group (blended group), which was examined during the 2019–2020 spring term, the first six weeks involved face-to-face learning, and the remaining nine weeks were conducted through distance education (Google Meet). The second group (distance group), which was examined during the 2020–2021 spring semester again used Google Meet for learning, with the class being entirely distance-based. The final group (face-to-face group) received face-to-face learning throughout the 2021–2022 spring semester. The block-based programming tool Scratch was used within the two-hour lessons of the Algorithm and Introduction to Programming course. The CT and short grit scales have administered at the beginning and end of each term. The main topics of the course comprised algorithms and flowcharts, variables, decision structures, and loops. In detail, 2 weeks for What is an algorithm? Exercises on algorithmic thinking, 2 weeks working on daily life problems with pseudo code and flowcharts were instructed. After the algorithmic thinking phase, the coding started with Scratch. At this stage 1 week for Introduction to block based programming with Scratch such as Code blocks, sprite, backdrop, costumes and sounds, 1 week for event and motion, 2 weeks for sensing, decision structures and operators, 3 weeks for loops, looks and sound were instructed. Also problem solving exercises were done with mentioned code blocks.

At the beginning of the course, theoretical information such as what an algorithm is and what flow diagrams do was given using the direct instruction method. Then the block-based coding language and its interface were introduced. In addition, code sections such as events, operators, sensing and control and their tasks are explained. At the end of this process, problem-based learning method was used to first solve simple arithmetic problems and then to solve problems based on a scenario.

4. Findings

The Before determining the differences between the groups, the similarity of the groups was checked using the Kruskal–Wallis Test, and no significant difference was found among the pretest results.

4.1. Is there a significant difference in pretest-posttest scores for CT and grit across the three different learning environments?

In the blended group, the Wilcoxon Signed Ranks Test demonstrated a statistically significant difference ($Z=-3.110$, $p<.05$), with a moderate effect size ($r=0.33$), between the pretest and posttest scores for the CT scale. When the sub-dimensions of the CT scale were evaluated, algorithmic thinking was found to have a substantial effect size ($r=.46$, $Z=-4.292$, $p<.001$), while critical thinking showed a moderate effect size with a significant difference ($r=.34$ $Z=-3.220$, $p<.05$). The PE component of the grit scale showed a significant difference with a moderate effect size ($r=.31$, $Z=-2.871$, $p<.05$).

For the distance-learning group, no significant differences were identified between the pretest and posttest results for the sub-dimensions of the grit scale. The CT scale demonstrated a statistically significant difference with a moderate effect size ($r=0.34$, $Z=-2.960$, $p<.05$). When the sub-dimensions of the CT scale were examined, a significant difference was identified for the dimensions of creativity and algorithmic thinking. The creativity dimension showed a moderate effect size ($r=.40$, $Z=-3.422$, $p<.05$), and the algorithmic thinking dimension showed a statistically significant difference with a moderate effect size ($r=.38$, $Z=-3.278$, $p<.05$).

In the final group, face-to-face, no significant difference was found for the grit scale sub-dimensions or the overall CT scale. A significant difference, with a moderate effect size, was found only for the cooperativity sub-dimension of the CT scale ($Z=-2.220$, $p<.05$).

4.2. Do the three different learning environments have a significant effect on students' CT skills?

The Kruskal–Wallis Test was performed to determine whether there was a significant difference among the blended, distance, and face-to-face groups regarding posttest CT scale scores. Ultimately, a significant difference was found ($\chi2(2)=11.14$, $p<.05$). Consequently, the Mann-Whitney U test was performed to determine between which groups the significant difference was, and the results are presented in Table 1.

Table 1.

Mann-Whitney U test results regarding intergroup CT posttest scores

Group	n	Mean Rank	Sum of Ranks	U	p
Blended	44	37.86	1666.00	336.000	.038
Face-to-face	23	26.61	612.00		*r=.27*
Distance	37	36.05	1334.00	220.000	.002
Face-to-face	23	21.57	496.00		*r=.40*
Blended	44	36.94	1625.50	635.500	.090
Distance	37	45.82	1695.50		

As shown in Table 1, there were significant differences in favor of the pre-pandemic (blended) and during-pandemic (distance) groups. The effect size of the significant difference was higher for the distance group than the blended group. There was no significant difference in CT skills between the pre-pandemic and during-pandemic groups.

For the CT scale sub-dimensions, the Kruskal–Wallis test revealed statistically significant differences between creativity ($\chi2(2)=12.35$, $p<.05$), algorithmic thinking ($\chi2(2)=11.81$, $p<.05$), and problem-solving ($\chi2(2)=6.33$, $p<.05$). The Mann-Whitney U test was then used to evaluate, between the blended and distance groups, the direction of the significant differences in creativity, algorithmic thinking, and problem-solving, and the results are presented in Tables 2, 3, and 4.

Table 2 shows significant differences in the creativity and algorithmic thinking dimensions, favoring the distance group. In the creativity dimension, the median value of the blended group was 34.00 and the median value of the distance group was 36.00. In the algorithmic thinking dimension, the median value of the blended group was 24.50 and the median value of the distance group was 27.00.

Table 2.

Mann-Whitney U test results comparing the blended and distance groups in terms of CT posttest scores.

Factor	Group	n	Mean Rank	Sum of Ranks	U	p
Creativity	Blended	44	36.05	1586.00	596.000	.038
	Distance	37	46.89	1735.00		*r=.23*
Algorithmic Thinking	Blended	44	36.26	1595.00	605.500	.047
	Distance	37	46.64	1725.50		*r=.22*

Table 3 presents the results of an analysis in which the blended and face-to-face groups were compared; this shows that the blended learning group achieved a better median, with a significant difference, in the creativity and algorithmic-thinking dimensions, with a moderate effect size. In the creativity dimension, the median value of the blended group was 34.00 and the median value of the face to face group was 32.00. In the algorithmic thinking dimension, the median value of the blended group was 24.50 and the median value of the face to face group was 23.00.

Table 3.

Mann-Whitney U test results comparing the blended and face-to-face groups in terms of CT posttest scores.

Factor	Group	n	Mean Rank	Sum of Ranks	U	p
Creativity	Blended	44	37.97	1670.50	331.500	.020
	Face to-face	23	26.41	607.50		*r=.28*
Algorithmic Thinking	Blended	44	37.77	1662.00	340.000	.028
	Face-to-face	23	26.78	616.00		*r=.27*

Results for the analysis of the distance and face-to-face groups are shown in Table 4. Significant differences, with moderate effect sizes, were observed between these two groups in regard to the dimensions of creativity, algorithmic thinking, and problem-solving, favoring the distance group.

Table 4.

Mann-Whitney U test results comparing the distance and face-to-face groups in terms of CT posttest scores.

Factor	Group	n	Mean Rank	Sum of Ranks	U	p
Creativity	Distance	37	36.04	1333.50	220.500	.002
	Face-to-face	23	21.59	496.50		*r=.40*
Algorithmic Thinking	Distance	37	36.04	1333.50	220.500	.002
	Face-to-face	23	21.59	496.500		*r=.40*
Problem Solving	Distance	37	34.78	1287.00	267.000	.015
	Face-to-face	23	23.61	543.000		*r=.31*

Comparing the different groups in terms of the sub-dimensions of the CT scale revealed that the distance group had the highest median scores for creativity, algorithmic thinking and problem solving (Md=36.00, Md=27.00, Md=25.00) followed by the blended group (Md=34.00, Md=24.50, Md=24.00) and the face-to-face group (Md=32.00, Md=23.00, Md=22.00), respectively.

4.3. Do the three different learning environments have a significant effect on students' grit?

The Kruskal–Wallis Test was administered to assess whether, for the blended, distance, and face-to-face groups, respectively, there was a statistically significant difference between the pretest and posttest scores for the grit scale. Consequently, a statistically significant difference was found between the CI ($\chi2(2)=6.67$, $p<.05$) and the PE sub-dimensions ($\chi2(2)=7.33$, $p<.05$).

The Mann-Whitney U test was performed to determine which groups featured statistically significant differences for the CI and PE dimensions; the findings are presented in Table 5. In the analysis of the sub-dimensions of the grit scale, the distance group obtained the highest median score (Md=13.00) for the CI sub-dimension, followed by the blended group (Md=12.00) and the face-to-face group (Md=11.00), respectively. The blended group ranked first for the PE dimension (Md=16.00), followed by the distance group (Md=15.00) and the face-to-face group (Md=13.00), respectively.

Table 5.

Mann-Whitney U test results regarding intergroup posttest scores for grit.

Factor	Group	n	Mean Rank	Sum of Ranks	U	p
CI	Blended	44	36.23	1594.00	604.000	.045
	Distance	37	46.68	1727.00		*r=.22*
PE	Blended	44	38,86	1710.00	292.000	.004
	Face-to-face	23	24,70	568.00		*r=.35*
CI	Distance	37	34.59	1280.00	274.000	.021
	Face-to-face	23	23.91	550.00		*r=.43*

4.4. Is there a significant relationship between CT and grit?

According to Table 6, with the exception of the cooperativity dimension all sub-dimensions of the CT scale are related to the sub-dimensions of the grit scale. No significant correlation was discovered between CI and creativity. Additionally, all significant correlations were positive, and the covariance level for the critical-thinking dimension reached a maximum of 37%. Further, PE showed greater values for common variance than CI.

Table 6.

Spearman correlation coefficient between CT and grit dimensions.

	Consistency of interest	Perseverance of effort
Creativity	.12	.47**
Algorithmic thinking	.21*	.44**
Cooperativity	.17	.11
Critical thinking	.31**	.61**
Problem-solving	.24*	.30**

** p<.001 (two-tailed)

* p<.05 (two-tailed)

5. Discussion

In this research, differences between pre-service teachers' CT skills and grit scores before, during, and after the COVID-19 Pandemic, and the relationship between these two variables, were examined. The experiment process was conducted by introducing Scratch, a block-based programming tool, to a course titled Algorithm and Introduction to Programming and observing the changes in the participants CT skills and grit under different learning environments. Blended courses were held in the spring semester of 2019–2020, distance courses were held during the spring semester of 2020–2021, and face-to-face courses were held during 2021–2022.

According to our analysis for our RQ1, there was a significant difference, with a moderate effect size, between the pretest and posttest CT scores of the blended and distance groups. In addition, there were differences in the sub-dimensions of algorithmic thinking and critical thinking in the blended group, and in the dimensions of algorithmic thinking and creativity in the distance group. Moreover, the blended group showed a significant difference regarding the PE dimension of the grit scale; however, this difference was not seen in the distance group or the face-to-face group. This is in line with the research results of Kerres and Buchner (2022) and Jerebic and Urh (2023). According to Kerres and Buchner (2022), when many universities reopened after the pandemic, returning to normal was not as easy as expected due to the reluctance of university students. As the reason for this reluctance, Jereb, Jerebic and Urh (2023) emphasize the decrease in motivation of higher education students and the difficulties experienced in focusing on learning after the pandemic. Similar results are also evident from the analysis results between groups. There were significant differences in favor of the pre-pandemic (blended) and during-pandemic (distance) groups. Examining the sub-dimensions of the CT scale revealed significant differences in the dimensions of algorithmic thinking, creativity, and problem-solving. In the algorithmic thinking and creativity dimensions, the distance group achieved much higher median values than the other two groups. Compared to the face-to-face group, the blended group similarly demonstrated significant and greater values. Further, comparing the distance group to the face-to-face group on the problem-solving dimension revealed a significant difference in favor of the distance group.

When considering the research results regarding CT in detail, a notable outcome is that, while there were significant differences between the pre-pandemic and during-pandemic groups, there were no such differences for the post-pandemic group. These findings differ from those of previous studies involving prospective teachers. For example, Gabriele et al. (2019) reported that, at the conclusion of a Scratch-based programming course, pre-service teachers in Italy had obtained intermediate–high-level ICT skills. Further, İlic (2021) observed significant differences in the CT sub-dimensions of creativity, algorithmic thinking, and critical thinking at the end of a 13-week study with preservice teachers. Lazarinis et al. (2018) similarly reported an increase in ICT skills among elementary and secondary school teachers after completion of a blended Scratch course. Meanwhile, Marcelino et al. (2018) demonstrated that, as a result of the online Scratch training they designed for classroom teachers, it is possible for teachers to learn CT, Scratch programming, and create meaningful products for classroom applications using this technology. The fact that these studies were conducted before the COVID-19 Pandemic can be considered the most important difference between these and the present research. From this perspective, it is clear that the effects of the pandemic on education must be further examined.

According to the Education in a Pandemic report (2021) by the United States Department of Education, the COVID-19 Pandemic significantly impacted academic advancement and exacerbated existing inequities. In addition, there are indications that some pupils fell further behind in fundamental areas such as mathematics and reading when compared to the pre-pandemic period. Similarly, Betthauser, Bach-Mortensen, and Engzell (2023) state that as a result of meta-analysis studies involving 42 studies from fifteen different countries, there are higher learning gaps in mathematics and in middle-income countries than in high-income countries. Cao et al. (2020) presented further evidence of this impact, reporting that 24.9% of university students have been affected by anxiety due to the COVID-19 Pandemic. Also Cao et al. (2020) suggested that, for university students, place of residence, parental financial status, whether they (the students) live with their parents, and whether a family or acquaintance is infected with COVID-19 are factors contributing to this effect. In addition, academic delays and the impact of the pandemic on daily life have been found to be moderately and positively connected with students' anxiety levels. According to Fong (2022), the COVID-19 Pandemic has had a significant effect on students' learning, well-being, and academic motivation. It is believed that the abrupt and unanticipated move to distance education contributed to reducing students' self-esteem, increasing their sense of isolation, and altering their interests, attitudes, and actions. Moreover, Corpus et al. (2022) reported that the identified and intrinsic motives of college students diminished significantly during the pandemic when compared to the pre-pandemic period. Two studies have indicated that the aforementioned negative impacts have persisted into the post-pandemic period. According to Caron et al. (2022), the pandemic's detrimental impacts on college students' focus, flow, motivation, and perception of time are ongoing. Further, Hu et al. (2022) conducted a study on 151 university students between January 17 and February 25, 2022, finding that 95.7% of the sample had moderate or severe mood disorder; in addition, when asked how much the pandemic had impaired their learning quality, participants reported a value of 7.6 out of 10.

Bozkurt et al. (2022), who researched the influence of the pandemic on education, examined 1,150 studies in terms of thematic patterns in the titles, abstracts, and keywords, as well as citation trends in the sampled publications' citations. The thematic patterns identified for title, abstract, and keywords were: (1) the great reset, (2) the shifting educational landscape and emerging educational roles, (3) digital pedagogy, (4) emergency remote education, (5) pedagogy of care, (6) social equity, equality, and (7) the future of education. Meanwhile, as a result of the citation analysis, the following thematic clusters were identified: (1) educational response, emergency remote education affordances, and continuity of education, and (2) psychological impact of COVID-19. The first thematic cluster is consistent with the fourth theme, emergency remote education, and the second thematic cluster, psychological impact of COVID-19, is compatible with the fifth theme, pedagogy of care. This emphasizes that education systems should be maintained continuously under all circumstances through the use of remote approaches if necessary, and that, to implement a caring pedagogy, the evaluation of students' psychological and emotional states should be the top priority. Notwithstanding their observation of persistent negative impacts such as a loss in motivation, mood disorders, difficulties with focusing and flow, feelings of isolation, and decline in self-confidence, studies conducted during the pandemic period have revealed similar results to the present study.

Despite the effects of the COVID-19 Pandemic, it can be stated that programming courses featuring block-based coding tools improve CT skills. However, despite the reopening of schools, it is believed that pupils' sense of uncertainty about the future can cause in learning deficits. The findings for the Short Grit Scale should be reviewed in order to more closely examine this potentiality. For the CI dimension, the order of the groups in terms of median values (highest to lowest) was distance, blended, and face-to-face, respectively, while for the PE dimension, the ranking was blended, distance, and face-to-face, respectively. Also, for the CI dimension the distance group showed significant differences when compared to the blended and face-to-face groups, respectively; for the PE dimension, a significant difference was detected between the blended group and the face-to-face group, with the blended group performing better. These research outcomes are distinct from those of other studies that found PE to potentially be a predictor of academic performance, but CI to not be correlated with achievement (Bowman et al., 2015; Hwang et al., 2018; Shirvan and Alamer, 2022; Wolters and Husain, 2015). In contrast, Neromi et al. (2022) stated, based on their study of the effects of academic self-efficiency, self-esteem, and grit on academic achievement in distance-based higher education, that only CI is a predictor of academic success. This indicates that online education institutions should focus on their students' CI to improve their academic success. In addition, Bono et al. (2020) stated that grit contributes to the subjective well-being of university students and their ability to cope with events such as pandemics.

Our findings relating to RQ4 are consistent with those of Christopoulou et al. (2018). Their systematic review of 29 papers published between 2012 and 2017 revealed weak to moderate relationships between grit and educational factors. They found PE to be a stronger positive predictor of academic performance; the co-variance of approximately 20% in the creative and algorithmic thinking dimensions and 37% in the critical-thinking dimension shows that PE produces remarkable results.

The uncertainty experienced by the groups may have had a significant impact on the research results. As the Short Grit Scale is a measurement tool that can evaluate individuals' level of grit, determination, persistence, and perseverance (Sarıçam et al., 2016), the present findings confirm that the difficulties experienced during the Pandemic continue both in cognitive and affective terms.

6. Conclusion

The results revealed significant and positive outcomes in terms of the development of CT in the blended and distance groups. However, the negative effects of the COVID-19 Pandemic were reflected in the research results for the face-to-face group. Also, the positive change in CT skills as a result of distance education, which allowed learners to feel safe during the pandemic, is evidenced through the differences between the groups. In addition, the results obtained for the Short Grit Scale emphasize the importance of non-cognitive elements in distance education, especially for boosting the CI dimension. The research results also reflect that PE is the primary component to be considered when describing CT skills.

As a result, when the negative effects of the pandemic are neglected, blended, face-to-face or distance block-based coding education can positively affect pre-service teachers' CT skills. Furthermore, it is expected that teacher candidates will be grittier. In the light of these findings, the availability of block-based coding courses for teacher training programs is essential for the development of computationally thinking teachers.

7. References

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