Where Are CoolThink Students Making the Greatest Learning Gains?

Linking CoolThink@JC Implementation With Student Outcomes

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Executive Summary

By the end of the 2021–22 school year, CoolThink@JC had scaled successfully to 131 Hong Kong primary schools. This topical report explores the relationship between CoolThink implementation and student learning during the 2021–22 school year in schools in their first or second year of adopting CoolThink@JC. The report draws on data collected for SRI's study of CoolThink implementation and for the Education University of Hong Kong's study of student outcomes to address the question, "What implementation factors are associated with greater student learning gains?"

To conduct this analysis, SRI modeled student gains on computational thinking assessments in spring 2022 as a function of individual implementation measures, holding student achievement and other characteristics at pre-test (spring 2021) constant. The relationships described in this report are correlational and not causal, so they do not provide conclusive evidence about implementation factors that promote stronger student learning. However, clusters of correlations between implementation factors and outcomes offer promising evidence to support hypotheses about which implementation factors are key to successful CoolThink adoption.

Students with greater exposure to active-learning, problem-solving, and design-thinking pedagogies had more positive perceptions of themselves as computational thinkers.

These differences were small. A typical student who participated in active learning more frequently (for example, when the teacher reported that lessons included active-learning pedagogies "often" rather than "sometimes") gained somewhat more than their peers on the CoolThink Computational Thinking (CT) Perspectives assessment. For a typical student, this gain was equivalent to moving from the 50th to the 53rd percentile on the CT Perspectives assessment. There was no relationship between active-learning, problem-solving, and design-thinking pedagogies and student gains in computational thinking knowledge or skills.

Students in classrooms where teachers reported fewer time limitations learned more than their peers in classrooms with greater time limitations.

Students' learning gains in computational thinking knowledge and skills, as well as their positive feelings about themselves as computational thinkers, were stronger when their teachers felt they were able to get through the content in the time available, and when their teachers followed the lessons as designed by CoolThink@JC without modifications. The size of this latter correlation was large: A typical student whose teacher did not modify materials moved from the 50th to the 65th percentile on the CT Practices assessment. These findings suggest that CoolThink instructional materials have a substantively meaningful effect on students' learning when implemented as designed, compared with when they are modified.

Students of higher-capacity teachers made greater learning gains on all three computational thinking assessments.

Student gains on all three assessments were higher for students of teachers who said they were more confident, felt better prepared, and experienced fewer challenges with teaching CoolThink lessons. These differences were relatively small—equivalent to moving from the 50th to the 53rd percentile on the computational thinking assessments. Although there was not a direct link between teachers' participation in CoolThink professional development and student learning, the professional development may have an indirect impact on student learning by increasing teacher confidence and capacity.

Parent support for CoolThink@JC appears to be correlated with greater student learning on all three computational thinking assessments.

Despite significant data limitations, SRI found that in schools where parents expressed greater support for CoolThink learning goals, students learned more in all computational thinking domains (concepts, practices, and perspectives). The size of the learning gains was large—equivalent to moving from the 50th to the 60th percentile or higher on the assessments of computational thinking concepts, practices, and perspectives. However, these results should be interpreted with caution because parent samples were extremely small and not representative of all parents at CoolThink schools.

In most cases, there was no relationship between school-level student demographics and student learning.

One exception was financial need. Students in schools where more students were eligible for financial aid learned less computational thinking content than their peers in lower-need schools did, although the size of this difference was very small and not substantively meaningful. Learning gains were not related to the percentage of special educational needs (SEN) students or non-Chinese-speaking students at a school.

Implications

The analysis presented in this report has several significant limitations. The samples do not include all CoolThink students, parents, teachers, and schools, and a correlation analysis cannot tell us definitively whether CoolThink implementation factors caused the learning gains measured by the computational thinking assessments.

Nevertheless, the findings offer **promising evidence** that **strong CoolThink implementation supports greater student learning gains**. Implementation success factors associated with greater student learning include:

1. full coverage of the CoolThink content in the time available and lesson materials that were not modified;
2. teacher capacity and readiness to teach CoolThink lessons;
3. active-learning pedagogies, a focus on problem-solving, and exposure to design thinking; and
4. parent engagement in CoolThink@JC.

Taken together, these findings confirm the importance of continuing to support strong CoolThink implementation as CoolThink@JC scales by:

1. paying close attention to the **design and feasibility of the CoolThink course sequence** so that teachers are **not prompted to modify lessons in unproductive ways**;
2. continuing to **develop teacher capacity** through **professional development and in-school support**; and
3. **enlisting parents' support** for student engagement and learning.

Introduction

CoolThink@JC is a 3-year course sequence designed to introduce computational thinking to students in the upper primary grades and to support the development of their digital creativity, problem-solving, and other 21st century skills. Created and funded by The Hong Kong Jockey Club Charities Trust (The Trust), CoolThink@JC is a collaboration between the Education University of Hong Kong (EdUHK), Massachusetts Institute of Technology (MIT), and City University of Hong Kong (CityU). CoolThink partners developed comprehensive instructional materials, intensive teacher professional development (PD) to support effective CoolThink instruction, and workshops to support public awareness of and parent engagement in computational thinking education. Rather than simply teaching students how to code, CoolThink courses are designed to promote the development of three essential domains of computational thinking: concepts, practices, and perspectives (see box).

After a successful pilot of 32 schools in two cohorts, CoolThink partners have undertaken an ambitious initiative to scale CoolThink@JC to a much larger "critical mass" of primary schools across Hong Kong. In 2020–21, a third cohort of 47 schools began teaching CoolThink lessons. A fourth cohort of 53 schools began teaching CoolThink lessons in 2021–22. A key objective of CoolThink's scaling phase is to ensure equitable access to high-quality CoolThink instruction across schools and classrooms, including those classrooms serving higher-need students.

To capture the lessons learned during CoolThink's scaling phase, The Trust engaged SRI to study CoolThink adoption and implementation in network schools. SRI's implementation study was designed to identify the conditions that support or impede successful adoption at the classroom and school levels, and to validate an implementation model that will help interested stakeholders learn from the CoolThink scaling experience. This report links data from this implementation study with the results of student assessments administered by EdUHK to identify implementation factors that correlate with stronger student learning. The results of this analysis are intended to inform the ongoing success of CoolThink adoption at scale.

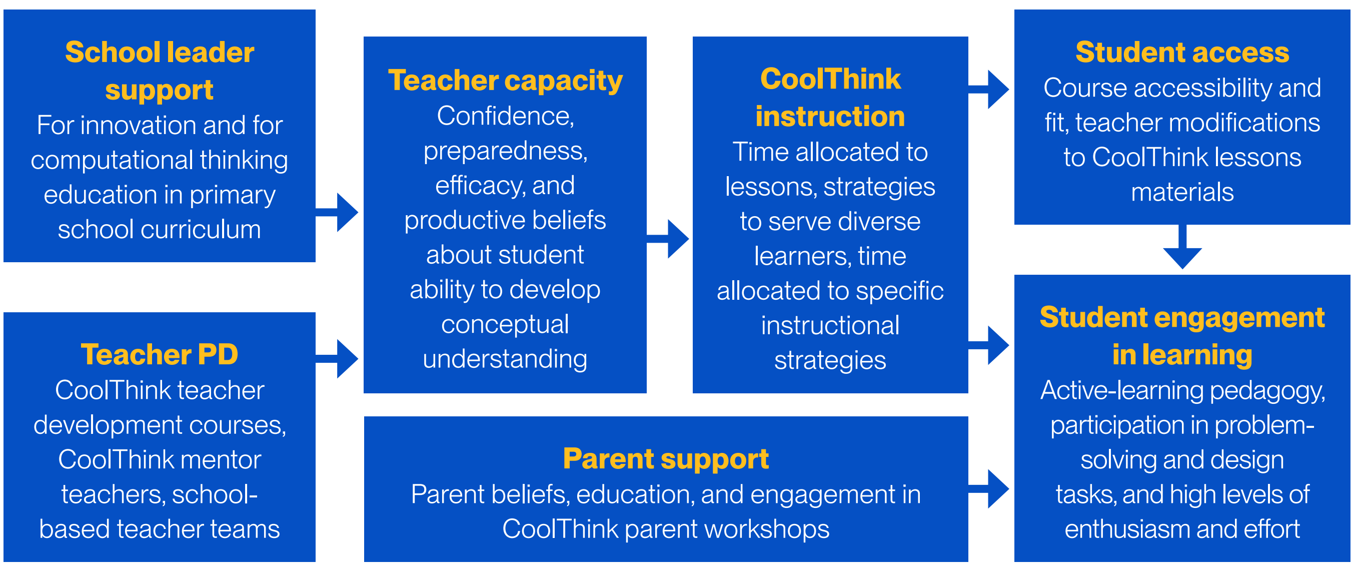
Computational thinking encompasses the thought processes and strategies required to understand, formulate, and solve a problem in such a way that a computer can carry out the solution (Wing, 2006). Central to current conceptions of computational thinking is the idea that computing is a means of self-expression and creativity. The essential domains of computational thinking include:

- **Concepts:** Content knowledge required for developing computational artifacts.
- **Practices:** Problem-solving and logical-thinking skills characteristic of computational thinking.
- **Perspectives:** Interest in and motivation for computational thinking, as well as perceptions of its nature and utility.

CoolThink success factors

This report leverages data from several concurrent CoolThink-related studies to explore the conditions in which CoolThink students are making the greatest gains in computational thinking knowledge, skills, and perspectives. From SRI's implementation study, key sources include annual teacher surveys that capture teachers' perceptions of the CoolThink curriculum and their experience teaching CoolThink lessons, and a series of monthly classroom logs that capture key dimensions of CoolThink instruction. Drawing on these and other data sources, the implementation study's midline report (Laguarda et al., 2023) described a set of "success factors" that appeared to characterize stronger CoolThink implementation (Exhibit 1). On average, these success factors were much more prevalent in CoolThink schools one or two years after their adoption of CoolThink materials than in those same schools at baseline. In addition, the prevalence of these success factors varied across CoolThink teachers and classrooms, depending in part on students' backgrounds and levels of need. Building on the findings from the midline report, this report uses the framework below to select and organize the implementation factors for the correlation analysis presented in the report.

Exhibit 1. CoolThink success factors



As shown in Exhibit 1, parent engagement and outreach is a key component of the CoolThink program, and partners believe that parent support is another important success factor in scaling CoolThink@JC. As the CoolThink partner responsible for parent outreach and education, CityU hosted 19 school-based parent workshops in Cohort 3 and Cohort 4 schools during the 2020–21 and 2021–22 school years.[1] At these workshops, CityU administered parent surveys to collect data on parents' education and prior experience with computer programming, their beliefs about the value of computational thinking education, and their satisfaction with the workshops.

[1] These workshops were designed to introduce parents to computational thinking learning goals, to enlist parents' support for their students' engagement in CoolThink lessons (in a context where many parents believe that their students should focus on core subjects of Chinese, English, and mathematics), and to encourage parents to support their children's work on and enjoyment of CoolThink activities at home.

In parallel with SRI's implementation study and CityU's parent surveys, the Trust also engaged EdUHK to study student learning outcomes in network schools during the CoolThink scaling phase. Student gains in computational thinking knowledge and skills, along with equity in outcomes across classrooms and schools, are the ultimate test of the success of CoolThink@JC. Understanding what drives gains in student learning is a primary motivation for the identification of the success factors in SRI's implementation study (see Exhibit 1).

In spring 2021 and spring 2022, EdUHK administered assessments of computational thinking concepts, practices, and perspectives to samples of students in Cohort 3 and Cohort 4 schools. The spring 2021 assessment served as a pre-test before each of the first two levels of CoolThink instruction, and the spring 2022 assessment as a post-test at the end of the school year.

Research questions

For this second topical report from the CoolThink implementation study, SRI leveraged the rich data sets from the 2021–22 school year in a correlation analysis to explore whether the success factors identified in Exhibit 1 are, in fact, correlated with stronger student outcomes. Because equity of access to high-quality computational thinking education and equity of outcomes are key goals of CoolThink@JC, SRI also conducted an analysis to explore whether student background and learning needs, as reflected in school-level aggregates, predict students' computational thinking outcomes. Because data on eligibility for financial aid, special education needs, and student language were not available at the student level, school-level aggregates were the only available proxy.

SRI's correlation analysis sought to address the following questions:

1. What classroom-level implementation factors are associated with greater student learning gains?
2. What parent engagement measures are associated with greater student learning gains?
3. Are school characteristics, especially student background characteristics measured at the school level, associated with greater student learning gains?

After linking implementation and student assessment data, SRI estimated the relationship between implementation factors and student learning using hierarchical linear modeling (HLM), a type of regression, to account for the nesting of students within schools or classrooms. We ran a separate HLM regression model for each implementation variable: The models predicted student learning gains on each computational thinking assessment as a function of changes in each implementation success factor. All models controlled for student characteristics that are typically correlated with post-test outcomes, including each student's pre-test score and their relative mathematics achievement at pre-test. For more detailed descriptions of these analyses, see the appendix of this report.

The relationships described in this report are correlational and not causal. If student gains are larger when an implementation measure is higher, it may mean that better CoolThink implementation causes students to progress at a faster rate. However, it is equally possible that the causal relationship runs the other way. Students' learning throughout the year (as reflected in their gain scores at the end of the year) may cause an implementation factor like teacher confidence to be stronger. Alternatively, students' successes or challenges on CoolThink lessons (as reflected by their gain scores at the end of the year)may cause teachers to change their practices or change other features of CoolThink@JC during the course of the year. For example, teachers may change the amount of time devoted to lessons, allow more time for student collaboration, or adopt new strategies for struggling students.

In some cases, strong correlations between implementation and outcomes offer promising evidence to support hypotheses about which implementation factors are key to successful CoolThink adoption. However, this evidence is only promising and not conclusive. Therefore, these correlational results should be interpreted with caution.

The following sections report the results of the correlation analysis for each research question in turn.

1. What classroom-level implementation factors are associated with student learning?

The CoolThink implementation study midline report (Laguarda et al., 2023) described a set of implementation factors that CoolThink partners have hypothesized are key to the impact of CoolThink@JC on student learning and to students' sense of agency as engaged, effective, and creative computational thinkers (that is, their computational thinking perspectives). The midline report focused on a set of "success factors" that were noteworthy for one or more of the following reasons:

- Their prevalence in CoolThink classrooms shifted substantially as teachers gained experience with CoolThink@JC. (For example, active-learning pedagogies were much more prevalent in CoolThink classrooms than they had been in the same teachers' information communication technologies (ICT) classes at baseline.)
- In some cases, success factors varied significantly across classrooms by student need, including students' eligibility for financial aid and whether the classroom was higher-ability or lower-ability, as reported by teachers. (For example, teachers were more likely to modify CoolThink-supplied lesson plans in lower-ability classrooms.)

- Some success factors were related in ways that appeared to confirm key hypotheses about the CoolThink program. (For example, teachers' participation in CoolThink PD was associated with their confidence in teaching CoolThink@JC.)

To date, reporting on the CoolThink@JC implementation study has described teacher responses to individual survey items. For the correlation analysis conducted for this report, SRI first aggregated these individual teacher survey items into multi-item scales. This step generated more robust measures of implementation factors that were less subject to random variation in teacher responses and reduced the number of data points to be tested in the correlation analysis (see appendix for detail).

Exhibit 2 summarizes the results of the HLM regression models using teacher-level implementation factors to predict student learning gains. To communicate the size of the learning gains estimated by these models, the gains are presented as the change in percentile rank for a student in the middle of the distribution (50th percentile) at pre-test. For every 1-point difference on the implementation measure being tested, a student who begins at the 50th percentile will gain (or lose) percentile ranks as shown in the table. Each cell with a statistically significant or marginally significant result contains the projected percentile rank for a student who began at the 50th percentile at pre-test. These percentile-rank gains are derived from the correlation coefficients estimated by the HLM regression models described in the introduction.

The table uses color coding to indicate which results are statistically significant. Dark green shading indicates a positive, statistically significant relationship between the teacher-reported implementation measure and student percentile rank gains (meaning that the higher the value of the implementation measure, the greater the average student gain on the CT assessment). Dark blue shading represents a negative, statistically significant relationship (meaning that the higher the value of the implementation measure, the smaller the average student gain on the assessment). Lighter shades of green and blue signify relationships that approach statistical significance ($p < .10$). Although these results offer less confidence that the percentile rank changes shown are different from zero, they are included in the table because they contribute to larger patterns of results across assessments. See the appendix for a more detailed discussion of the regression models underlying the results summarized in Exhibit 2.

Exhibit 2. Correlations between CoolThink implementation success factors and student learning

Implementation measure	Predicted student percentile rank, for a student at the 50th percentile		
	CT Concepts	CT Practices	CT Perspectives
Student engagement in learning			
Active learning			53.0
Problem-solving			52.4
Design thinking			52.7
Practice coding			
Enthusiasm and interest		54.6	
Student access			
Course accessibility and fit			52.2
Too much content for time available	47.4	47.8	48.4
Did not modify lesson (log)		65.7	
CoolThink instruction			
Time for instruction (14+ hours)			54.3
Multiple strategies to support diverse learners			
Addressed specific misunderstandings		53.7	
Problems as engaging for girls as for boys		58.6	
Teacher capacity			
Confidence	53.3	51.9	51.9
Preparedness	53.1	53.2	52.6
Lower perception of challenges	53.3		
Beliefs about CTE			
Teacher PD			
EdUHK development courses (completed 2 or more)			
CoolThink mentor teacher (any interactions)			
School-based CoolThink teacher team membership		54.0	

Key:

$p < .05$	Positive and statistically significant relationship
$.05 \le p < .10$	Positive and marginally significant relationship
$.05 \le p < .10$	Negative and marginally significant relationship
$p < .05$	Negative and statistically significant relationship
$p > .10$	Blank cells represent relationships that are not statistically significant (not different from zero)

Exhibit reads, for example: On average, every 1-point gain on the 5-point active-learning survey scale is associated with an increase from the 50th to the 53rd percentile on the CT Perspectives assessment, holding student characteristics at pre-test constant. This positive relationship is statistically significant at p < .05.

Note: *CT = Computational Thinking; CTE = computational thinking education; PD = professional development; EdUHK = Education University of Hong Kong.*

Source: *SRI analysis of CoolThink@JC implementation study spring 2022 teacher surveys linked with CoolThink computational thinking assessment data, spring 2021 and spring 2022.*

Students with greater exposure to active-learning, problem-solving, and design-thinking pedagogies had more positive perceptions of themselves as computational thinkers.

There was a positive, statistically significant relationship between the prevalence of active-learning, problem-solving, and design-thinking pedagogies in CoolThink classrooms and student gains on the CT Perspectives assessment. Among the set of success factors that describe students' experiences in CoolThink lessons, the prevalence of active-learning and problem-solving pedagogies has increased substantially since schools first joined CoolThink@JC, compared with teacher practice in ICT classrooms at baseline (Laguarda et al., 2023). Because CoolThink adoption has prompted a measurable shift in these practices, the positive correlation between these practices and gains in CT Perspectives scores (see Exhibit 2) offers promising evidence that students' experiences of CoolThink@JC supported gains in their perception of themselves as computational thinkers (that is, their sense of efficacy, agency, and creativity in exercising computational thinking skills). CoolThink's "to play, to think, to code, to reflect" pedagogy includes reflection as a key stage in students' learning process, so the correlation between CoolThink-aligned pedagogies and growth in students' computational thinking perspectives offers some evidence to validate this aspect of the materials' design.

The increased prevalence of CoolThink-aligned pedagogical strategies, as measured by teacher surveys, was not related to gains in CT Concepts or Practices scores, which reflect whether students have learned new computational thinking concepts or skills. CoolThink's creators hypothesized that greater participation in student-centered learning would support students' acquisition of computational thinking knowledge and skills, but this particular set of correlations offers no evidence of this relationship. There are two possible reasons for this lack of evidence: either SRI's survey-based measures of classroom pedagogy are not sensitive enough or not well enough aligned with the pedagogy CoolThink's creators envisioned, or these relationships do not exist. However, another set of correlations shows that students of teachers who implemented CoolThink lessons with no modifications made greater gains in CT Concepts and CT Practices, suggesting that CoolThink pedagogies do support learning in these domains. See discussion below.

Finally, although most CoolThink teachers make time for students to practice coding in every lesson, the prevalence of this practice is not related to gains on CT Concepts, Practices, or Perspectives assessments. This is consistent with CoolThink's theory of action, which holds that computational thinking is a much more complex and higher-order set of knowledge and skills than simply mastering a coding language.

Students who displayed greater enthusiasm and interest in CoolThink learned more about computational thinking practices than their peers did.

Student enthusiasm and interest in CoolThink classrooms also has a very small, significant correlation with gains on the CT Practices assessment. A difference of 1 point on a 5-point scale measuring teachers' perceptions of student enthusiasm was associated with 4.6 percentile-rank increase (from 50th to 54.6th percentile) on the CT Practices correct ratio (that is, the number of correct items divided by total number of items). However, it is possible that students' success in learning computational thinking practices may in turn increase their enthusiasm and interest, rather than the other way around (with enthusiasm leading to learning gains). If this hypothesis is true, it suggests that student enthusiasm is better understood as a leading indicator of learning gains, rather than a success factor that contributes to those gains. Alternatively, the causal relationship could run in both directions at the same time, in a kind of virtuous cycle where success breeds more success: Student enthusiasm and interest support faster progress on the development of computational thinking practices, which in turn generates greater enthusiasm and interest.

Students in classrooms where teachers reported fewer time limitations learned more than their peers in classrooms with greater time limitations.

Perhaps the most significant correlations shown in Exhibit 2 are those related to the category "student access." There is a large correlation between student gains on the CT Practices assessment and whether teachers modified the CoolThink-supplied daily lesson in any way: Students of teachers who consistently did not modify their lessons scored 15.7 percentile-points higher (from 50th to 65.7th percentile) on the CT Practices correct ratio than students of teachers who consistently did.[2] Other implementation data suggest that modifications are often designed to reduce the problem-solving burden for students who are having trouble completing their work, which might explain the reduction in CT Practices scores when teachers make modifications. This finding suggests that CoolThink instructional materials have a positive effect on student gains when implemented as designed, compared with when they are modified. Similarly, the statistically significant, negative relationship between student learning and teachers' reports that CoolThink materials have too much content to teach in the time available is notable because it is one of the few findings in Exhibit 2 that is consistent across all three computational thinking assessments. These findings are important because the implementation measures under "student access" vary by classroom need—both students' financial need and whether the classroom is higher-ability or lower-ability (Laguarda et al., 2023). Taken together, the correlation results provide some evidence that variation in student access to well-implemented CoolThink instruction has important consequences for student learning.

[2] This correlation may be larger than the others presented in Exhibit 2 because the implementation factor used in the analysis ranges from 0 to 1, compared with other factors that have larger ranges (for example, a 5-point scale or a 4-point scale). As a result, the coefficient shown represents the gain associated with the difference between the minimum possible value and the maximum possible value of the range. This is not the case for other correlations.

Under the "CoolThink instruction" category in Exhibit 2, there is some evidence that time spent on CoolThink instruction matters. Teachers who report spending more than 14 hours on instruction had students who made greater progress on CT Perspectives assessment, although there was no relation with gains on the other two assessments. In addition, teachers' adoption of specific strategies to support diverse learners was associated with small gains on the CT Practices assessment, although the number of different practices that teachers adopted did not appear to matter.

Students of higher-capacity teachers made greater learning gains on all three computational thinking assessments.

Finally, most measures of teacher capacity had very small but statistically significant or marginally significant correlations with student gains on all three computational thinking assessments. These correlations are notable for their consistency across the three assessments and across multiple measures of teacher capacity. (Notably, teachers' beliefs about the value of computational thinking education were not related to student learning gains, according to this analysis.) Teacher participation in various forms of CoolThink-sponsored teacher PD was not directly related to student learning gains, although prior SRI analysis has shown that teacher participation in PD is related to the measures of teacher capacity shown in Exhibit 2 (Laguarda et al., 2023). It is possible that the impact of teacher PD on student learning is mediated by its effect on teacher capacity; thus, teachers' participation in PD may indeed promote stronger student learning gains, but the relationship is too distal to detect in a direct test of the correlation between the two variables.

Many other CoolThink implementation factors appeared to have no relationship with student learning.

In addition to the correlations reported in Exhibit 2, SRI ran additional regression models that showed no relationships between the implementation measure being tested and student gain scores on the computational thinking assessments. These models included tests of the following measures:

- medium of instruction (in-person, virtual, or hybrid), from classroom logs
- instructional mode (whole-class, small-group, or individual), from classroom logs
- whether class was shortened because of the COVID-19 pandemic, from classroom logs
- time spent on specific instructional activities (for example, unstructured exploration, unplugged activities, designing a computer program, collaborating with other students), from classroom logs
- class ability level (whether higher-ability or lower-ability), from classroom logs

2. What parent engagement measures are associated with student learning?

Parent engagement and outreach is a key component of CoolThink@JC, and the 312 parent education workshops presented by CityU between September 2020 and March 2023 represent a significant investment by The Trust. Although data on parent perceptions that can be linked to student outcomes are limited, SRI used parent surveys from school-based workshops delivered between September 2020 and March 2022 to test the relationship between parent perceptions and student learning gains.

Very small sample sizes and a lack of representativeness mean that the results presented here may not be generalizable. Parent survey data are only available for 19 schools, and the small number of parents who completed a survey at each school (fewer than 30 per school) means that the parent sample is almost certainly not representative of all parents in each school. Instead, the respondents are more likely representative of those parents who were conscientious enough or interested enough in CoolThink@JC or coding education—or whose students were enthusiastic enough about CoolThink@JC—to attend a workshop.

The results of this correlation analysis are presented in Exhibit 3. The table uses color coding to indicate which results are statistically significant, and each cell with a statistically significant result shows the percentile rank for a student who began at the 50th percentile if parent perceptions as measured by the survey were one point higher (e.g., from "agree" to "strongly agree"). These percentile-rank differences were estimated via regression models (three for each implementation factor, with one for each of the three computational thinking assessments). Cells in which the correlation coefficient was not statistically different from zero are left blank.

Exhibit 3. Correlations between parent survey measures and student learning

Parent survey measure	Predicted student percentile rank, for a student at the 50th percentile		
	CT Concepts	CT Practices	CT Perspectives
Parent support and engagement			
At-home support for CoolThink@JC and computational thinking education	61.9		53.7
Satisfaction with workshop		66.6	
Benefits of workshop	69.6	65.8	
Beliefs about computational thinking			
Parent background and comfort with coding			
Parent programming task completion	59.3		
Parent education (bachelor's degree & higher)	28.4		
Parents' coding knowledge			

Key:

Dark green	$p < .05$	Positive and statistically significant relationship
Light green	$.05 \le p < .10$	Positive and marginally significant relationship
Light blue	$.05 \le p < .10$	Negative and marginally significant relationship
Dark blue	$p < .05$	Negative and statistically significant relationship
Blank	$p > .10$	Blank cells represent relationships that are not statistically significant (not different from zero)

Exhibit reads, for example: On average, every 1-point difference on the 5-point survey scale that measures parents' at-home support for CoolThink@JC is associated with a 11.9 percentile-rank increase (from the 50th to the 61.9th percentile) in student gains on the CT Concepts correct ratio, holding student characteristics at pre-test constant. This positive relationship is statistically significant at p < .05.

Note: *CT = Computational Thinking.*

Source: *SRI analysis of 2021–22 CoolThink parent surveys linked with CoolThink computational thinking assessment data, spring 2021 and spring 2022.*

Parent support for CoolThink@JC appears to be correlated with greater student learning on all three computational thinking assessments.

Despite the limitations of the parent survey data, parents' support for and engagement in CoolThink appears to have relatively large and consistent correlations with student gains across all three computational thinking assessments. For example, every 1-point difference on the 5-point survey scale that measures parents' at-home support for CoolThink@JC is associated with a with an 11.9 percentile point increase (from the 50th to 61.9th percentile) in student gains on the CT Concepts correct ratio. Additionally, parents' at-home support for CoolThink@JC has a positive relationship with student gains on the CT Perspectives assessment that is approaching statistical significance. Similarly, schools with parents who were more positive about the benefits of the CoolThink parent workshop for their students' learning had students with significantly higher gains on the CT Concepts and Practices assessments. These gains were relatively large (increases of 19.6 and 15.8 percentile points, respectively), compared with the gains predicted in other correlation analyses. As with teachers, however, this analysis suggests that beliefs about the value of computational thinking education are not related to students' learning gains.

In general, parents gave very positive responses to survey items, and there is limited variation in the parent survey measures (called a "ceiling effect"). For example, the survey item with the greatest variation yields school-level means that range from 3.7 to 5. Therefore, even if the learning gains associated with a one-point increase (for example, from 3.7 to 4.7) on a given parent survey measure are large, the ceiling effect suggests that this gain might only be possible for schools starting at the lowest end of the scale.

The evidence offered by this survey on parents' background knowledge and its effects on student learning is mixed. Schools with parents who were able to complete the programming task in the workshop (suggesting greater knowledge or facility with coding tasks) had students with higher gains on the CT Concepts assessment, as might be expected. Surprisingly, however, parent education level is negatively correlated with gains in CT Concepts that is approaching statistical significance, although it is not related to gains in CT Practices or CT Perspectives. It is possible that, in this instance, the small number of parent surveys available for analysis has undermined the accuracy of the results, especially if the parents who responded to the survey are not representative of all parents at their school in terms of their education level.

3. Are school-level student demographics associated with student learning?

This analysis explored the relationship between student demographic variables, aggregated at the school level, and student learning. Because demographic data at the student level a not available in Hong Kong for research studies like these, school-level aggregates are the next best proxy for these measures.

The school characteristics examined in this analysis were:

- percentage of students receiving financial aid[3]
- percentage of students with special educational needs (SEN)
- percentage of non-Chinese-speaking students
- student enrollment

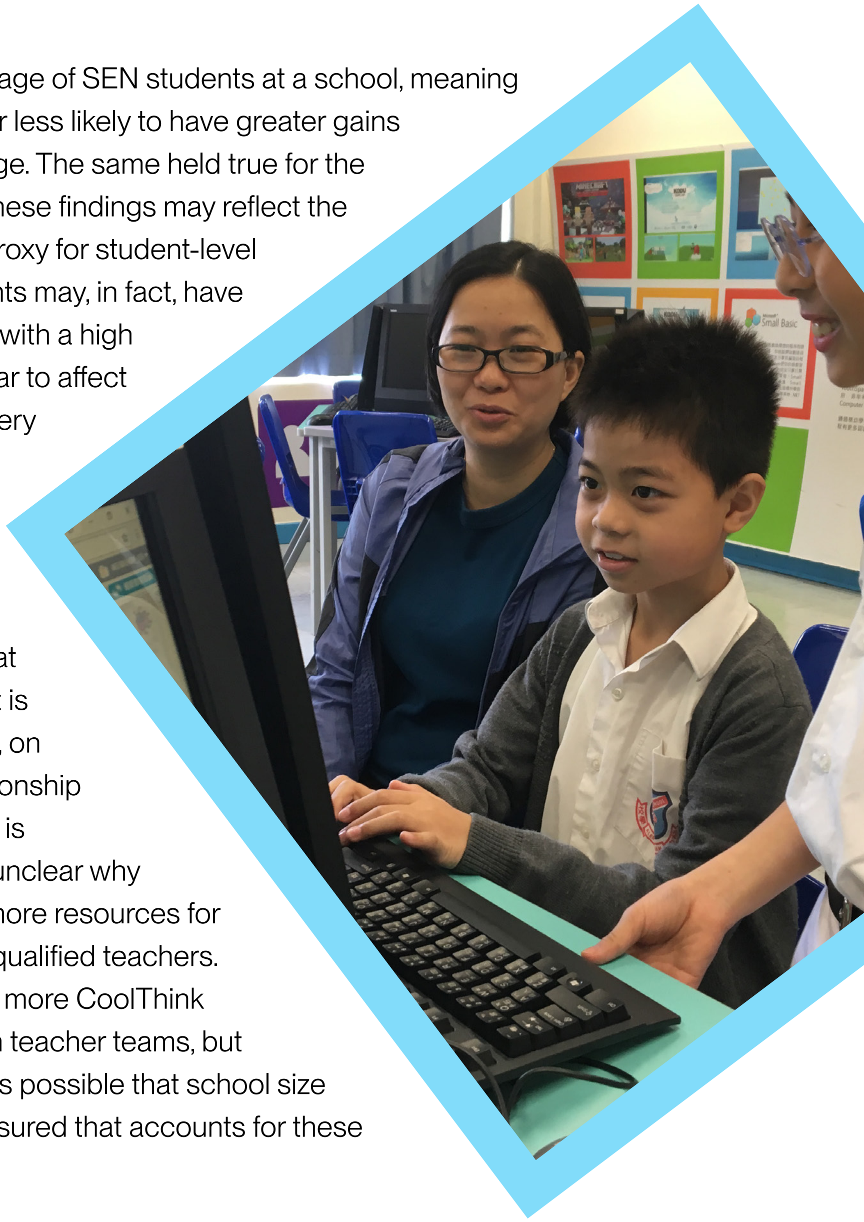
The results of regression models that used school-level student demographics to predict student learning are in Exhibit 4, which uses percentile ranks and color coding (as in Exhibits 2 and 3) to convey the magnitude and statistical significance of the association between school-level student demographics and student learning.

[3] EdUHK's data collection partner Ipsos also collected data on the percentage of students from households receiving comprehensive social security assistance (SSA). However, because these data were missing for multiple schools, the results are not included in this report.

In most cases, there was no relationship between student demographics measured at the school level and student learning.

One exception was financial need. Students in schools where more students were eligible for financial aid learned less computational thinking content than their peers in lower-need schools did, although the size of this difference was very small. On average, every 10-point increase in the percentage of students receiving financial aid is associated with a decrease of 0.3 percentile points (from the 50th to the 49.7th percentile) on the CT Concepts correct ratio.

Assessment gains were not related to the percentage of SEN students at a school, meaning that students in low SEN schools were not more or less likely to have greater gains than students in high SEN schools were, on average. The same held true for the percentage of non-Chinese-speaking students. These findings may reflect the limitations of using school-level aggregates as a proxy for student-level background characteristics. Individual SEN students may, in fact, have lower gains than their peers, but being in a school with a high overall proportion of SEN students does not appear to affect how the average student progresses toward mastery of computational thinking concepts, practices, and perspectives.



Student enrollment had a small, statistically significant, positive relationship with gains in computational thinking concepts, which means that student learning of computational thinking content is slightly stronger in schools with larger enrollments, on average. Enrollment also has a small positive relationship with gains in computational thinking practices that is approaching statistical significance, although it is unclear why this might be the case. Larger schools may have more resources for learning in computational thinking, such as highly qualified teachers. SRI investigated whether larger schools may have more CoolThink teachers and more opportunities to collaborate on teacher teams, but neither of these factors appears to be the case. It is possible that school size is correlated with some other variable not yet measured that accounts for these small differences in outcomes.

Exhibit 4. Correlations between school characteristics and student learning

School characteristic	Predicted student percentile rank, for a student at the 50th percentile		
	CT Concepts	CT Practices	CT Perspectives
Percentage students receiving financial aid	49.7		
Percentage SEN students			
Percentage non-Chinese-speaking students			
Student enrollment (per 100 students)	51.9	51.3	

Key:

Dark green	$p < .05$	Positive and statistically significant relationship
Light green	$.05 \leq p < .10$	Positive and marginally significant relationship
Light blue	$.05 \leq p < .10$	Negative and marginally significant relationship
Dark blue	$p < .05$	Negative and statistically significant relationship
Blank	$p > .10$	Blank cells represent relationships that are not statistically significant (not different from zero)

Exhibit reads, for example: On average, every 10-percentage point increase in the percentage of students receiving financial aid is associated with a very small decrease in student learning (moving from the 50th percentile to just under the 50th percentile) on a measure of computational thinking content learning, holding student characteristics at pre-test constant. This negative relationship is statistically significant at p < .05.

Note: *CT = Computational Thinking; SEN = special educational needs.*

Source: *SRI analysis of school demographic data collected in fall 2022 linked with CoolThink computational thinking assessment data, spring 2021 and spring 2022.*

Implications and Conclusion

The analysis presented in this report has several significant limitations. First, the measures are noisy: Both the survey-based implementation measures and the computational thinking assessments used in this analysis contain some degree of measurement error that makes modeling the relationship between the two sets of variables more difficult. For example, more than a third of CoolThink students scored lower on the CT Concepts assessment at the end of the year than they did at pre-test, although it is unlikely that students' understanding of computational thinking concepts actually declined during that time. Second, the analytic samples do not include all CoolThink students, parents, teachers, and schools, and it is difficult to assess whether students, parents, or schools are systematically missing in a way that may bias our results. Finally, a correlation analysis cannot tell us definitively whether CoolThink implementation factors *caused* the learning gains measured by the computational thinking assessments.

Nevertheless, this analysis offers some promising evidence that the implementation factors identified in SRI's implementation study are, in fact, linked to one or more measures of student outcomes. The hallmark characteristics of CoolThink instruction, including active-learning pedagogies, a focus on problem-solving, and exposure to design thinking, all predict stronger gains on computational thinking perspectives. Various aspects of student access to the full CoolThink learning experience are related to student gains on all three assessments. Teacher perceptions that the CoolThink curriculum contains too much content for the time available, perceptions of course accessibility and fit, and reports on whether teachers modified daily lesson plans are all related (significantly or with results approaching significance) to one or more of the three assessments. Various measures of teacher capacity are related to student gains across assessments, although the magnitude of these relationships is small. Finally, parents' at-home support for students' engagement in CoolThink@JC and parents' engagement in CoolThink workshops also appear to support student learning gains in all three domains.

These clusters of correlations, especially where they appear across assessments and across closely related measures of implementation, provide evidence that helps confirm the CoolThink partners' hypotheses about the aspects of implementation that are most important to monitor and address during scaling. It remains important, therefore, to continue to pay close attention to the design and feasibility of the CoolThink course sequence so that teachers are not forced to modify lessons in unproductive ways; to develop teacher capacity through PD and in-school support as CoolThink@JC scales; and to enlist parents' support for the program.

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Appendix: Data Sources and Methods

General approach

SRI linked student gain scores on Computational Thinking (CT) Concepts, Practices, and Perspectives assessments to school-level data via school ID (for the first and third research questions) and to teacher-level implementation data via class ID recorded on the spring 2022 post-test. Students entered their class section ID on all CoolThink assessment forms, and teachers entered their class section IDs on surveys and logs administered during the 2021–22 school year. SRI linked parent surveys to outcome data via school ID. The Education University of Hong Kong (EdUHK) had previously linked student pre-test and post-test scores by student ID before sharing the data with SRI.

Once implementation and outcome data were linked, SRI estimated the relationship between implementation factors and student outcomes using hierarchical linear modeling (HLM) regression models to account for the nesting of students within schools or students within teachers (depending on the research question).[4] SRI ran a regression model for all school characteristic variables, to examine each variable in the context of the others. SRI also ran a separate regression model for each implementation variable of interest to predict student gain scores as a function of a single implementation variable (either teacher-level implementation factors or parent data aggregated to the school level). All models controlled for student-level variables that are typically correlated with post-test outcomes, including each student's pre-test score and their relative mathematics achievement at pre-test (see box). Including these student-level controls ensures much more accurate estimates of the relationship between the implementation variable being tested and student gain scores because student-level controls account for the variation in gain scores that is due solely to student characteristics. In this way, the regression models estimate the relationship between implementation and outcomes within groups of students who were similar at pre-test. A larger share of the variation in gain scores that remains can then be attributed to the implementation variable.

Student-level controls included in all HLM regression models

- Pre-test score (spring 2021)
- Spring 2021 mathematics score (standardized within school)
- Gender
- Grade level
- Cohort membership (proxy for previous exposure to CoolThink@JC)
- Interaction between cohort and pre-test score (to account for prior exposure to CoolThink@JC on the pre-test)

[4] While traditional statistical approaches treat students as independent of each other, HLM regression models account for the fact that students in nested structures, such as classrooms, share common experiences and therefore may have similar outcomes.

CoolThink assessments

The analysis in this report draws on student assessment data from Cohort 3 and Cohort 4 schools, collected in spring 2021 and spring 2022, that measured students' progress on their computational thinking knowledge, skills, and perspectives during the 2021–22 school year.

Assessment design

Assessments in this study were originally designed by SRI for the pilot phase of CoolThink@JC, using a rigorous approach called evidence-centered design (ECD; Mislevy, 2007). The assessment questions and administration/analysis methods were then adapted by EdUHK for use in the current scaling phase.

The assessments that were administered by EdUHK and its data collection partner, Ipsos, for the current study include:

- **CT Concepts:** subject matter knowledge related to computational thinking. Separate assessments were designed for each level of the curriculum, aligned to the target constructs at each level (namely, *repetition, conditionals, sequences,* and *procedures* for Level 1; and *repetition, conditionals, data structure,* and *procedures* for Level 2). Both the Level 1 and Level 2 assessments consisted of 17 multiple choice items. The analysis reported for this assessment uses data from students in a randomly selected sample of 50% of Cohort 4 schools[5] that completed the Level 1 assessment as a pre-test prior to the beginning of CoolThink instruction and again as a post-test at the end of the 2021–22 school year. For Cohort 3, the analysis uses data from students in the 50% of schools that completed the Level 2 assessment as a pre-test in spring 2021 and as a post-test in spring 2022. Scores computed by EdUHK on the CT Concepts assessment are expressed as the correct ratio (the number of correct items divided by total number of items).
- **CT Practices:** problem-solving and logical-thinking skills characteristic of computational thinking. The CT Practices assessment focuses on the practices of *testing and debugging, reusing and remixing, abstracting and modularizing,* and *algorithmic thinking*. The CT Practices assessments that EdUHK administered were in two forms: Form A designed for students in Primary 4 and Form B for students in Primary 5–6. To ensure comparability of pre- and post-test scores from students of different years, SRI calculated scores for the analyses in this report using the 21 items that overlapped on both forms. EdUHK administered the CT Practices assessment to a sample of students in Cohort 3 and Cohort 4 schools.[6] Scores computed by EdUHK for the CT Practices assessment are expressed as the correct ratio.

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[5] Within each cohort, schools were randomly selected for the administration of a particular level of assessment in order to reduce overall testing burden.

[6] For CT Practices, to reduce testing burden on students, only one grade level of students (Primary 4, 5, or 6) in any given school was included in testing in spring 2022. As a result, the number of students who took the CT Practices assessment as a post-test in spring 2022 was smaller than the number of students who took CT Concepts, although the number of schools participating in the CT Practices assessment was larger.

- **CT Perspectives:** students' interest in, motivation for, and other perceptions of computational thinking. The CT Perspectives survey evaluates seven subconstructs, including *self-efficacy, meaningfulness, impact, creativity, interest, collaboration,* and *aspiration*. It is important to recognize that while CT Concepts and CT Practices relate to students' computational thinking knowledge and skills, CT Perspectives instead relates to students' positive engagement, confidence, and future goals for computational thinking. The compositive CT Perspectives score used in this analysis is an average of the subconstruct scales, which were computed as composite scale scores from Likert-scale items, ranging from *strongly disagree* (1) to *strongly agree* (5).

For each of the three assessments, students took the baseline assessment in spring 2021 and outcome assessments in spring 2022. Because Cohort 3 schools adopted CoolThink@JC in the 2020–21 school year, the pre-test for these schools was administered after one year of CoolThink instruction, while for Cohort 4 the pre-test is a true baseline. The models used in SRI's analysis control for this timing difference and for the fact that pre-test scores may different across cohorts because of students' prior exposure to CoolThink instruction.

The student outcomes data sets used in this analysis included linked pre-test and post-test scores for 7,546 students in 52 schools for the CT Concepts assessment, 5,862 students in 85 schools for the CT Practices assessment, and 11,628 students in 73 schools for the CT Perspectives assessment (see Exhibit A8 for detail). For more information about the design of the CoolThink assessments and their administration during the CoolThink scaling phase, see Snow et al., 2017, and EdUHK, 2022, 2023.

Spring 2022 student gains

For this correlation analysis, SRI computed a gain score for each student by subtracting the score on their pre-test assessment from the score on their post-test assessment. The gain scores represent students' learning of computational thinking concepts and practices, and students' progression in their computational thinking perspectives, during the 2021–22 academic year. For Cohort 4 students, these 1-year gain scores show progress from baseline, before CoolThink instruction began. For Cohort 3 students, these 1-year gain scores reflect progress during schools' and most students' second year of engagement with CoolThink@JC.

Exhibit A1 presents basic descriptive statistics for the pre-test, post-test, and gain scores collected for the 2021–22 school year. It includes the average pre-test, post-test, and gain scores and sample sizes for the CT Concepts, Practices, and Perspectives assessments, respectively. On average, the gain in CT Concepts from pre-test to post-test was moderately large, at 8 percentage points on the correct ratio; this gain represents nearly 40% of a standard deviation on the pre-test CT Concepts score. The gain in CT Practices was small, at 2 percentage points on the correct ratio, or about 10% of a standard deviation on the CT Practices pre-test score. Mean scores decreased slightly between pre-test and post-test on the CT Perspectives assessment, by about 10% of a standard deviation on the pre-test score.

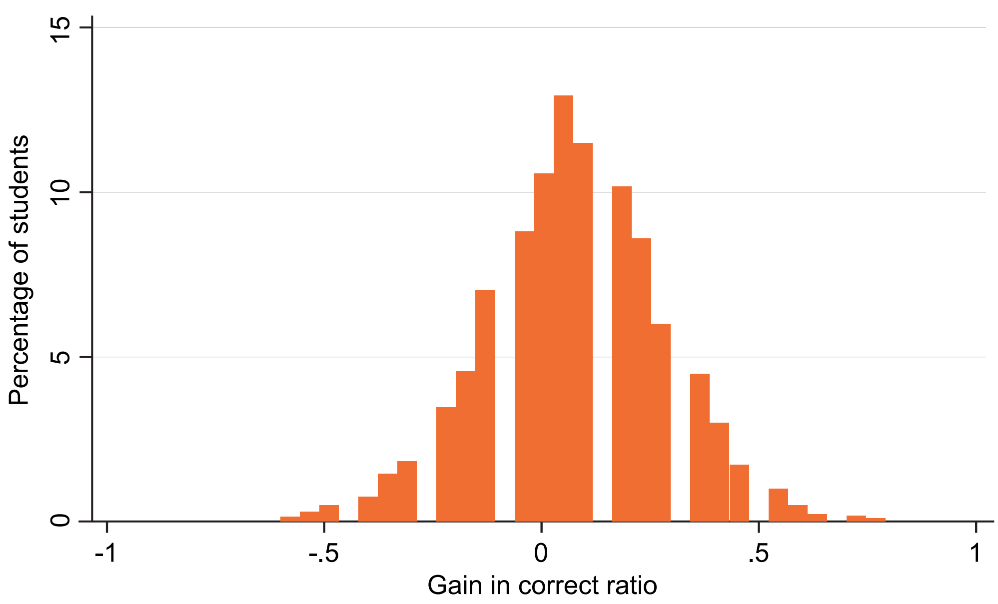
Exhibit A1. Mean computational thinking assessment scores at pre-test and post-test

Assessment	Pre-test (spring 2021)	Post-test (spring 2022)	Gain	Sample size
CT Concepts				
Correct ratio	.44	.52	.08	7,546 students
(Standard deviation)	(.21)	(.23)	(.21)	52 schools
CT Practices				
Correct ratio	.46	.49	.02	5,862 students
(Standard deviation)	(.24)	(.25)	(.24)	85 schools
CT Perspectives				
Mean on scale of 1–5	3.85	3.78	–.08	11,628 students
(Standard deviation)	(.81)	(.85)	(.90)	73 schools

Note: *In this exhibit, the pre-test score plus the gain score does not always equal the post-test score due to rounding.*
Source: *SRI analysis of EdUHK student assessment data, spring 2021 and spring 2022.*

The standard deviations shown in Exhibit A1 summarize substantial variation among individual students. As an example, Exhibit A2 presents the distribution of student-level gains from pre- to post-test on the CT Concepts assessment. Student gains ranged from a low of just under –.5 (meaning that the student's correct ratio fell by more than .5, or 50 percentage points), to a high of more than .5 (meaning that the student's correct ratio rose by more than 50 percentage points). Most students' gain scores fell within one standard deviation of the mean (meaning that most students experienced a change in correct ratio between –.13 and .29).

Exhibit A2. Distribution of student gains in CT Concepts scores from spring 2021 to spring 2022



Classroom-level implementation measures

SRI and its Hong Kong-based data collection partner Ipsos administered surveys to all CoolThink teachers in spring 2022. Response rates are in Exhibits A3 and A4.

Exhibit A3. Spring 2022 CoolThink teacher survey response rates, by cohort

Cohort	Total number of teachers	Spring 2022 responses	Spring 2020 response rate
Cohort 3	386	254	66%
Cohort 4	339	254	75%
Total	**725**	**508**	**70%**

Source: *Cohort 3 and 4 teacher follow-up survey, spring 2022.*

Exhibit A4. 2021–22 classroom log sample and response rates, by cohort

Cohort	School sample	Teacher sample	Log responses	Log-level response rate	Teacher responses	Teacher-level response rate
Cohort 3	30	151	444	59%	135	89%
Cohort 4	31	148	464	63%	144	97%
Total	**61**	**290**	**908**	**61%**	**275**	**94%**

Note: *Teacher sample includes up to five teachers, selected at random, in each sampled school. Teachers were asked to complete a total of five logs over five successive months in 2021–22. The teacher-level response rate reflects all teachers who completed at least one log.*
Source: *CoolThink classroom logs, 2021–22.*

For each general topic related to teachers' implementation of CoolThink materials or their experience of CoolThink@JC, teachers responded to a series of closely related items on both the teacher survey and the classroom logs. SRI conducted exploratory factor analysis to examine the psychometric properties of these series and to determine how to aggregate individual items into measures that each represent a single underlying construct.

Factor analysis explores the theoretical constructs that might be represented by a set of survey items by examining the pattern of correlations between the observed items. Highly correlated items usually represent the same underlying construct (for example, the prevalence of active-learning pedagogies in CoolThink classrooms), while relatively uncorrelated items can be assumed to measure different constructs. Exploratory factor analysis allows SRI to group individual survey items into scales, each measuring a single (and distinct) construct. SRI then assessed how well a set of items in a survey scale measured an underlying construct by estimating an internal reliability coefficient (Cronbach's alpha). In general, the internal reliability is considered acceptable if Cronbach's alpha is greater than .6 on a scale of 0 to 1. All of the scales SRI identified via factor analysis have a Cronbach's alpha of .7 or higher, indicating a high level of consistency among the items that make up each measure.

Exhibit A5 describes the measures that resulted from this process, including the number of items in each scale and the nature of the response options. The aggregate implementation measures are grouped by category, to support mapping back to the success factor framework presented in the introduction to this report.

Exhibit A5. CoolThink success factors and associated measures

Measure	Description	Data source
Student engagement in learning		
Active learning	Frequency with which students engaged in active learning during CoolThink lessons (e.g., unstructured exploration, student collaboration)	Teacher survey 4-item scale *Never* (1) to *always* (5)
Problem-solving	Frequency with which students engaged in various kinds of problem-solving activities during CoolThink lessons	Teacher survey 3-item scale *Never* (1) to *always* (5)
Design thinking	Extent to which students engaged in design thinking tasks during the CoolThink final project	Teacher survey 5-item scale *Not at all* (1) to *a great extent* (4)
Enthusiasm and interest	Teacher perceptions of students' enthusiasm and effort, and whether CoolThink connected to students' interests	Teacher survey 2-item scale *Strongly disagree* (1) to *strongly agree* (5)
Practice coding	Frequency with which students practiced coding/programming skills during CoolThink lessons	Teacher survey Single item *Never* (1) to *always* (5)
Student access		
Course accessibility and fit	Extent to which teachers believed CoolThink course materials were understandable for most students, easy to use, and appropriately paced	Teacher survey 4-item scale *Strongly disagree* (1) to *Strongly agree* (5)
Too much content	Extent to which teachers agreed that CoolThink materials had too much content to be taught for too short an amount of time	Teacher survey Single item *Strongly disagree* (1) to *strongly agree* (5)
Modifications to the daily lesson	Whether the teacher made no modifications or made any modification to that day's CoolThink-supplied lesson plan (e.g., skipped activities, used supplemental resources)	Classroom log 6 items (1/0 response), each analyzed separately

Exhibit A5. CoolThink success factors and associated measures (continued)

Measure	Description	Data source
CoolThink instruction		
Time for instruction	Average time allocated to CoolThink lessons for a single class of students	Teacher survey 14 hours or more (1), less than 14 hours (0)
Support for diverse learners	Whether the teacher adopted strategies to support diverse learners (e.g., paired higher-ability students with lower-ability students, followed up on specific student misunderstandings, identified problems to engage girls as well as boys)	Teacher survey 6 items (1/0 response), each analyzed separately
Teacher capacity		
Confidence	Confidence incorporating computational thinking concepts, practices, and perspectives into instruction	Teacher survey 3-item scale *Not at all confident* (1) to *extremely confident* (5)
Preparedness	Extent to which teachers felt prepared to teach CoolThink@JC (e.g., teach lesson content, use Scratch or App Inventor, meet the needs of diverse students)	Teacher survey 9-item scale *Strongly disagree* (1) to *strongly agree* (5)
General perception of challenges	Extent to which teachers found various aspects of teaching CoolThink@JC to be a challenge (e.g., students with no coding background, the range of student ability, too much content to be taught for short amount of time)	Teacher survey 9-item scale *Not at all challenging* (1) to *very challenging* (4)
Beliefs about CTE	Extent to which teachers believed in the benefits of computational thinking education for student learning	Teacher survey 6-item scale *Not at all important* (1) to *extremely important* (5)
Teacher professional development		
EdUHK teacher development courses (Cohort 4 only)	Whether CoolThink teachers completed two or more teacher development courses	Teacher survey 2 or more courses (1), fewer than 2 courses (0)
CoolThink mentor teacher	Number of times teachers interacted with a CoolThink mentor teacher	Teacher survey Yes (1 to 10+ times) / No (0)
CoolThink teacher team	Whether CoolThink teachers met with others as a team to collaborate, plan, and/or discuss CoolThink instruction	Teacher survey Yes (1) / No (0)

Source: *CoolThink implementation study, spring 2022 teacher survey and 2021–22 classroom logs.*

The response options for some items were dichotomous (yes or no, or values of 1/0), and factor analysis did not support combining these items with others on the survey. However, because they measured theoretically important constructs, these single items were analyzed separately.

To correlate each of these measures with student gain scores on the computational thinking assessments, SRI calculated the simple average of all responses across all items in each survey scale, and used this measure in further analysis.

Exhibit A6 includes the full text of all of the items included in each survey scale, along with response scales and Cronbach's alpha (α), a measure of the internal reliability (that is, the extent to which each of the items in the scale is related to the others, and the extent to which together they measure a single underlying construct). Cronbach's alpha ranged from .70 to .94 on all surveys, indicating that these measures all had strong internal reliability.

Exhibit A6. CoolThink success factors and associated measures, full item text

Implementation measure	Items	Data source, response scale, and internal reliability
Student engagement		
Active learning	Unstructured exploration of games, apps, or sample computer programs Completed unplugged (paper based) activities to learn and practice key concepts Designed and planned a computer program or artifact before attempting to code Shared work or computing artifacts with other students	Teacher survey *Never* (1) to *always* (5) (α = .70)
Problem-solving	Applied new computational thinking concepts or skills to solve novel problems. Identified problems to solve or generate ideas for new programs, apps or other computing artifacts Collaborated with other students to solve problems or create computing artifacts	Teacher survey *Never* (1) to *always* (5) (α = .91)
Design thinking	Took the perspective of others to gain a deeper personal understanding of the problem they were trying to solve Defined a problem statement for the project Came up with multiple ideas or potential problem solutions before they implemented a specific problem solution Developed a prototype project that is tested before they build the final project Rigorously tested their projects to make sure their projects address the problems they set out to solve.	Teacher survey *Not at all* (1) to *a great extent* (4) (α = .88)

Exhibit A6. CoolThink success factors and associated measures, full item text (continued)

Implementation measure	Items	Data source, response scale, and internal reliability
Enthusiasm and interest	Students demonstrate enthusiasm and effort in completing assigned tasks CoolThink connects to students' interests	Teacher survey *Strongly disagree* (1) to *strongly agree* (5) (α = .74)
Practice coding	Practiced coding/programming skills in Scratch or App Inventor	Teacher survey *Strongly disagree* (1) to *strongly agree* (5)
Student access		
Course accessibility and fit	CoolThink course materials are: Easy to use Self-explanatory and understandable Understandable for the majority of my students Pacing of CoolThink curriculum is suitable for the majority of my students	Teacher survey *Strongly disagree* (1) to *strongly agree* (5) (α = .89)
Too much content for time available	Too much content to be taught for short amount of time	Teacher survey *Not at all challenging* (1) to *very challenging* (4)
CoolThink instruction		
Time for instruction	On average, how much class time did you allocate to CoolThink this school year (2021–22) for a given class of students?	Teacher survey 14 hours or more (1), less than 14 hours (0)
Modifications to daily lesson	What if any changes did you make to the CoolThink-supplied lesson plan for today? Skipped activities Added content to the lesson Modified activities to suit my students Provided students with premade code snippets Used supplemental resources I did not make any changes	Classroom log Analyzed each response separately

Exhibit A6. CoolThink success factors and associated measures, full item text (continued)

Implementation measure	Items	Data source, response scale, and internal reliability
Support for diverse learners	Paired high-ability students with lower-ability students in cooperative groups Modified the curriculum to make it more accessible to lower-ability students and/or make it more challenging to high-ability students Provided additional scaffolding for students who struggled with CT concepts and skills Identified and followed up on specific student misunderstandings Identified problems and challenges that are as engaging for girls as they are for boys Provided extra practice for students to try at home	Teacher survey Scale representing the number of strategies reported from a list of select all that apply responses Also analyzed each response separately
Teacher capacity		
Confidence	Confidence incorporating the following into your teaching: CT concepts, including procedures, data structures, variables; CT practices, including abstraction and modularization and algorithmic thinking; CT perspectives, including digital empowerment and computational identity	Teacher survey *Not at all confident* (1) to *extremely confident* (5) (α = .94)
Beliefs about CTE	Critical for fostering problem solving, creativity, and other 21st century skills Helps students to learn and perform better across all disciplines Develops students' collaboration skills Develops students' problem-solving skills Develops students' communication skills Requires teachers adopt different pedagogy, compared with instruction in other core subjects	Teacher survey *Not at all important* (1) to *extremely important* (5) (α = .91)

Exhibit A6. CoolThink success factors and associated measures, full item text (continued)

Implementation measure	Items	Data source, response scale, and internal reliability
Preparedness	After CT PD I felt prepared to: Teach the lesson content Use Scratch in my instruction Use App Inventor in my instruction Teach computational thinking Use unplugged activities during instruction Complete CT activities successfully Support diverse students Support students with using design thinking their final projects Teach CT online during COVID restrictions	Teacher survey *Strongly disagree* (1) to *strongly agree* (5) (α = .92)
General perception of challenges	Teaching students with no coding background before Coping with range of student ability I have never taught this area before Too much content to be taught for short amount of time Time it takes to prepare for CT compared to other courses Sparking students' interest in computing Helping students take the next step when they were stuck Helping students to think logically Not enough training offered to teach the curriculum	Teacher survey *Not at all challenging* (1) to *very challenging* (4) (α = .91)
Teacher professional development (PD)		
EdUHK teacher development courses (Cohort 4 only)	PD Course 1: Understanding CTE and Scratch Programming PD Course 2: Understanding CTE and App Inventor Programming PD Course 3: Advanced App Inventor& AI Awareness PD Course 4: Programming Robotics & School-based Curriculum	Teacher survey 2 or more courses (1), fewer than 2 courses (0)
CoolThink mentor teacher	How many times have you interacted with a CoolThink mentor teacher?	Teacher survey 1 or more (1), zero (0)
CoolThink teacher team	Do you meet with other CoolThink teachers as a team to collaborate, plan, and/or discuss CoolThink instruction?	Teacher survey Yes (1) / No (0)

Source: *CoolThink implementation study, spring 2022 teacher survey.*

Parent survey measures

At each parent workshop, participants were asked to respond to a short survey describing their prior experience with coding, their beliefs about computational thinking, and their satisfaction with and experience in the workshop. As with the implementation measures derived from teacher surveys and classroom logs, SRI conducted a reliability analysis to determine if survey items addressing the same topic had strong internal consistency and could be combined in aggregate measures for later analysis. Exhibit A7 describes the survey measures derived from the parent surveys administered by City University of Hong Kong (CityU) at school-based education and outreach workshops. All parent survey scales have a Cronbach's alpha of .89 or higher, indicating a high level of consistency among the items combined in each measure.

Exhibit A7. Parent survey measures

Measure	Description	Scale
At-home support for CoolThink and CTE	Parents discuss CoolThink with their children and support children to learn computational thinking	3-item scale Likert scale ranging from 1 to 5
Satisfaction with workshop	Parents satisfaction with workshop content, teaching, and logistic arrangements	4-item scale Likert scale ranging from 1 to 5
Workshop benefits	Parents believe that workshops can help children's growth, provide a positive view, and increase adults' knowledge	3-item scale Likert scale ranging from 1 to 5
Parent programming task completion	Whether parents were able to complete the assigned programming tasks in the workshop	Single item Likert scale ranging from 1 to 5
Parent education (bachelor & higher)	Parents having a bachelor's degree or higher	Individual item Dichotomous variable (1/0)
Parent coding knowledge	If parents know how to program or code	Individual item Dichotomous variable (1/0)
Parent beliefs about computational thinking	Parents believe that computational thinking enhances children's creativity, problem-solving skills, and future prospects	4-item scale Likert scale ranging from 1 to 5

Analytic samples and regression models

SRI's analytic samples and regression models differed for each research question (RQ).

RQ1: What classroom-level implementation factors are associated with greater student learning gains?

To address the second research question, SRI merged classroom-level implementation data collected from teachers with gain scores on assessments of CT Concepts, Practices, and Perspectives. The students included in this analysis are a subset of all Primary 4–6 students in CoolThink schools. To be included in the analysis, each CoolThink student needed to have taken the relevant CoolThink assessment (either CT Concepts, Practices, or Perspectives) *and* have a CoolThink teacher who responded to an implementation study survey or classroom log. EdUHK sampled students for its assessments of computational thinking; SRI sampled schools and teachers for the classroom logs; and not every CoolThink teacher responded to the implementation study survey, although response rates were high (see Exhibit A3).

The analytic samples for the analysis in this report include those CoolThink students who:

- attended Cohort 3 and Cohort 4 schools
- took the CoolThink pre-test (spring 2021) and post-test (spring 2022) assessments
- could be linked to teachers who completed CoolThink implementation surveys and classroom logs

Analytic samples varied by outcome (CT Concepts, Practices, or Perspectives) and by success factor (from teacher surveys and logs). Exhibit A8 shows the maximum number of students and schools included in the analytic samples linking student outcomes with success factors defined by logs and surveys. Average pre-test and post-test scores are similar across samples from the survey, log, and the whole assessment in all three computational thinking measures, suggesting that the survey and log samples are not systematically different from the overall group of students who took the computational thinking assessments. Note that the students who took EdUHK's computational thinking assessments are a subset of all students in Cohort 3 and Cohort 4 schools, and without more information about how students were sampled for these assessments, it is difficult to assess whether they are representative of all CoolThink students at these schools.

SRI applied a two-level model with student and teacher levels and considered each teacher-level measure separately, running three regression models for each measure to predict student gain on each of the three computational thinking assessments. All models adjust for student pre-test scores, their standardized baseline mathematics score at pre-test (if available), student gender, grade level, and school cohort. The models included an interaction term between cohort and the pre-test score to account for the fact that most Cohort 3 students took the pre-test after one year of exposure to CoolThink instruction, while Cohort 4 students took the pre-test before receiving any CoolThink instruction.

Exhibit A8. Computational thinking assessment means and sample sizes for analyses linking teacher surveys, classroom logs, and assessment data

Assessment	CoolThink assessment sample		Implementation survey sample		Classroom log sample	
CT Concepts	**Mean**	***SD***	**Mean**	***SD***	**Mean**	***SD***
Pre-test (spring 2021)	**0.44**	0.21	**0.45**	0.21	**0.44**	**0.20**
Post-test (spring 2022)	**0.52**	0.23	**0.52**	0.24	**0.52**	**0.23**
Student n	7,546		5,960		1,854	
Teacher n	n/a		184		103	
School n	52		43		29	
CT Practices	**Mean**	***SD***	**Mean**	***SD***	**Mean**	***SD***
Pre-test (spring 2021)	0.46	0.24	0.46	0.24	0.46	0.22
Post-test (spring 2022)	0.49	0.25	0.49	0.25	0.46	0.25
Student n	5,862		4,644		1,455	
Teacher n	n/a		209		71	
School n	85		78		38	
CT Perspectives	**Mean**	***SD***	**Mean**	***SD***	**Mean**	***SD***
Pre-test (spring 2021)	**3.85**	0.81	**3.87**	0.81	**3.82**	0.82
Post-test (spring 2022)	**3.78**	0.86	**3.78**	0.86	**3.76**	0.87
Student n	11,628		9,390		3,029	
Teacher n	n/a		304		164	
School n	73		69		44	

Note: *The total population of CoolThink students is 16,170 Primary 4–6 students in 99 Cohort 3 and Cohort 4 schools. (Student enrollment data were collected by Ipsos from each CoolThink school in fall 2022.) The CoolThink assessment sample includes all students who took each computational thinking assessment. The implementation survey sample is the subset of students who took the CoolThink assessment and had a teacher who responded to the implementation survey. The classroom log sample is the subset of students who took the CoolThink assessment and had a teacher who completed one or more classroom logs.*
Source: *SRI analysis of CoolThink implementation study spring 2022 teacher surveys linked with CoolThink computational thinking assessment data, spring 2021 and spring 2022.*

RQ2: What parent engagement measures are associated with greater student learning gains?

Because SRI had no way of linking parents who responded to the CityU surveys with individual students, SRI first aggregated parent survey measures from school-based workshops (where parents could be linked to schools) at the school level and linked those measures with the student assessment data collected from that school. For this analysis, SRI used all survey data available from all school-based workshops held before EdUHK began administering post-tests in April 2022. In total, 240 parents in 19 Cohort 3 and Cohort 4 schools attended a school-based parent workshop and responded to the survey during this period. Among these 19 schools, more than half (10) had 10 or fewer parent survey responses; all schools had fewer than 30 responses. SRI calculated a school-level average for each parent survey measure and merged these data with student gain scores for each of the computational thinking assessments using school ID. The final analysis included 1,468 students in 7 schools for CT Concepts, 1,194 students in 16 schools for CT Practices, and 2,057 students in 13 schools for CT Perspectives.

SRI applied a two-level model with student and school levels to look at the relationship between each of the parent perception measures and student gain in each of the CT outcomes, adjusting for student characteristics, pre-test scores, and school cohort as in the previous analyses.

RQ3: Are school characteristics, especially student background characteristics measured at the school level, associated with greater student learning gains?

To address the first research question, SRI merged school-level demographic variables for each Cohort 3 and Cohort 4 school with gain scores for CT Concepts, Practices, and Perspectives. Ipsos collected school-level demographic data from all CoolThink network schools in fall 2022. One school was missing any school-level data and was omitted from the analysis. The final analytic sample included 7,250 students in 51 schools for CT Concepts, 5,785 students in 84 schools for CT Practices, and 11,350 students in 72 schools for CT Perspectives.

To estimate the relationship between school-level student demographics and student learning, SRI applied a two-level HLM regression model with student and school levels to account for the nesting of students within schools. SRI controlled for student differences at pre-test. In each model, SRI controlled for all other school characteristics at the same time.

Interpreting regression model output

The general HLM regression model SRI used to generate all of the correlational results reported in the main body of this report takes the following form. Individual student gains appear on the left side of the equal sign and are estimated as a function of the implementation factor being tested, student characteristics at pre-test, school or teacher random error (to account for nesting), and some additional random error (often described as "noise" in the data). In plain language, the equation reads:

Gain score for student x in school y or teacher y = $\beta 1$ (implementation factor value for school or teacher y) + $\beta 2$ (student x's pre-test values) + school y or teacher y random error + additional random error

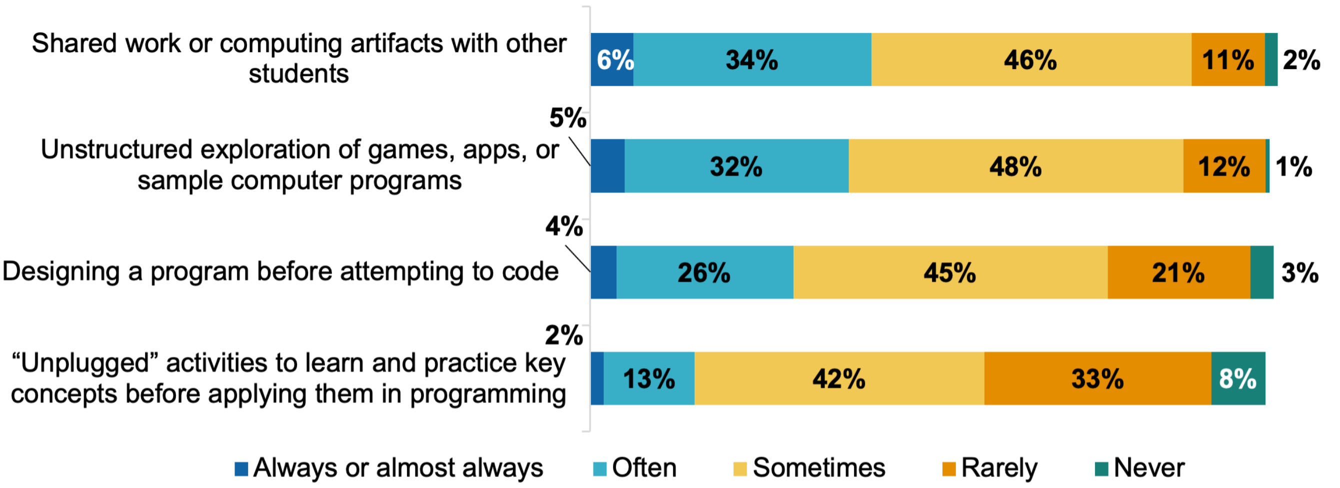
The result that is most important is the coefficient $\beta 1$. This coefficient, like the slope in a simple line graph, describes both the direction and the magnitude of the relationship between the implementation factor and the gain score (holding constant student characteristics at pre-test). Because there is noise (random error) in the data, this regression model can only estimate the value of $\beta 1$. Tests of statistical significance on $\beta 1$ help to determine whether the correlation is statistically different from zero.

This value, $\beta 1$, is reported in all correlation exhibits that follow (Exhibits A9–A13). Interpreting $\beta 1$ requires paying close attention to the gain score units on the left side of the equation and the implementation factor units on the right side. So, for example, gains on the CT Concepts assessment are expressed as a change in the correct ratio from pre-test to post-test (the correct ratio expressed as a decimal ranging from 0 to 1). Most survey-based implementation variables are measured by Likert scales that run from 1 to 5. If the value of $\beta 1$ in a model testing the relationship between teacher confidence and gain in CT Concepts is .05, that coefficient can be interpreted as follows: On average, a 1-point increase on a 5-point survey scale measuring teacher confidence is associated with a .05 gain in the CT Concepts correct ratio (that is, a 5 percentage point increase in the percent of questions answered correctly). All else being equal, a student whose teacher scores 1 point higher on the confidence scale is expected to have a gain score that is 5 percentage points higher than another student whose teacher does not.

Several examples of implementation measures taken from teacher surveys and their relationship with student learning gains are presented below. The slope of the line modeling each correlation reflects the magnitude of the correlation between implementation and student learning. To help with the interpretation of the size of these correlation coefficients, they have been converted to percentile-rank changes in the summary tables in the main report.

Exhibit A9. How is active learning related to student gains in CT Perspectives?

Active learning scale, item-level frequencies



Source: *Cohort 3–4 follow-up teacher survey (summer 2022).*

Regression model of the relationship between active learning and student gains on the CT Perspectives assessment

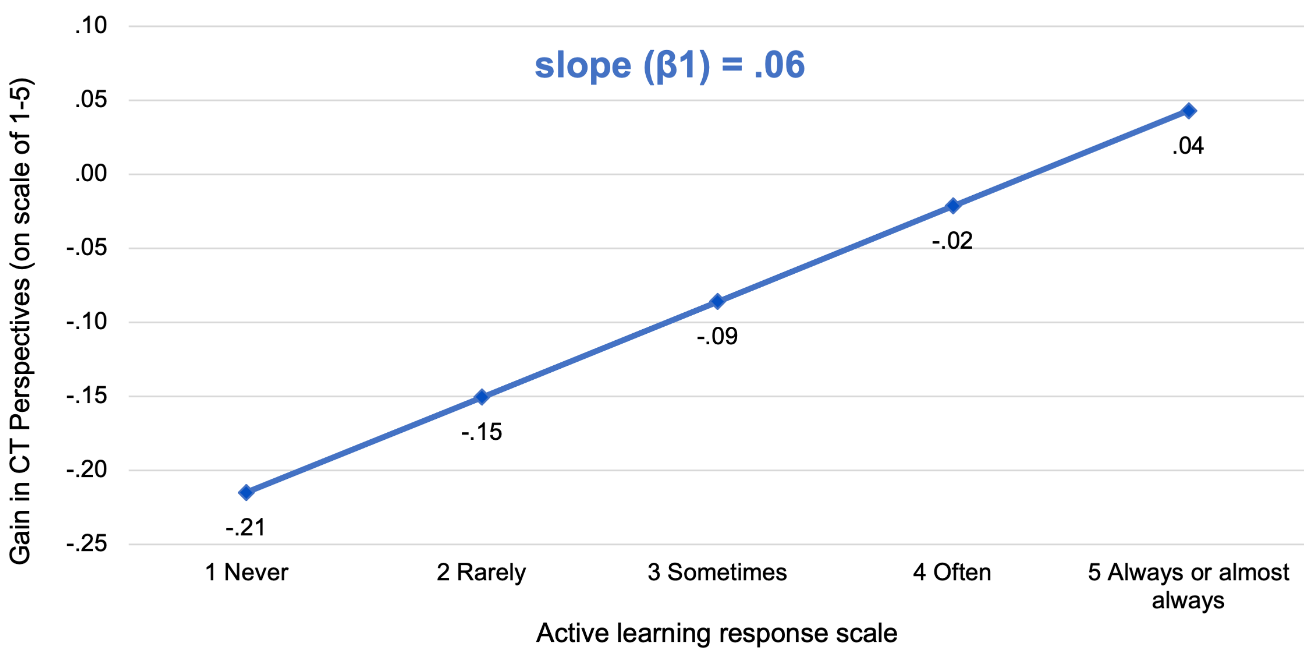
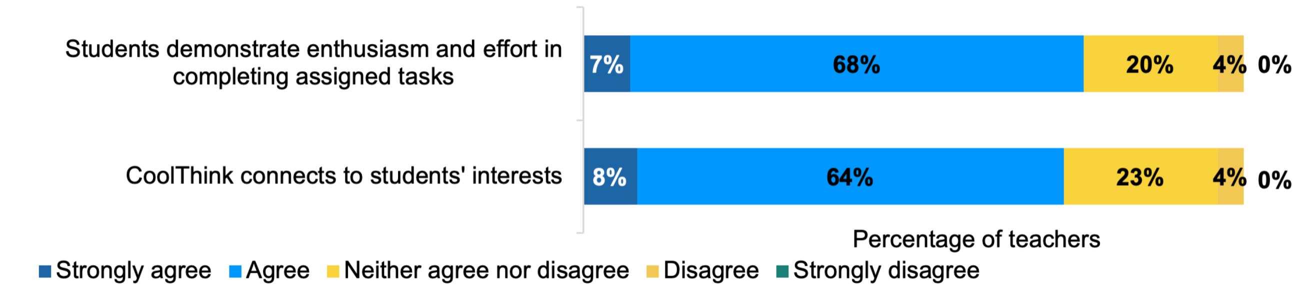


Exhibit A10. How is student enthusiasm and interest related to student gains in CT Practices?

Student enthusiasm and interest scale, item-level frequencies



Source: *Cohort 3–4 follow-up teacher survey (summer 2022).*

Regression model of the relationship between student enthusiasm and student gains on the CT Practices assessment

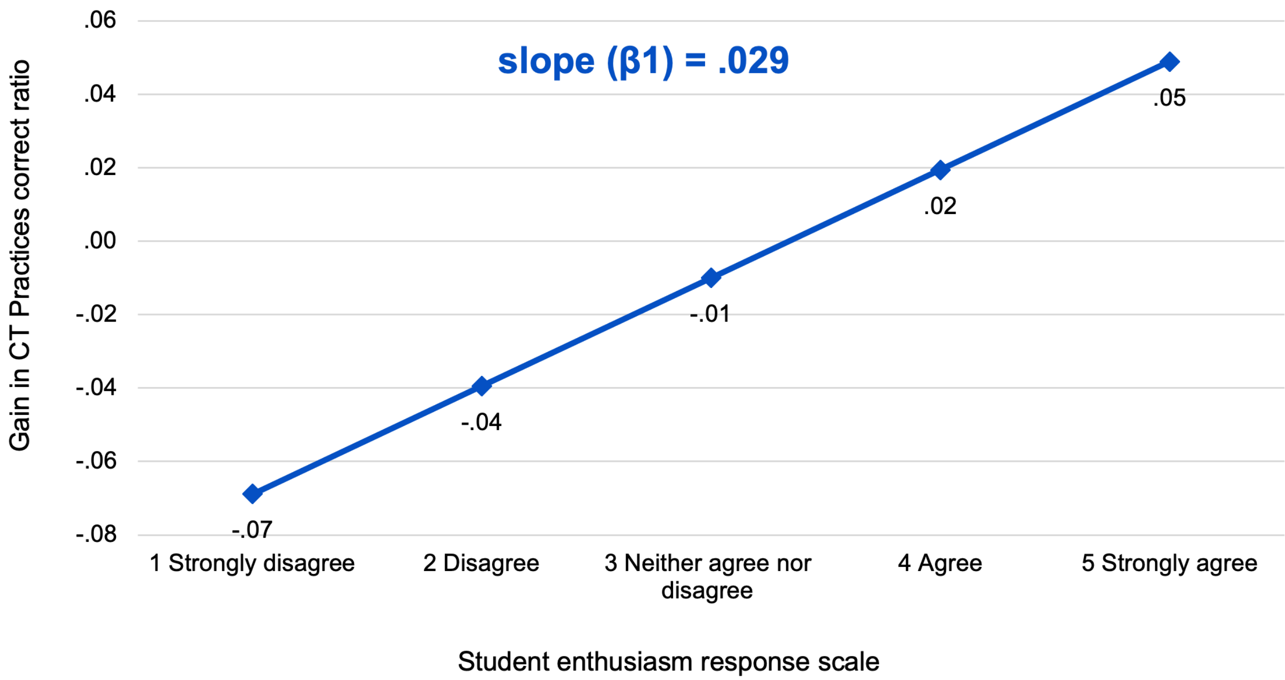
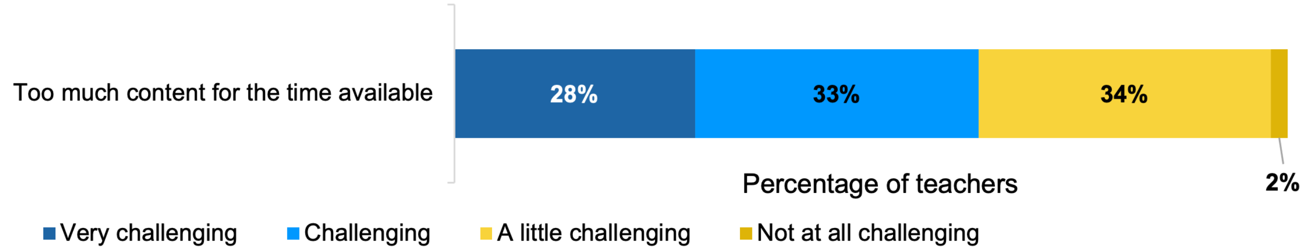


Exhibit A11. How are teacher perceptions of CoolThink courses related to student gains in CT Concepts?

Item-level frequencies



Source: *Cohort 3–4 follow-up teacher survey (summer 2022).*

Regression model of the relationship between teacher perception of course content and student gains on the CT Concepts assessment

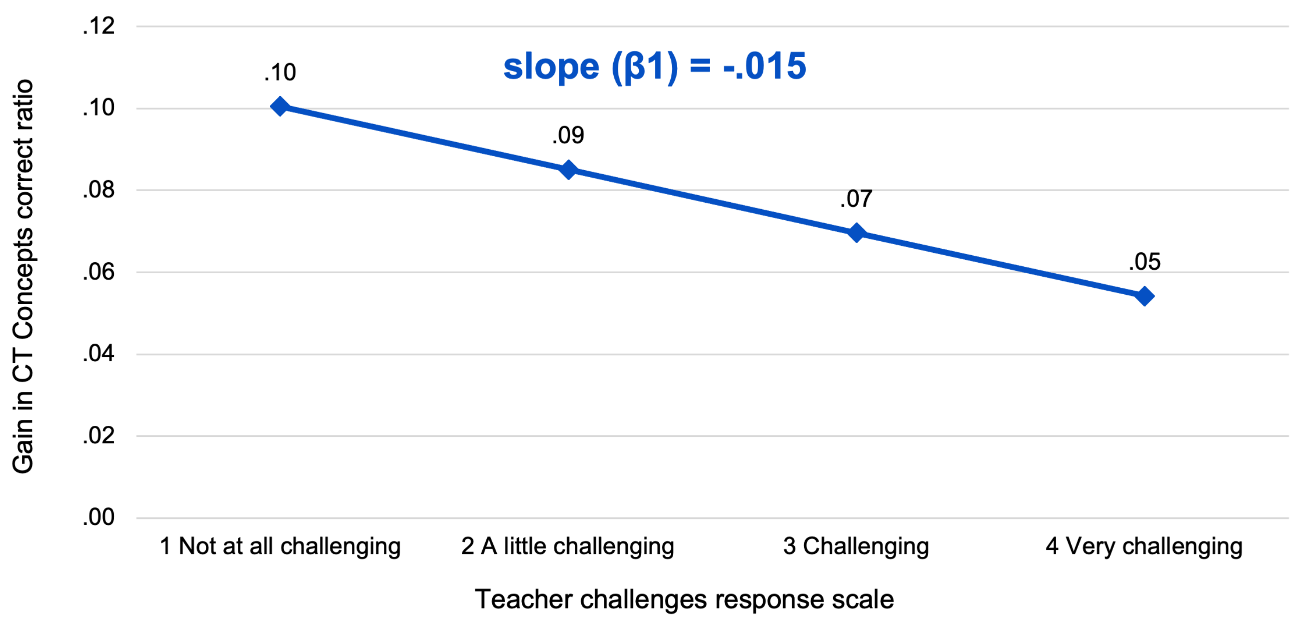
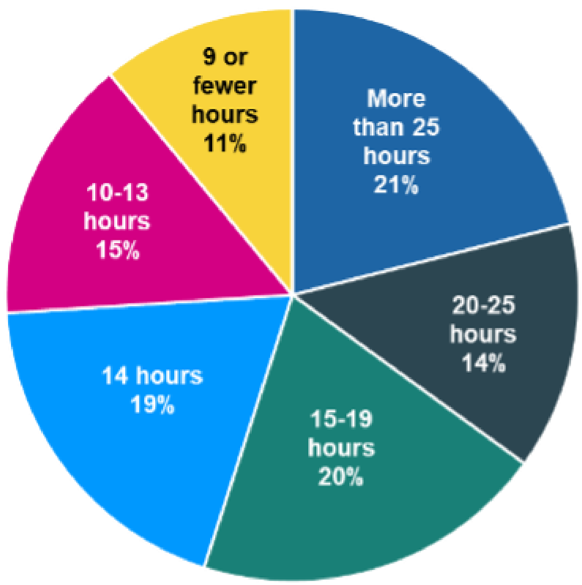


Exhibit A12. How is the amount of time devoted to CoolThink instruction related to student gains in CT Perspectives?

Item-level frequencies



Source: *Cohort 3–4 follow-up teacher survey (summer 2022).*

Regression model of the relationship between the time spent on CoolThink instruction and student gains on the CT Perspectives assessment

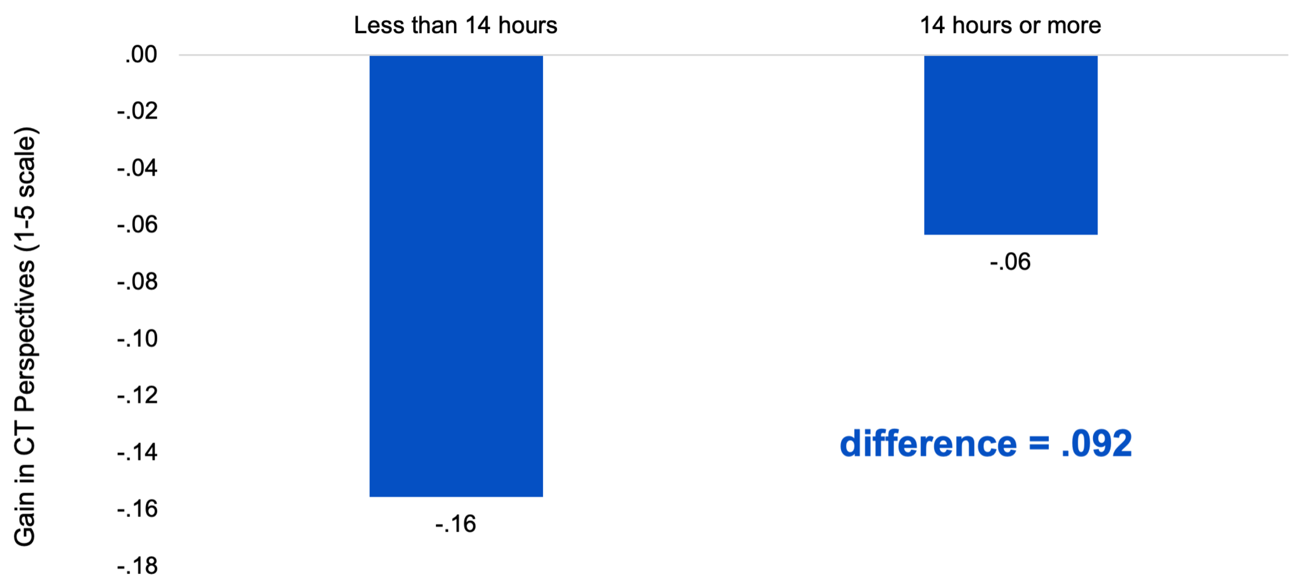
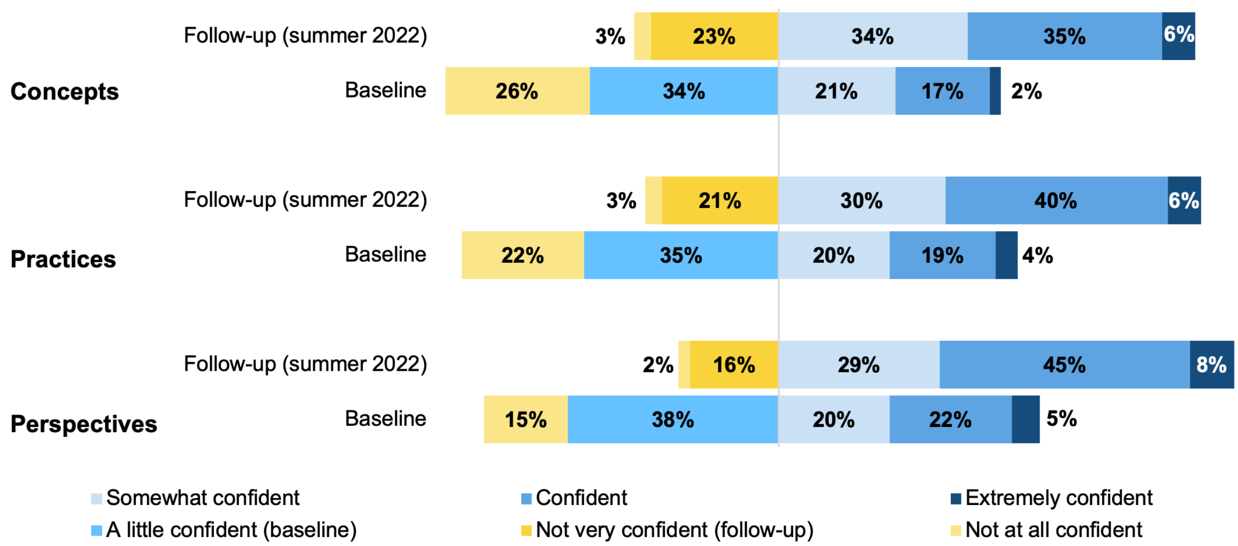


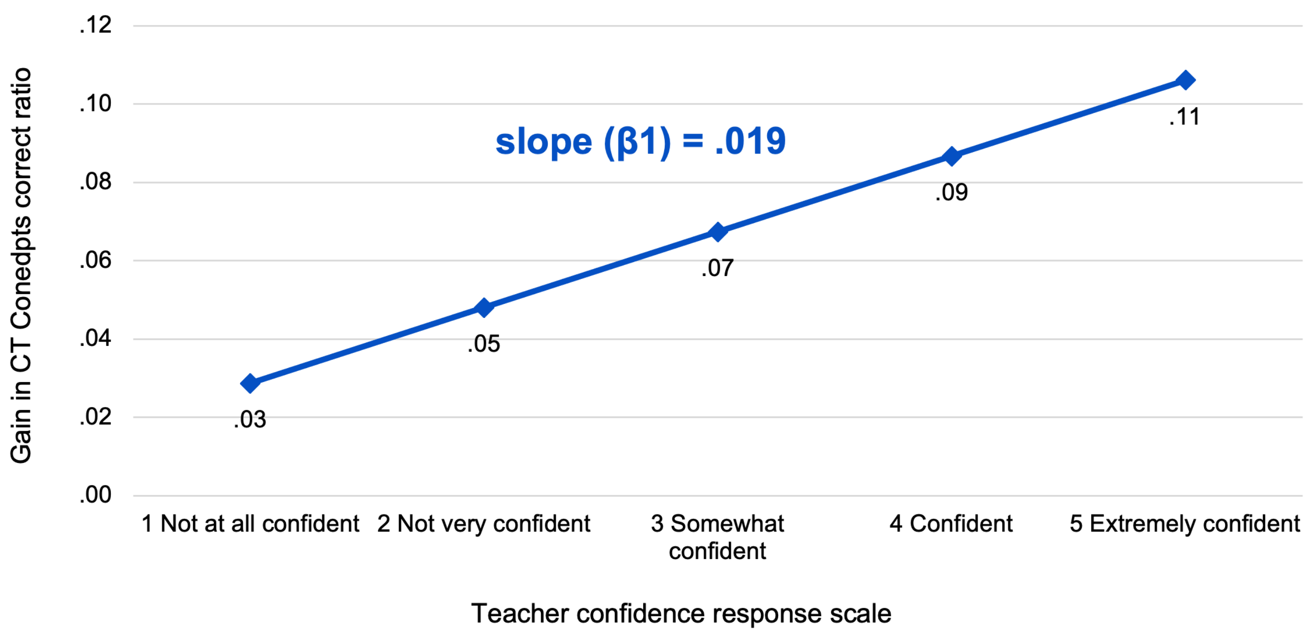
Exhibit A13. How is teacher confidence related to student gains in CT Concepts?

Teacher confidence scale, item-level frequencies



Source: *Cohort 3–4 follow-up teacher survey (summer 2022).*

Regression model of the relationship between teacher confidence and student gains on the CT Concepts assessment



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