Bridging Computational Thinking skill gaps with ASSET and Mindspark CT

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Abstract: This paper analyses findings from the ASSET (Assessment of Scholastic Skills through Educational Testing) Computational Thinking (CT) extension, drawing on data from 8,994 Indian students (Grades 3–10). Despite recent reforms advocating CT in curricula, test scores mostly remain between 30% and 50% across four core domains—logical reasoning, pattern recognition, algorithmic thinking, and data interpretation. We spotlight four representative misconceptions that underscore the need for explicit, domain-focused instruction in Indian K–12. Furthermore, we introduce Mindspark CT, an interactive, theme-based program by Educational Initiatives that uses scaffolded puzzles, coding projects, and real-world data analysis to transform students from technology consumers into creators.

Keywords: computational thinking, skill gaps, diagnostic test, ASSET CT, Mindspark CT

1. Introduction

Computational Thinking (CT) has emerged as a critical 21st-century skill, regarded as fundamental for all (Wing, 2006). Many countries have integrated CT into K–12 curricula; for instance, India's National Education Policy 2020 calls for increased emphasis on mathematical and computational thinking through puzzles and games (NEP, 2020).
However, despite this growing recognition, there is a lack of systematic assessments to gauge students' CT skills at scale. Most CT education efforts focus on coding activities or small-scale evaluations, with few large-scale diagnostics outside of contests like Bebras. As a result, educators have limited data on which CT concepts students grasp or struggle with most. Addressing this gap requires structured assessment tools capable of pinpointing specific student skill deficiencies.
Problem Statement: This study addresses the need for systematic CT assessments by employing ASSET CT, a diagnostic test covering four computational thinking skills—Logical Thinking, Pattern Recognition, Algorithmic Thinking, and Data Analysis—to uncover prevalent skill gaps and student misconceptions among Indian learners.

The research questions we intend to answer are:

a) *Which computational thinking concepts and skills do Grades 3–10 students struggle with the most, as evidenced by assessment outcomes?* and
b) *What common misconceptions emerge from students' responses?*

2. Computational Thinking Assessment Framework (ASSET CT)

ASSET CT was developed as part of ASSET (Assessment of Scholastic Skills through Educational Testing), a diagnostic tool designed by Educational Initiatives to evaluate fundamental academic skills systematically. The ASSET diagnostic tests in Math, English and Science have been taken by over 2 million children since 2005.

2.1 Reliability and Validity of ASSET

ASSET employs single-administration methods—specifically Cronbach's alpha—to ensure internal consistency, with alpha values consistently falling within acceptable reliability ranges of 0.7–0.95 (Nunnally, 1978). ASSET utilizes Item Response Theory (IRT), particularly the 2-Parameter Logistic (2PL) model, to ensure items effectively measure intended constructs. Difficulty parameters beyond ±4, inadequate item discrimination, or poor point-biserial correlations trigger careful review or removal of items.

Although no exact parallel to ASSET exists in India, ASSET scores correlate significantly with international benchmarks. For example, Dubai schools' ASSET scores showed substantial correlations with PISA 2022 results (Reading: 0.81, Math: 0.74, Science: 0.41), underscoring ASSET's validity as a robust diagnostic tool. However, the CT extension of ASSET remains a work-in-progress. Future validation steps, including extensive IRT analyses and continued refinement of CT-specific items, will further enhance its diagnostic precision.

2.2 CT Assessment Framework (ASSET CT)

The design of ASSET CT was informed by key CT frameworks in the literature – notably the programming-focused concepts of Brennan & Resnick (2012), the broader CT facets of Shute et al. (2017), and the K–12 CT practices identified by Weintrop et al. (2016). Our framework defines CT in terms of four main skill categories (**Logical Thinking**, **Pattern Recognition**, **Algorithmic Thinking**, and **Data Analysis**), each subdivided into specific subskills. Based on these existing frameworks, we identified seven core CT sub skills for assessment, spanning traditional programming concepts (e.g. sequencing steps, using conditionals) as well as general reasoning abilities (logical inference, spatial reasoning, etc.).

Each subskill is mapped to an accepted dimension in CT – for example, Brennan & Resnick's coding concepts (sequence, loops, conditionals) , Shute et al.'s six CT facets (**decomposition**, **abstraction**, **algorithm design**, **debugging**, **iteration**, **generalization**), and Weintrop et al.'s emphasis on data and problem-solving practices. By covering a range of subskills, our assessment captures both computational concepts (like sequences and conditionals) and practices (like logical reasoning and pattern identification), consistent with component-based CT assessments in literature (Wiebe et al., 2019). Notably, we include Spatial Reasoning as a subskill given evidence that spatial ability supports CT development (Román-González et al., 2017), even though it is not always explicit in CT curricula.

Table 1. Computational Thinking Skills Taxonomy

ASSET CT Main Skill	ASSET CT Subskill	Brennan & Resnick (2012)	Shute et al. (2017)	Weintrop et al. (2016)
Logical Thinking	Logical Conclusions	Testing & Debugging	Generalization	Problem-Solving Practices
	Problem Solving	Algorithmic Thinking	Decomposition, Debugging	Problem-Solving Practices
Pattern Recognition	Identifying Sequences	Sequences, Patterns	Abstraction	Data Practices
	Spatial Reasoning	Representation	Abstraction	Modelling Practices
Algorithmic Thinking	Sequencing Commands	Sequences	Algorithm Design	Programming Practices
	Conditional Logic	Conditionals, Debugging	Algorithm Design	Programming Practices
Data Analysis	Data Interpretation	Data Representation	Abstraction, Analysis	Data Practices

2.3 Test Structure

Using the above framework, we developed a set of multiple-choice questions targeting these subskills. The test instrument underwent expert review to ensure content validity for each skill area. ASSET CT was then administered in Summer 2024 as a paid diagnostic test to schools across India in Grades 3–10. 8,994 students from 38 schools participated, providing a large dataset of responses. Each student's test was scored by subskill, enabling analysis of proficiency and misconceptions per skill. Below, we present the findings in relation to our research questions.

2.4 Participants

Each grade-level ASSET CT test (Levels 1–4) included 30 multiple-choice items—except Grades 3–4, which had 25. As 115 unique questions repeated across grade-bands, the dataset recorded 230 total "item records." Items emphasized conceptual proficiency (puzzles, stepwise logic, multi-field data) rather than code syntax. To measure item quality, we computed point-biserial correlation (PBC)—higher PBC (>+0.30) indicates stronger discrimination between high- and low-performers (Frisbie, David A. 1988).

3. Skill Gaps and Illustrative Misconceptions

3.1. Grade-wise scores

Table 2 shows the average percentage score, standard deviation, and highest marks per grade. While Grade 10 achieved 52.3% on average—higher than younger grades— scores typically remain in the 30–50% band across grades, confirming widespread CT skill gaps.

Table 2. ASSET CT Performance by Grade (N=8,994)

Grade	Paper Code	Students	Avg. Score	Std. Dev.	Highest
3	73124	1,241	37.8%	17.4%	25
4	74124	1,129	42.7%	18.4%	24
5	75124	1,154	36.8%	14.1%	30
6	76124	1,211	41.2%	16.0%	28
7	77124	1,055	36.2%	14.5%	29
8	78124	1,308	45.1%	17.5%	28
9	79124	1,032	46.5%	17.9%	29
10	7A124	864	52.3%	18.5%	30

While Grades 5 and 10 had some top scorers achieving 100%, these were exceptions. High standard deviations (up to ~18.5%) reflect wide performance variability, indicating that even within the same class, certain learners can excel, whereas many others demonstrate foundational gaps in multi-step reasoning or data interpretation.

3.2. Skill gaps and misconceptions

The ASSET-CT results reveal significant and persistent gaps across the four core computational thinking skills: Logical Thinking, Pattern Recognition, Algorithmic Thinking, and Data Analysis, and their respective subskills. While simple skills showed some improvement across grades, complex, multi-step tasks exposed consistent difficulties. Below, we discuss the results skill by skill, grounding each finding in specific performance data.

3.2.1 Logical Thinking (problem solving and drawing logical conclusions)

In a Grade 3/4 task, students were tasked to determine the total number of people in a line based on dual ranking clues (5th from left, 15th from right). Fewer than 20% answered correctly; even in Grade 8, the correct rate was only about 28%, with many incorrectly adding the ranks without adjusting for overlap. Similarly, in a Grade 7/8 task involving prediction of bucket motion based on gear connections (direct, open belt, cross belt), a large proportion of students selected wrong answers, indicating challenges in tracing multi-step mechanical causality. These patterns reveal persistent gaps in systematically applying multiple logical rules to solve complex problems.

3.2.2 Pattern Recognition (identifying patterns in numbers, shapes and language)

In a Grade 5 question based on Gauss's summation strategy, students were shown the method for adding numbers from 1 to 100 and asked to apply it for 1 to 50. Only about 32% answered correctly. Common mistakes included incorrect calculation of the number of pairs or errors in summing them, suggesting that students struggled to abstract and transfer the demonstrated strategy to a new situation. Similarly, in visual pattern continuation tasks at Grades 3/4, around 30–40% selected the correct next figure, with many wrong choices reflecting focus on surface features rather than understanding the generative rule.

3.2.3 Algorithmic Thinking (sequencing commands and conditional logic)

In a Grade 7/8 problem, students were tasked to guide a robot mouse to collect nuts in a 50×50 grid, issuing forward, turn, and repeat commands. When asked to compute the total number of commands required if the repeat feature was disabled, approximately 30% of students selected the correct answer. Many students missed counting turns as separate commands or miscounted the exact number of cells to traverse, indicating difficulties in breaking down repetitive tasks into explicit step-by-step instructions. Similarly, in a Grade 9 task involving systematic swaps between cards indexed by positions (swap i with i+3), fewer than 32% answered correctly. Students struggled to predict the outcome of iterative step-by-step execution, suggesting challenges in mentally tracing algorithms across multiple operations.

3.2.4 Data Analysis (representation and interpretation)

Students showed modest successes in simple data retrieval but struggled with relational and multi-condition reasoning. In a historical reasoning task, only 38.5% of students could deduce the correct battle date by integrating multiple timeline clues. In a coin-combination puzzle, fewer than 25% identified the correct grouping, revealing difficulty with exhaustive case analysis and elimination strategies. In a GDP graph interpretation, around 30% correctly isolated Germany's peak year, with many students distracted by overall graph height instead of focusing on the specific country's trend. These findings suggest that while students can read basic data points, they falter when deeper comparison, elimination, or cross-referencing is required.

3.3 Performance across skills

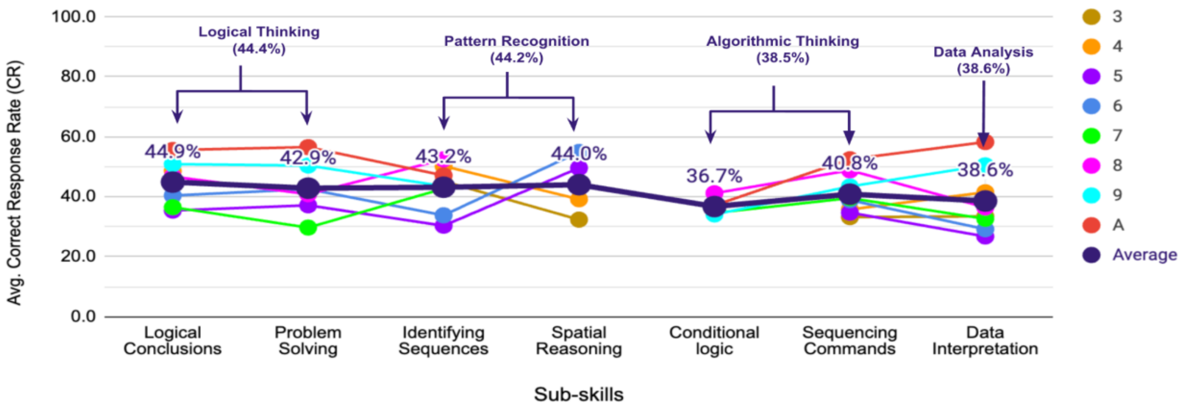

Figure 1. Skill-wise performance across grades 3 to 10. Some grades lack data for certain subskills, e.g., grade 3/4 was not tested on conditional logic problems; grade 9/10 was not tested on spatial reasoning.

Algorithmic Thinking (averaging ~38–39%) and Data Analysis (38.6%) remain the largest gaps overall, whereas Logical Thinking (~43–44%) and Pattern Recognition (~43–44%) perform slightly better. Grade 10 (recorded as 'A') tends to outscore younger grades in most subskills, reinforcing a slow upward trend, but subskills like Conditional Logic remain low across all cohorts. Such tasks require carefully tracing or formulating step-by-step procedures—skills typically not emphasized in standard curricula (Yadav, Hong, & Stephenson, 2016).

4. Future Work: Mindspark CT Intervention and iterations of ASSET CT

To remediate these gaps, a targeted adaptive learning platform called Mindspark CT has been initiated, integrating diagnostic insights directly into instruction. The Mindspark CT pilot provides structured exercises explicitly addressing misconceptions identified by ASSET CT, such as logical reasoning puzzles and conditional logic scenarios. Moreover, detailed item-level validation through advanced IRT analyses is planned for ASSET CT, leveraging now sufficient data from thousands of student responses. This rigorous validation will refine ASSET CT’s capability to pinpoint precise skill gaps further and guide targeted instructional intervention.

5. Conclusion

This study demonstrates the value of systematic assessment of computational thinking in the K–12 context. The findings reveal that many students, even up to grade 10, have not mastered core CT skills such as Data Analysis, Pattern Recognition, and Algorithmic Thinking. These gaps are not unique to a single region but reflect broader challenges in CT education – however, our work provides much-needed data from an Indian and global south context, balancing a literature often focused on western settings.

Although limited by its multiple-choice format and preliminary nature, our assessment establishes a valuable baseline for understanding CT competencies across diverse student groups. Future efforts should focus on iterative refinement of both assessment tools and instructional methods, ensuring that educational practices concretely develop strong computational thinking skills for navigating the challenges and opportunities of the 21st century.

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