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Eliciting Multimodal Strategies: Early CT Assessment by Design

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Abstract: Performance assessments can provide meaningful insights into young children's knowledge; however, documenting assessment responses as incorrect or correct limits our understanding of students' abilities. One method of improving our ability to measure student understanding is by documenting the strategies students use to engage with assessment tasks. In this study, we describe how purposeful assessment design can provide insight into students' thinking by qualitatively examining how students solve performance assessment items using multimodal strategies.

Introduction

Performance assessments allow for documentation of the process used in solving a task and the outcome. For example, the Research-Based Early Math Assessment (REMA; Clements et al., 2019) documents correct and incorrect responses as well as additional student response codes. These additional codes, called strategy codes, provide insight into *why* a student may or may not answer the assessment questions correctly. Accounting for the *strategies* (student performance observables) students use makes it possible to interpret student understanding, not just discrete skills. This paper describes how purposeful assessment design can provide insight into students' thinking by examining how students solve performance assessment tasks using various multimodal strategies. We designed our assessment to measure computational thinking (CT) in early childhood. We begin by describing a design process for building an early childhood CT assessment, then present an analysis of students' strategies in responses to assessment items. Finally, we discuss how students' multimodal strategies allowed us to interpret their CT skill understanding.

Framing perspectives

We used the Evidence Centered Design (ECD) framework to design our assessment, an approach in which designers make explicit the behaviors and evidence associated with specific tasks. ECD is designed around fundamental questions about whom we assess, for what purposes, and under which constraints. The five layers of ECD include: (1) domain analysis, (2) domain modeling, (3) the conceptual assessment framework, (4) assessment implementation, and (5) assessment delivery (Oliveri et al., 2019). In the first two layers, the focus is on the purposes of the assessment, the nature of knowing, and structures for observing and organizing knowledge. In the third layer, the focus is on the student model (the skills being assessed), the evidence model (how do we measure it), and the task model (situations that elicit the behaviors/evidence). In prior work, we have written about the first three layers in our assessment design process (see Clarke-Midura et al., 2021). In the present study, we focus on the conceptual assessment framework (CAF). We designed our assessment to measure early childhood computational thinking (CT), which involves "the conceptual foundation required to solve problems effectively and efficiently…with solutions that are reusable in different contexts" (Shute et al., 2017, p. 151). We view coding as an important context for developing CT and use tangible robot coding toys as a context for promoting CT.

Participants, data, context

Seventy-seven kindergarteners (5–6 yrs.) in two Title 1 schools (n=17, n=60) in the western United States participated in a pilot CT assessment. The interview-based format accounted for kindergarteners' emerging literacy skills and took about 15 minutes to administer. We analyzed video of 77 participants responding to 14 pilot assessment items (approximately 9.5 hours). Students were asked in the assessment to enact, sequence, or debug programs depicted by coding cards in order to move an agent (a small figurine) around a 10"x10" grid. The program codes consisted of four directional arrow commands that instructed the agent to move forward, backward, rotate left, and rotate right. For example, in Algorithmic Thinking item 8 (AT8), children were asked to write a program (FORWARD, FORWARD, ROTATE LEFT, FORWARD, FORWARD) for moving the agent from one point to another as marked on the grid. This current analysis focuses on the *strategies* children used to reach this goal- not the programs or *products* themselves.

Data analysis

To understand students' strategies, we asked two questions: *What strategies do children demonstrate?*, and *Do students use these strategies to engage in the assessment tasks?* We conducted iterative rounds of qualitative analysis of the assessment events. First, we conducted iterative rounds of open coding to systematically document assessment strategies for sub-sets of items designed to measure specific CT components. Next, we applied focused coding to categorize observable indicators and identified three engagement modalities: *gesture and body movement* (G), *interacting with the assessment materials* (M), and *language/sound use* (L).

We observed G strategy indicators in students' head movements, hand gestures, and body orientations. An example of a G strategy is *gestures along path in various parts,* wherein students trace a path with their finger. When exhibiting M strategies, students moved the agent and/or manipulated coding cards. Students using the M strategy *enacting incremental movement* might move an agent in a hopping motion. L strategies provided insight into students' thinking through students' use of directional language (i.e., forward, turn), number words (i.e., two, one more), sequencing language (i.e., first, then), and nonsense sounds (i.e., onomatopoeia, popping sounds).

Some strategies were multimodal, meaning students demonstrated the strategy using two of the three primary modalities. For example, some students used the *make a sound for each enacted movement* by attaching a nonsense sound to each agent movement, combining M and L modalities. We accounted for multimodal strategies by adding the categories *gesture and movement + material use* (G+M), *material use + language use* (M+L), and *language use + gesture and movement* (L+G) (See Table 1).

Table 1
Number of Strategies Categorized as Each Modality

	G	G+M	M	M+L	L	L+G
Total Strategies (*N=33*)	2	2	18	5	5	1
Observed Strategies (*N=26*)	2	2	13	5	3	1

Results
For AT8, students exhibited 26 of 33 pre-identified strategies. The most common strategies were *visually references the path and program* (G; 47% of students), *enacts/builds program in chunks* (G+M; 37%), *enacts with incremental movements* (M; 35%), *enacts program after writing it* (M; 27%), *puts multiple codes on a program at once* (M; 23%), and *tests the program while building it* (M; 15%). All other strategies were each used by 10% (*n*=6) or fewer students. We accounted for the different number of strategies per category by averaging the number of students using each strategy with the strategies/category. The average number of students using G were 17, using G+M were 12, using M were 7, using M+L was 4.7, using L were 5.3, and using L+G was 1.

Discussion
Designing early childhood assessments to elicit students' knowledge through multimodal means allows preliterate learners to demonstrate their knowledge, which may otherwise be inaccessible through traditional assessment measures. For example, a student using the *enacting incremental movement* strategy moved an agent in a hopping motion when enacting a program. By using this strategy, the child indicated an understanding that one code equals one discrete movement, a critical skill for programming in early grid-based CT contexts. Applying an understanding of one-to-one relationship is also a key skill in early childhood mathematics. Only examining a student's final answer limits an assessor's inference of student's knowledge to a single point of evidence whereas connecting strategies to a student's performance provides multiple inference points and a more comprehensive perspective of a student's knowledge. Increasing points of inference is important for implementing equitable assessments with preliterate children and for operationalizing computational thinking in early childhood.

References

Clarke-Midura, J., Silvis, D., Shumway, J. F., Lee, V. R. & Kozlowski, J. (2021). Developing a Kindergarten computational thinking assessment using evidence-centered design: The case of algorithmic thinking. *Computer Science Education, 31* (2), 117-140.

Clements, D. H., Sarama, J. Wolfe, C. B., Day-Hess, C. A. (2019). *REMA—Research-based Early Mathematics Assessment*. Kennedy Institute, University of Denver.

Oliveri, M. E., Lawless, R. & Mislevy, R. J. (2019). Using evidence-centered design to support the development of culturally and linguistically sensitive collaborative problem-solving assessments. *International Journal of Testing, 19*, 3, 270-300.

Shute, V. J., Sun, C., & Asbell-Clarke, J. (2017). Demystifying computational thinking. *Educational Research Review, 22*, 142–158. https://doi.org/10.1016/j.edurev.2017.09.003