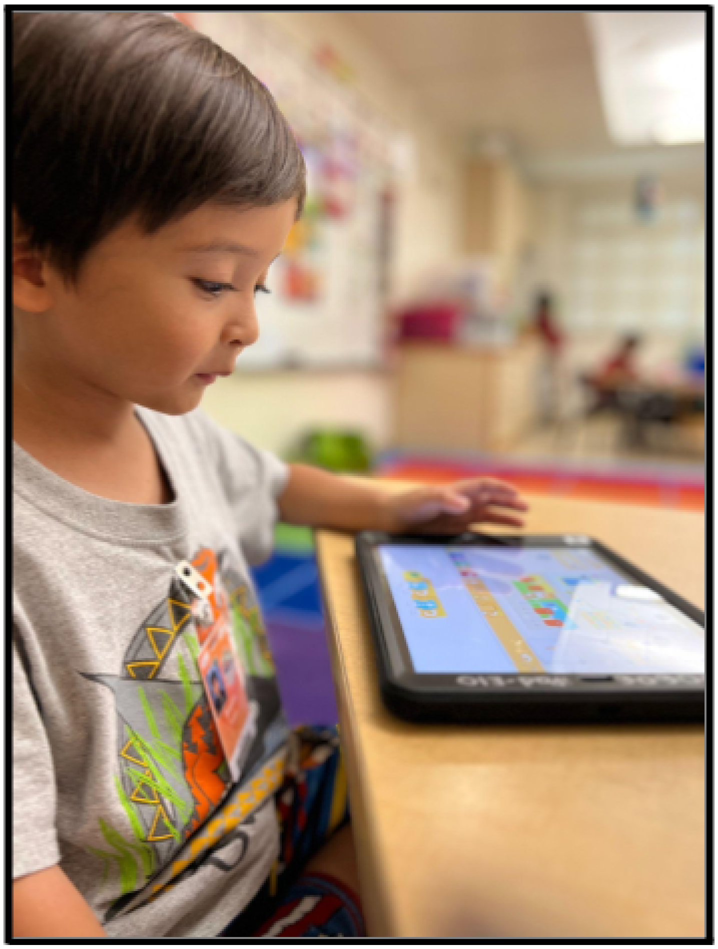
Elementary Student Attitudes and Cognition for Coding

BootUp Evaluation 2023-24



Evaluation conducted by:

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Executive Summary

During the 2023-24 school year, elementary teachers participating in BootUp PD in several school districts across the U.S. were encouraged to administer two surveys to their students at the beginning of the school year and again at the end of the school year. One survey measured students' cognitive ability for coding (i.e., computational thinking or CT) while the other measured their attitudes for coding. Teachers were not compelled but rather volunteered to administer the surveys. This study sought to gauge students' attitudes and cognitive ability for coding before and after their teachers learned to teach elementary coding using the BootUp approach. The overall results revealed the following findings:

1. Younger students (i.e., 3rd graders) tended to show more significant gains on the CT from pre to post. However, most students did not report overall changes in either attitude or computational thinking (CT).

2. There was a weak negative correlation between students' confidence for coding and their change in CT from pre to post. Contrariwise, there was a significant but weak positive correlations between students' utility value (i.e., understanding of the usefulness of coding) and their math self-efficacy (i.e., confidence to do well in math) and their CT scores.

3. There was a weak but positive correlation between students' coding experience and their post-survey interest scores.This suggests that as students engage in coding more, their interest in coding may increase.

4. Younger students tended to show greater interest in coding, with interest decreasing slightly from grade to grade. It would be valuable to see if more experience (as noted in finding #3) would change these same students' interest in coding over time and lead to higher interest in coding for older students.

5. To increase confidence in these results, we need to establish a better system to recruit participating teachers so that we have a large group of students completing both the pre and post test results.

1. Methods

BootUp Districts were encouraged to collect student data at the beginning and ending of the school year using a pre/post model. Data were collected on students' attitudes for coding and their cognitive ability to think computationally. Attitude was measured using the Elementary Student Coding Attitude Survey (ESCAS; Mason & Rich, 2021). Computational Thinking ability was measured using the Computational Thinking test (CTt), developed by Román-González et al. (2016). Both of these measures have been validated with 1000s of elementary-aged students and are commonly used around the globe.

Teachers were instructed to give the pre-tests prior to giving coding instruction. Depending on when their school began engaging with BootUp, this may have been anywhere from August to December, 2023. Post-tests began in March and continued through May, 2024.

2. Results

In this section, we will provide descriptive statistics (e.g., mean, standard deviation, counts, etc) for each measure, individually. In the ensuing section, we look at potential relationships between the measures and between student sub-groups in those measures.

2.1. Data Preparation

We received about 1000 student surveys for each measure. To prepare these for further data analysis, we cleaned the data in several ways. First, we threw out any result that was incomplete or suspect. Often, these results were completed in very short timeframes. We received completed student surveys from a class of 6th, 7th, and 8th graders. Given the focus on elementary education, we excluded these students from this analysis.

Finally, in order to maintain anonymity with students, we asked that they use their student IDs to identify themselves on the pre and post measures. This would allow us to pair baseline answers with final answers. Several students failed to provide any identification, though they provided complete data. In this case, we included their data in the overall analysis. In the "Comparisons" section of this document, we do a paired samples analysis with the students that we were able to reliably identify as the same person in the pre and post measures.

2.2. ESCAS Results

The Elementary Student Coding Attitude Survey measures students' attitudes for coding in six areas: Confidence for coding, Interest in coding, Utility value for coding, Perceptions of coders, Social Value of coding, and Math self-efficacy (which has been shown to correlate with coding attitudes). We provide a brief explanation of each of these attitudes below:

- *Confidence*: Students' self-efficacy for their own coding ability.
- *Interest*: Students' expressed interest in coding and coding-related activities.
- *Utility value*: The usefulness students find in learning to code for several life events and opportunities.
- *Perceptions of coders*: Students expressed bias for attributes common to those who code.
- *Social value*: Students' perceptions of what their peers and parents think of coding.
- *Math self-efficacy*: Students' confidence in their ability to think mathematically.

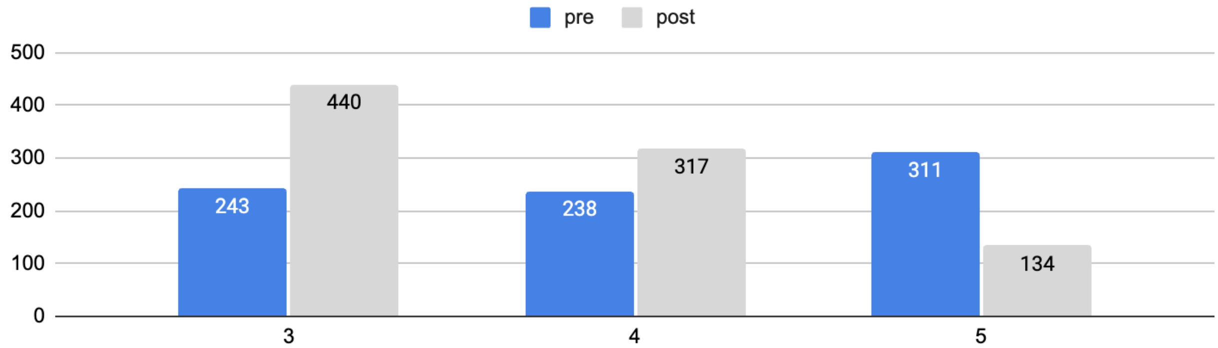
The ESCAS consists of 23 Likert-type items on a 6-point scale, ranging from "strongly disagree" to "strongly agree." Students indicate their level of agreement with each statement. Scores for each of the sub-constructs are then aggregated across questions pertaining to that attitude.

Overall, the students in this year's cohort completed the ESCAS in an average of 11 minutes, 31 seconds. Boys completed the survey in about 10 minutes, 42 seconds, while girls took a bit longer at 12 minutes 10 seconds. Third graders took the longest to complete the survey (15.4 min), with 4th (11.6 min) and 5th graders (9 min), each cutting a few minutes off of the total completion time.

2.2.1. Demographics

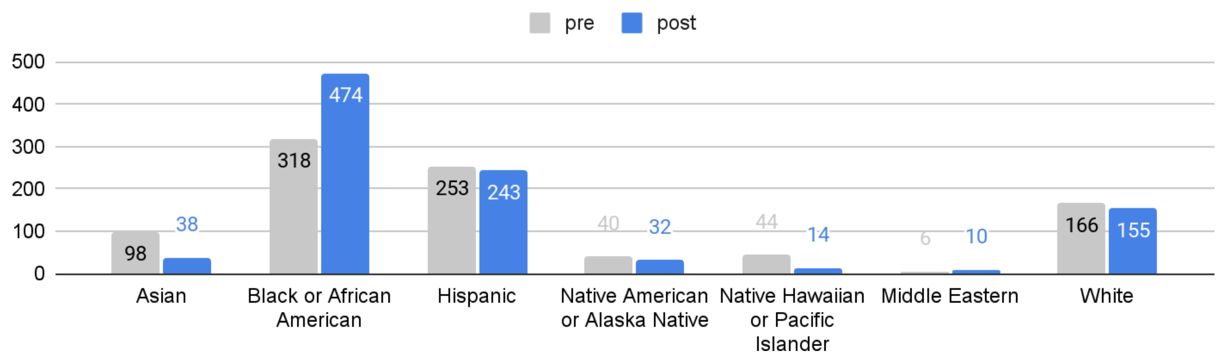
There were 792 usable results from 3rd, 4th, and 5th graders on the pre-survey and 891 on the post-survey, as demonstrated in the following chart).

Figure 1. Elementary Students participating in ESCAS, pre vs. post



The majority of students on both assessments were Black/African American or Hispanic. The third most common race/ethnicity was “white.” Racial and ethnic distribution of results are reflected in the chart below.

Figure 2. Race/Ethnicity pre vs. post



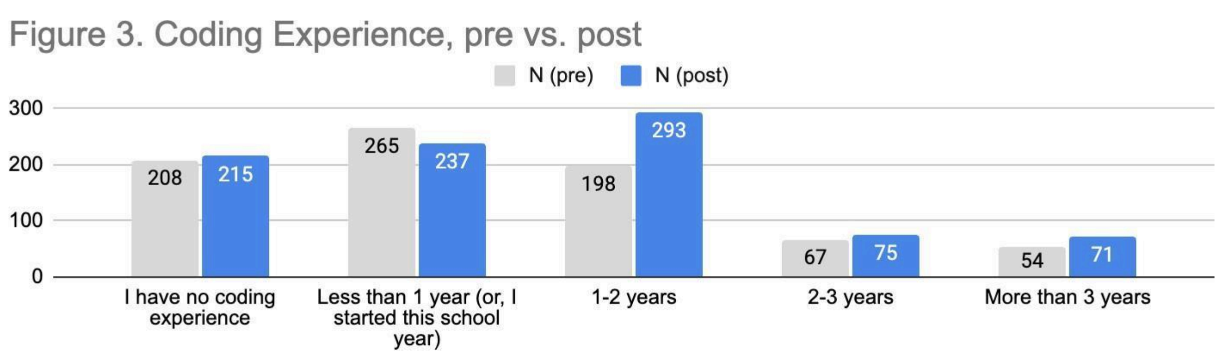
These results came from students representing 12 different school districts in the pre-survey, though students from only 6 districts complete the post survey (see Table 1).

Table 1. *Student ESCAS results by district*

DISTRICT		PRE	POST
District A		79	49
District B		20	0
District C		12	17
District D		158	62
District E		132	0
District F		25	0
District G		69	96
District H		77	0
District I		32	316
District J		133	351
District H		10	0
District I		45	0
	TOTALS	**792**	**891**

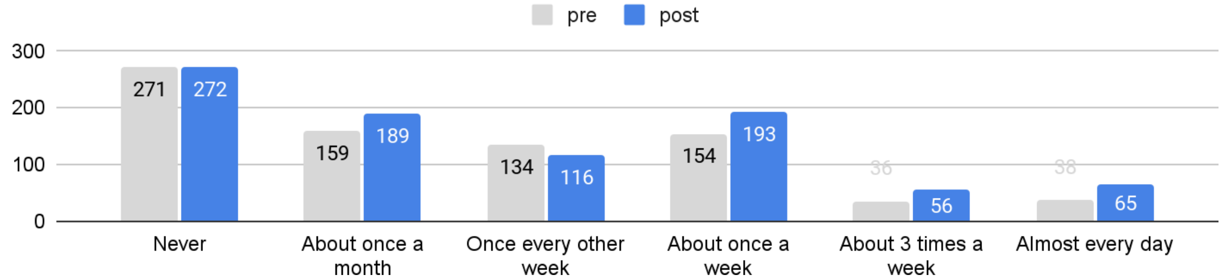
2.2.2. Coding Experience

We asked students how much experience they had coding as well as how often they coded (see Figures 4 & 5). As expected, students did not have much experience coding, with the majority indicating they had less than a school year or no coding experience. However, a fair portion of students indicated that they had at least 1-2 years or more of coding experience.



We saw similar patterns when asking students how frequently they coded, with the largest proportion indicating they never coded or coded once a month. However, there was a sizable portion that indicated that they coded weekly or more often (about 40%).

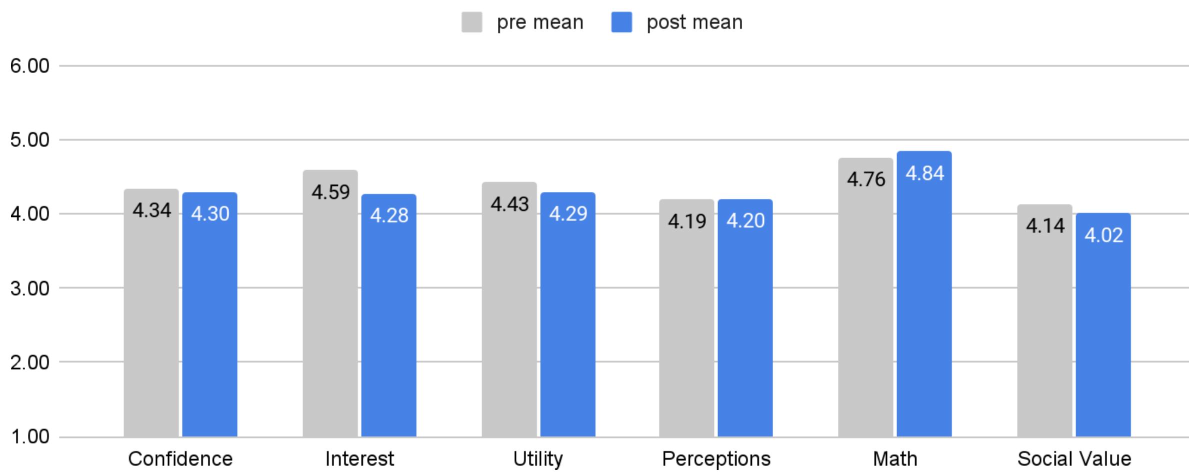
Figure 4. Coding Frequency, pre vs. post



2.2.3. Attitudes

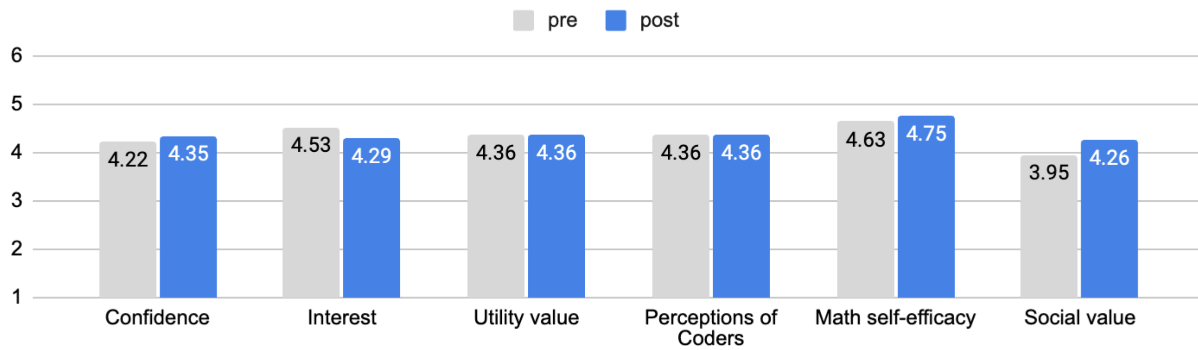
Generally speaking, students' attitudes were slightly higher on the pre survey than on the post survey. In both assessments, most results hovered around the “somewhat agree” range, both pre and post (see Figure 3). Students’ attitudes for math were the highest of all the categories, coming closer to “agree” than “somewhat agree.” They were also the only category that showed an increase in scores.

Figure 5. Student Attitudes for Coding/CT pre vs. post



To determine if any of the observed differences were statistically significant, we ran a paired-samples t-test. This required identifying students who completed both the pre and post surveys. A paired samples analysis is important because it’s possible that those who completed only the pre test or only the post test would have had different results. There were 193 students for whom we were able to identify both pre and post surveys. It’s possible that there were more, but these 193 were those for whom we were able to identify the same student_id, school, gender, and grade being used for both the pre and post surveys. Figure 6 shows the pre and post attitude scores for students who completed both surveys.

Figure 6. Attitudes for Coding pre vs. post (paired samples)



Note that attitudes were much closer to each other in this comparison, with social value increasing more from pre to post. Math self-efficacy was also slightly lower, with a smaller overall difference. The t-test results for the changes in attitudes from pre to post are reported in Table 2:

Table 2. *Paired samples t-test comparison between pre and post attitudes*

Attitude	Mean difference (post-pre)	SD (pre)	SD (post)	t statistic	p-value
Confidence	0.13	0.995	0.974	-1.62	.108
Interest	-0.23	1.10	1.26	2.41	.017*
Utility Value	-0.01	0.978	0.975	-0.08	0.938
Perceptions of Coders	0.00	0.804	0.916	-0.03	.975
Math self-efficacy	0.17	1.349	1.317	-1.38	.169
Social Influence	0.26	1.165	1.052	-3.08	.002*

The paired samples comparison of means shows that students experienced a change in two attitudes: interest and social influence. Interest went down significantly while social influence increased significantly. Using Cohen's *d* to calculate the effect size helps us to determine the practical effect of these differences. Cohen's *d* for interest was -0.175 while Cohen's *d* for social influence was 0.225. These results suggest that while there were statistically significant changes in interest and social influence, the practical significance of these changes is small.

2.2.4. Mediating Factors

On each survey, we collected a variety of information about students (gender, grade level, experience, and frequency of coding). In this section, we examine how a few of these indicators may have influenced student attitudes for coding.

2.2.4.1. Grade level differences

Table 3 shows the distribution of scores by grade level for the different attitudes.

Table 3. *Student attitudes on the post assessment by grade level*

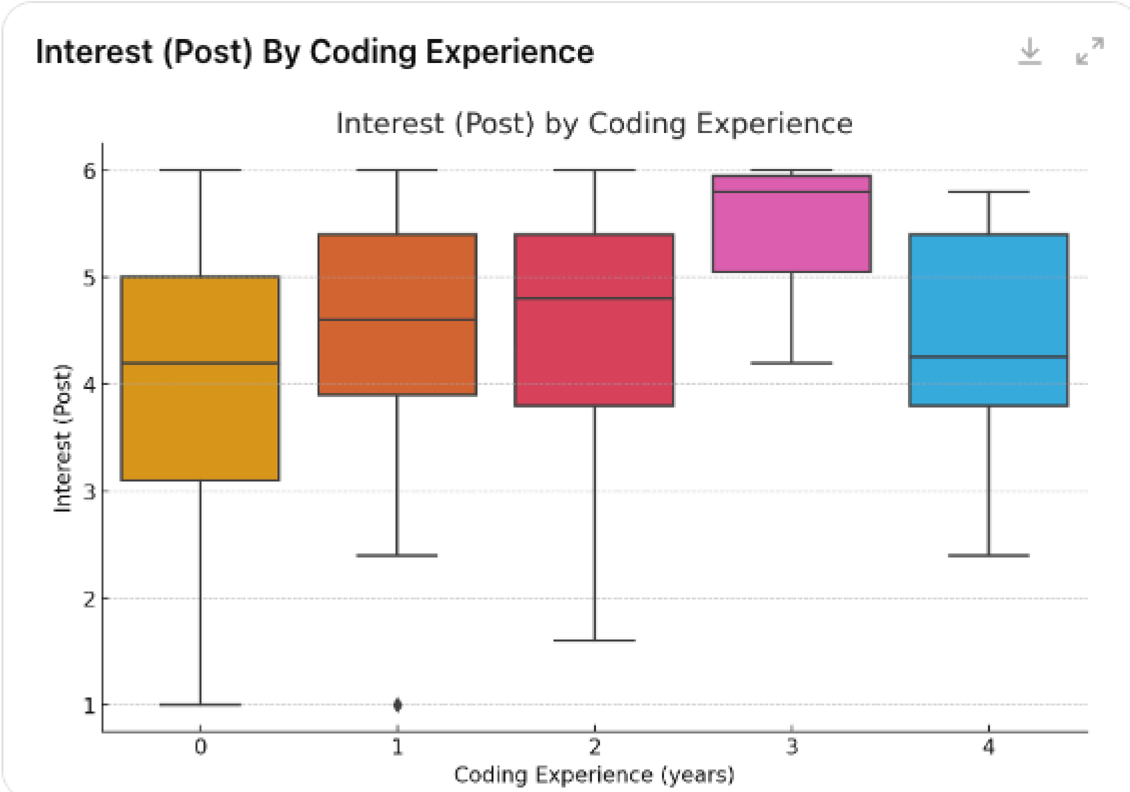
Grade	Confidence	Interest	Utility	Perceptions of Coders	Math self-efficacy	Social Influence
3rd	4.41	4.53	4.40	4.24	4.77	4.31
4th	4.25	4.07	4.16	4.61	5.04	4.22
5th	4.30	4.02	4.47	4.32	4.45	4.17

Visual inspection shows that 3rd graders reported higher scores in four of the attitudes. Interest (I-post): The mean interest score decreases slightly from grade 3 (4.53) to grade 5 (4.02). There is a statistically significant difference in “Interest” attitudes across grade levels with a small effect size ($\eta^2 = 0.030$). The changes in other attitudes across grade levels are not statistically significant, though there are variations in the mean scores. This suggests that as students progress from grade 3 to grade 5, their interest in coding tends to decrease slightly. The effect size indicates that this change is small.

2.2.4.2. The effect of experience

To delve into the interest factor further, we looked at the effect that experience might have on interest (see Figure 7). A box and whiskers plot helps to show the interest, mean, and distribution by years of experience.

Figure 7.



The correlation between coding experience and post-survey Interest scores *r* = .180. The correlation coefficient indicates a positive relationship between coding experience and interest. However, the strength of this relationship is weak. This suggests that as students' experience in coding increases, their interest in coding tends to increase slightly, but the relationship is not strong.

2.3. CTt Results

The Computational Thinking test (CTt) purports to measure young students' ability to solve problems computationally. The test is composed of 7 tetrads of questions. Each tetrad has four questions of increasing difficulty. The items test students' computational concepts, practices, and perspectives, as follows:

- **Computational Concepts**: sequences, loops, events, parallelism, conditionals, operators, and data.
- **Computational Practice**: Experimenting and iterating
- **Computational Perspectives**: Expressing, Connecting, Questioning

A sample time below shows how a CTt item is set up (Román-González, 2016, p. 5).

M. Román-González et al. / Computers in Human Behavior xxx (2016) 1–14

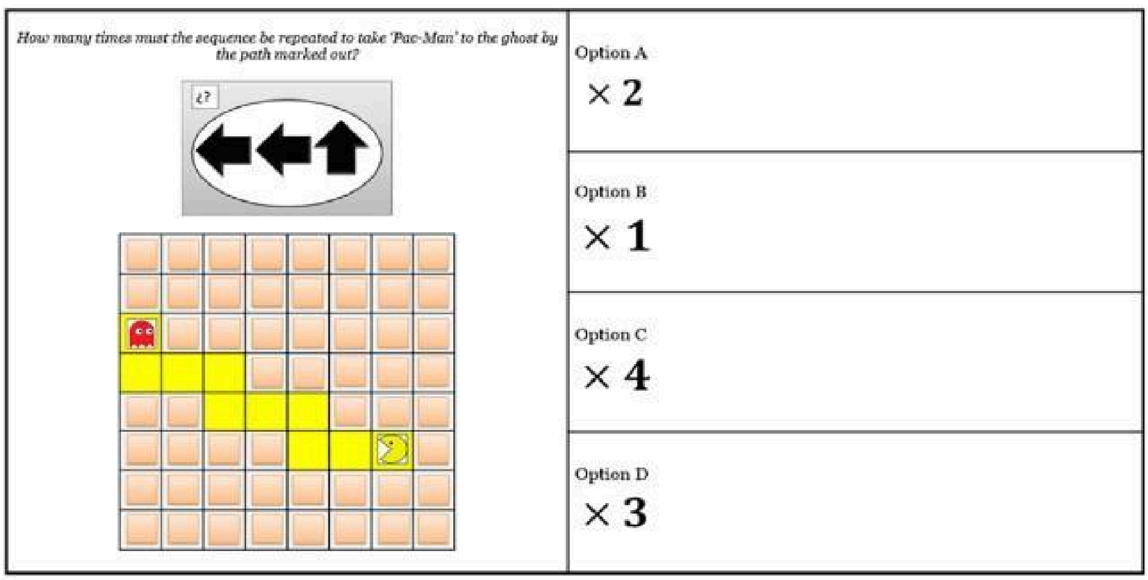
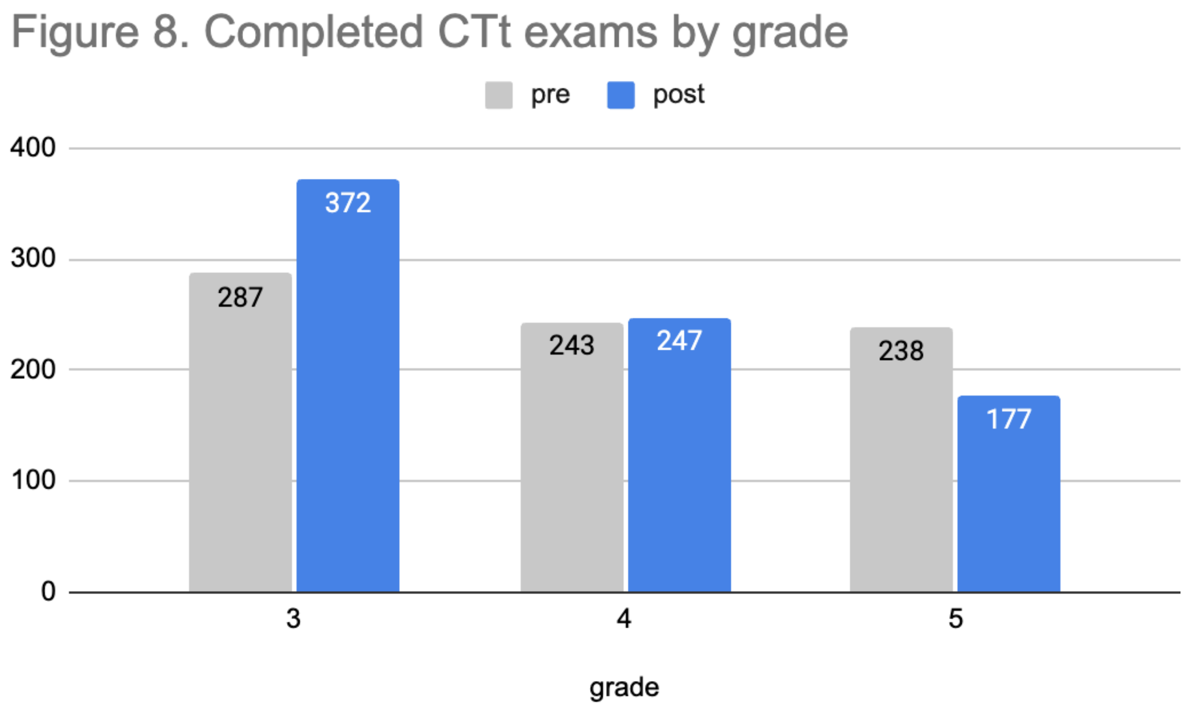


Fig. 1. CTt, item 6: loops–repeat times; 'The Maze'; visual arrows; no-nesting; completion.

2.3.1. Demographics

972 elementary students took the CTt at the beginning of the year, while 953 students took the CTt at the end of the school year. In contrast with the ESCAS, it's reasonable to expect that a student might not complete the test while still attempting to do so in the time that a teacher might give in a single sitting (e.g., 30 minutes). However, several tests seemed to have been completed rather quickly. Consequently, we consulted with Dr. Román-González, the creator of the CTt, as to what the minimum amount of time a student might reasonably spend on the CTt while trying to legitimately complete it. He

recommended that it would be highly unlikely for a student who was trying to do well on the test to complete it in fewer than 10 minutes. Using this counsel, we reduced the number of usable results to 768 and 784 pre and post-tests, respectively. Figure 8 breaks down the remaining tests completed by 3rd, 4th, and 5th grade students.



Students represented a variety of races, as noted in Table 4. Students were able to identify if they identified as belonging to more than one race, which explains why the sum total is greater than the total # of usable exams. The most common races were Black/African American, White, and Hispanic.

Table 4. *Racial breakdown of students who completed the CTt.*

Race	pre	post
Asian	55	46
Black	396	536
Hispanic	356	288
Native_American	34	27
Pacific_Islander	19	17
White	234	137
Middle_Eastern	18	13
Other	187	118

Curiously, it took students longer to complete the post exam than the pre exam. Students completed the CTt pre assessment in 25 minutes, while the post exam took 30 minutes. This appears to be due to 3rd graders taking longer on the post exam, though 4th and 5th graders took about 2 minutes longer on average to complete the post exam than the pre exam.

The average scores of the pre and post CTt are presented in Table 5 below. Scores were a little on the low-end, but still within range of what might be expected from 3rd-5th graders. Curiously, 4th grade students' scores were about on par with 5th graders' scores on the pre assessment but then decreased on the post assessment.

Table 5. *Average Student CTt scores by grade level*

Grade	Mean (pre)	Mean (post)	Standard Deviation (pre)	Standard Deviation (post)
3	8.2	9.3	3.5	3.7
4	10.6	9.0	4.1	4.6
5	10.5	10.8	4.4	5.2

2.3.2. Paired Sample Results

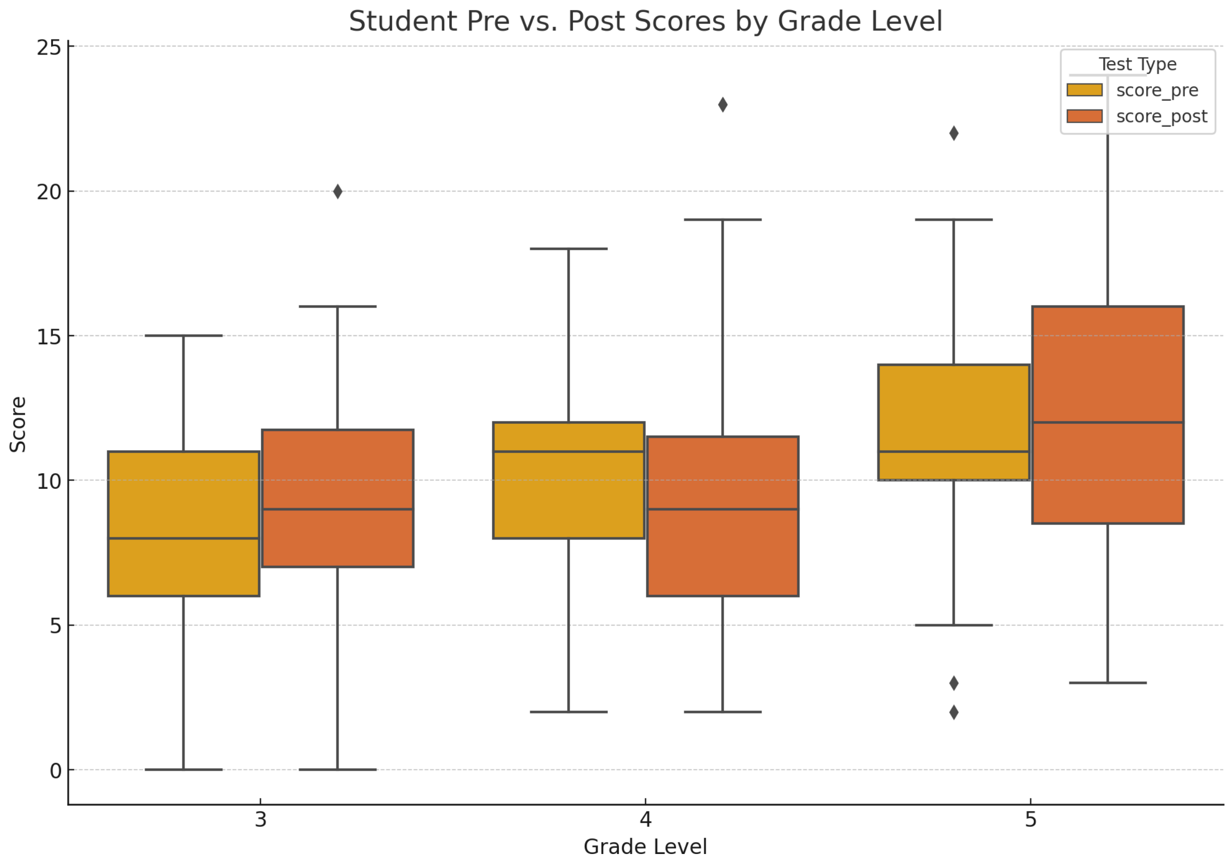
We were able to identify 176 students who: (a) completed both the pre and post, (b) took at least 10 minutes, and (c) were in 3rd-5th grade. To better compare pre and post results, we ran a paired samples t-test using only these 176 students. This painted a different picture (see Table 6). In this sample, the 3rd and 4th graders had lower starting scores, while 5th graders had significantly higher and ending scores. All three grades showed less variance in their initial standard deviations but greater variance in their post score standard deviations.

Table 6. *Average PAIRED student CTt scores by grade level*

Grade	Mean (pre)	Mean (post)	SD (pre)	SD (post)
3	7.8	9.1	3.3	3.8
4	10.0	9.7	3.1	5.2
5	11.6	12.4	3.7	5.2

Figure 9 provides a visual representation of pre vs. post-test scores by grade level. Scores were normally distributed across all grades. Visual inspection shows that scores were generally higher by each grade level. To determine if students grew in their ability to think computationally, we conducted a paired samples t-test, controlling for grade level.

Figure 9.



Results revealed that only 3rd grade students experienced significant growth. While an eyeball test would have suggested that 5th graders also grew significantly, their increased variance in scores likely played a factor.

Table 10. *Paired Samples Comparison of Means*

Grade	N	Test Statistic (*t*)	p-value
3	70	-2.410	.019*
4	43	0.443	.660
5	63	-1.412	.163

Unfortunately, we did not ask students how often they experienced coding activities throughout the school year. Thus, we cannot determine if the change that 3rd graders experienced was due to normal cognitive growth or due to more hands-on time engaged in coding activities. Future surveys should ask students to indicate how often they coded throughout the year. This response could then be used to examine the extent to which participation in coding at school and at home during the year correlates with changes in CT ability.

2.3.2.1. Gender comparisons

When we break down students' scores further, we see that gender may have played a factor. Doing so reveals that the only sub-group that experienced a statistically significant change were the 3rd grade boys (see Table 11), though 5th grade boys came close to the
.05 cutoff for determining statistical significance.

Table 11. *Paired Sample Comparison of Means by Grade and Gender*

grade	gender	t-statistic	p-value	N
3	Boy	-2.311	0.026	40
3	Girl	-1.104	0.279	30
4	Boy	0.479	0.637	21
4	Girl	0.165	0.87	22
5	Boy	-1.992	0.056	31
5	Girl	-0.172	0.865	32

There is a historically well-known difference between boys and girls on CS measures. In fact, the validation of the CTt found about a 1-point difference between boys and girls scores. However, considering the low numbers of students in each group when they're broken down this way and considering that the gender difference only occurred with a single group of boys, one should exercise caution when making any gendered claims. Further research is needed to confirm this finding.

2.3.2.2. Correlations

The CTt has a few additional questions asked of all students. Students answered the question, "how comfortable are you with computers?" They were also asked to predict the score they believe they earned on the CTt. In this section, we examine the extent to which answers to these questions correlate with students' overall scores.

2.3.2.2.1. Predicted Performance

After completing the CTt, students were asked to predict how many questions they believed that they got correct out of 28. This is referred to as a "calibrated judgment of learning" (CJOL). Calibration is tied to students' metacognitive abilities, which are thought to improve overall learning. Some researchers have found that students with more accurate calibrations are more likely to stick with a learning task longer and also to retain what they learn better (Dunlosky & Rawson, 2011). To look at the relationship between students' actual and their predicted scores, we calculated the Pearson correlation coefficient (r). We also looked at statistical significance.

For this comparison, we are not comparing pre and post scores. Consequently, we decided to use the post-test CTt data for the full set of 3rd-5th grade students. Post test results (see Table 12) show a few interesting trends. Negative results for the mean difference between students' CTt score and their CJOL indicates that they overestimated their performance by that many points. Students overestimated their performance regardless of grade or gender. Older students had more accurate calibrated judgments than younger students. This suggests that students get better at judging their performance as they get older.

Table 12. *Students' Calibrated Judgements of Learning on the Post-test*

Grade	Gender	Mean_Score	Mean_CJOL	Mean_Difference	Count	p_value	Correlation
3	Boy	9.929	17.768	-7.839	168	< .000	0.213
3	Girl	9.885	16.166	-6.28	157	< .000	0.158
4	Boy	10.488	19.155	-8.667	84	< .000	0.236
4	Girl	9.806	17.366	-7.559	93	< .000	0.195
5	Boy	13.056	18.169	-5.113	71	< .000	0.406
5	Girl	11.364	16.939	-5.576	66	< .000	0.107

To determine if gender had an effect on scores, we conducted a Kruskal-Wallis test, which yielded the following results:

3rd grade: test statistic (H) = 3.849; p = .050
4th grade: H = 1.415, p = .234
5th grade: H = 0.096, p = .756

These results indicate that there was no effect due to gender for 4th and 5th graders. Third graders showed a marginally significant effect (inasmuch as it was right at the .05 level).

The effect of grade level was significant (H = 9.830, p = .007), indicating that there is a statistically significant effect between students' grade level and their ability to predict their score on the test. The effect size (ε^2) was 0.012, which indicates a small practical effect. Thus, even though students tend to get better at predicting their scores as they get older, it is a small change from grade to grade.

2.3.2.2.2. Comfort with Computers

Students were also asked the extent to which they were comfortable with computers. The purpose of collecting this information is to judge if there is a relationship between students' CTt scores and how good they believe they are with computers. If there is a relationship, teachers could use that info as an indicator to predict who may do more or less well in demonstrating computational thinking.

Table 13. *Correlation between students' scores and their comfort with computers*

Grade	Gender	Mean Score (0-28)	Computer Confidence (0-10)	Count	p_value	Correlation
3	Boy	9.929	7.577	168	0.071	0.14
3	Girl	9.885	7.631	157	0.024*	0.18
4	Boy	10.488	8.214	84	0.828	0.024
4	Girl	9.806	7.441	93	0.177	0.141
5	Boy	13.056	7.648	71	0.124	0.184
5	Girl	11.364	7.273	66	0.298	-0.13

There was only a statistically significant correlation for 3rd grade girls. While positive, the size of the correlation is weak, suggesting that there is some tendency for 3rd grade girls' confidence with computers to correlate with their CT ability, but there are other, unidentified, factors that play a larger role. For other students, we are not able to use their confidence with computers as an indicator of how well they will perform computational thinking tasks.

3. Comparisons Between Attitudes and Cognition

The final analysis we performed is to see what relationship there is, if any, between students' affective perceptions of coding and their cognitive abilities. In order to run this analysis, we needed to utilize the data from students who we could match up on both assessments. We decided to further utilize the data from those who completed both the pre and post assessments.

We conducted a multiple regression analysis to compare students' CTt scores with their ESCAS scores on the pre test and post test, as well as the correlation between their change from pre to post on the CTt. We analyze and interpret each of these individually.

Pre-test Comparison

Table 14. *Relationship between students' attitudes and CTt scores (pre assessment)*

Attitude (pre)	Coefficient	p-value	Effect size (Cohen's f^2)
Confidence	-1.387	.016	.059
Interest	1.622	.002	.097
Utility Value	1.031	.067	.032
Perceptions of Coders	-0.17	.765	.001
Math	0.322	.290	.01
Social Value	-1.019	.035	.044

The multiple regression analysis revealed that two attitudinal measures, *interest* and *utility value*, were significant predictors of pre-test scores, with p-values of 0.002 and 0.029, respectively. The effect sizes for these variables were small to medium (Cohen's f-squared of 0.103 for interest and 0.047 for utility value). The other attitudinal measures did not show significant relationships with pre-test scores, and their effect sizes were small or negligible. Efforts to improve student performance on pre-tests might focus on strengthening students' interest in and utility value for coding.

Post-test Comparison

To determine if the relationship noted holds true across time, we ran another multiple regression on the post data (see Table 15)

Table 15. *Relationship between students' attitudes and CTt scores (post assessment)*

Attitude (pre)	Coefficient	p-value	Effect size (Cohen's f^2)
Confidence	0.739	.446	.006
Interest	0.709	.305	.01
Utility Value	0.659	.373	.008
Perceptions of Coders	-0.979	.185	.017
Math	0.165	.707	.001
Social Value	-0.154	.802	.001

The multiple regression analysis of the post data shows that among the attitudes measured, none of the post-test attitudes have statistically significant relationships with post-test scores. The effect sizes are generally small or negligible, suggesting limited practical impact. Interest had the largest positive coefficient, indicating a small positive but non-significant effect on post-test scores. While not statistically significant, improving attitudes measured by I-post might still be beneficial.

Growth Changes

Finally, we conducted a multiple linear regression analysis to assess the impact of changes in students' attitudes for coding (confidence, interest, utility value, perception of coders, math self-efficacy, and social value) on students' score changes on the Computational Thinking test (CTt). The analysis included all attitude difference scores as predictors and the score change as the dependent variable. The regression coefficients, p-values, and effect sizes (f-squared) were calculated to determine the significance and impact of each attitude.

Cohen's f^2 is an effect size measure used primarily in the context of multiple regression to assess the impact of individual predictors or sets of predictors. It quantifies how much variance in the outcome variable is explained by a predictor (or group of predictors) over and above what is already explained by other predictors in the model. Cohen proposed the following general guidelines for interpreting f^2:

- Small effect size: $f^2 = 0.02$
- Medium effect size: $f^2 = 0.15$
- Large effect size: $f^2 = 0.35$

Table 16. *Relationship between students' changes in attitudes and changes in CTt scores*

Attitude (pre)	Coefficient	p-value	Effect size (Cohen's f^2)
Confidence	-1.400	.001	.134
Interest	0.187	.302	.017
Utility Value	0.392	.032	.045
Perceptions of Coders	0.213	.247	.020
Math	0.481	.022	.050
Social Value	0.244	.149	.028

While the relationships between attitude and CTt scores are interesting, no single attitude demonstrated anything stronger than a small effect, suggesting that attitude for coding is only a weak predictor of students' CT abilities. The results from the multiple regression analysis provide insights into the combined effects of different attitudes on score changes:

1. Confidence: This attitude showed a significant negative relationship (p = 0.001) with score changes, with a small effect size of 0.134. Counterintuitively, students who experienced a decrease in their confidence tended to show greater improvements in their test scores. It is not clear why this would happen. It is possible that as students engage in more coding, they get a better sense for what is required to do well with it and are more cautious in expressing confidence. Thus, though their abilities may increase, their confidence may decrease. More research is needed to verify if these results are consistent across different times and populations.
2. Interest: The relationship was not statistically significant (p = 0.302), indicating that changes in interest levels had a minimal impact on score changes. The effect size was 0.017.
3. Utility Value: This attitude showed a significant positive relationship (p = 0.032), with a small effect size of 0.045, indicating a subtle influence on score changes. Students who perceived higher utility value in coding tended to have greater improvements in their CTt scores. This suggests that teachers and parents may be able to positively increase students' CT ability by helping them to better understand its usefulness.

4. Perception of Coders: The relationship was not statistically significant ($p = 0.247$), suggesting a smaller independent impact on score changes. The effect size was 0.020.
5. Math Self-Efficacy: This attitude had a significant positive relationship ($p = 0.022$), highlighting the importance of math self-efficacy in predicting score changes. The effect size was small at 0.050. Math self-efficacy is students' confidence to succeed in math. Thus, students who have higher confidence in their math abilities tend to have more positive attitudes toward coding. This relationship between math and computer programming is well-known and has been demonstrated in multiple studies (Scherer et al., 2018).
6. Social Value: The relationship was not statistically significant ($p = 0.149$), indicating a weaker influence on score changes compared to other attitudes. The effect size was 0.028.

Overall, the analysis underscores the importance of confidence, utility value, and math self-efficacy in influencing students' changes in computational thinking abilities, while the other attitudes had a lesser impact when considered together. The negative correlation with confidence suggests that an increase in confidence did not necessarily translate to improved performance, which warrants further investigation. However, given that the effect is small, I would caution against putting too much stock on this relationship.

4. References

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