# Comparing Cognitive and Sociocultural Assessments of Learning in Middle School Computer Science

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**Abstract**: As K-12 Computer Science becomes a mainstream subject, there has been recognition of a need for dialogue between various theoretical framings of learning. However, even in research showing the importance of sociocultural factors, quantitative assessment of Computer Science learning has been predominantly cognitive. This study presents an example of how quantitative assessments of learning, based on cognitive and sociocultural framings of learning, can be put into dialogue by developing measures of learning on internal individual terms and understood as participation in a community of practice. We develop two participation-based constructs assessed using methods from learning analytics, and show that each is significantly associated with better performance on a cognitively-based summative assessment of computer science content. These associations are mediated by the content of students' programs. Beyond serving as contextual factors for cognitive assessments, we propose treating these constructs as primary evidence of learning.

**Keywords**: computer science education, computational literacy, learning analytics, sociocultural learning

### Introduction

As Computer Science education becomes a mainstream subject in US K-12 schools, questions have emerged about the essential nature of the discipline, how learning should be framed and assessed, and who should participate in making these decisions (Proctor, Bigman, & Blikstein, 2019). These questions are grounded in the recognition that computer science has historically been an exclusive subject, a desire for high-quality and rigorous implementations, and an awareness that schools are contested and political spaces which often serve some of their stakeholders better than others. In response, efforts such as the K-12 Computer Science Framework (2016) have attempted to synthesize a consensus definition, while others have categorized the various visions and justifications for Computer Science (Vogel, Santo, & Ching, 2017; Blikstein, 2018).

If educational research is to contribute fully to the design and implementation of K-12 Computer Science education, we need to articulate these theoretically-grounded visions into methods of characterizing and measuring learning. To date, there is a substantial body of research showing the need for sociocultural and critical framings of learning in computer science, but this research has still tended to measure learning on cognitive terms. In this paper, we develop an approach to measuring Computer Science learning based on a sociocultural framing using methods from learning analytics. Kafai, Proctor, & Lui (2019) stressed the need for dialogue between multiple theoretical approaches to learning in Computer Science education research. Here, we take the next step of creating dialogue between evidence of learning grounded in cognitive and sociocultural framings of learning.

# Background

#### Assessing learning in K-12 computer science

Despite its roots in Constructionism (Papert, 1980), recent Computer Science education research has been dominated by a cognitive paradigm. That is, assessment of Computer Science learning has tended to assume that the nexus of learning is "the individual mind in isolation, context-free problem-solving and mental representations and reasoning" (Tenenberg & Knobelsdorf, 2014, p. 1). In this framing, assessments would ideally be validated as consistently measuring students' mastery of content regardless of context (Tew & Guizdal, 2011; Tew & Dorn, 2013). Among the minority of computer science education assessments which are validated, most have a cognitive framing (McGill, Decker, McKlin, Haynie, 2019). This approach aligns well with the infrastructure of policy and research, as learning outcomes can be taxonomized a priori, programs built around these goals, and measures based on these outcomes can be used to compare different approaches with a common target.

Equity-oriented research, aimed at addressing computer science's legacy of stereotypes and structural barriers to participation, has in contrast often adopted sociocultural and critical framings which center students' relationships to context and the power relationships mediating their access to learning opportunities, opportunities

to participate, and ability to convert learning into subsequent opportunity. These framings tend to see learning in terms of participation (Burke & Kafai, 2012), identity-building (Shaw & Kafai, 2020b), and critical computational action (Tissenbaum et al., 2018). The empirical work in this area has shown the importance of sociocultural factors. For example, Fields, Vasudevan & Kafai (2015) studied a collaborative approach to support interest-driven creation of digital media through observations, interviews and programming artifacts. Çakır et al. (2017) investigated the impact of a game-design workshop on girls' attitudes towards computing through surveys and focus groups. Grover, Pea, and Cooper (2014), Friend (2015) and Hansen et al. (2017) examined how youth perceive computer scientists using surveys and drawings. However, when so-called non-cognitive constructs are included in empirical research, they are typically used as contextual factors influencing achievement and learning as measured by other assessments, rather than as prima facie evidence of achievement and learning (McGill, Decker, McKlin, Haynie, 2019).

### **Computational literacy**

Computational literacy has been proposed as a construct capable of accommodating multiple theoretical framings of Computer Science learning (diSessa, 2001; Jacob & Warschauer, 2018). We view computational literacy as community of practice in which interactions between readers and computational texts (e.g. computer programs and artifacts implemented with code) play a central role. As such, computational literacy offers multiple levels of analysis at which to study various framings of learning. A cognitive approach can study how individuals master skills and knowledge. A sociocultural approach might study the development of community practices, and the trajectories of individuals within them. And a critical approach might consider how different forms of practice, including formal computer science, informal computing, and other literacies, come to be seen as legitimate and important. While the present study does not address identity directly, all three approaches have implications for the development of computational identities (Shaw & Kafai, 2020b). There is a dialogic relationship between a literacy place (Dourish, 2006) and the kinds of identities which are recognized and welcome, between potential audiences and the possibilities for authorship (Bakhtin, 1981; Gresalfi & Hand, 2019). This study considers a literacy-based approach to Computer Science which explicitly seeks to take advantage of these dynamics at multiple levels to create learning opportunities.

We rely on methods from Social Learning Analytics, which quantify situated social interactions (Shum & Ferguson, 2012), to describe and measure learning in social context. Learning analytics have previously been used to study the trajectories of learners in Computer Science and related fields (Worsley, 2018; Proctor, 2019). Several recent reflections on the future of the learning sciences have emphasized the potential of learning analytics to capture fine-grained accounts of learning trajectories and to analyze it at scales which are infeasible for qualitative methods alone (Shaffer, 2017; Sommerhoff, 2018).

# Context

This research was set in "Riverton," a small city in the American midwest where the first author collaborated with a sixth-grade computer science teacher on a ten-week curriculum unit using a literacy-based approach to teaching introductory computer science. The students had computer science for an 80-minute block period two or three times a week, for a total of 27 hours of classroom time for each student. The school's students are reported as 57% white, 25% black, and 10% two or more races. 55% of students are eligible for free or reduced lunch and the school is in the tenth percentile for state test results. Of 149 students across six sections, 50 participated in this research. Very few had prior exposure to computer science. Beyond these demographics, we collected surveys, reflections, fieldnotes, and extended interviews with focus students.

The unit was taught using a web application called Unfold Studio (Proctor & Blikstein, 2019) providing an environment for interactive stories. These are prose-based computer programs which implement single-player interactive narratives in the style of choose-your-own-adventure books or narrative games (see Figure 1). The site allows authors to publish stories, search for, read, and comment on peers' stories, and to follow other users via a feed which has many of the affordances of social media. Using Unfold Studio, classroom time was organized as writer's workshop, reading and writing each others' stories. The curriculum introduced computer science concepts alongside writing craft lessons and scaffolding critical action through identity authorship and voice.

Figure 1 shows the code (left) and the running story (right) of "Egg Hatching Simulator," a story by zdev (a pseudonym chosen by the student). In this game the player hatches new pets from eggs, inspired by Pokémon. While it is not necessary to read the code in detail, the code does illustrate two elements of syntax which will be analyzed later. Divert statements (->) redirect the story's flow to another part of the story. Lines beginning with a tilde (~) contain code which interacts with the execution environment, rather than emitting story output. Most often, code lines are used to manipulate state: initializing, updating and checking variables to keep track of what has happened in the story.

"Literacy App" Browse stories Books New Story	Groups 26 (Blinded) [Log out				
Egg Hatching Simulator by zdev <3 2 [Replay] [Hide code] [Fork] [History/Comment]					
<pre> openegg5 You open the egg. ~ luck = random()</pre>	What egg do you want to hatch?				
{ - luck > 0.999:	SEASONAL Harvest				
Soo, this is the secret pet. You got an <h2>Electric Shock.</h2> This is not meant to be in the game yet. If you hatch this and have proof	You open the egg.				
EXAMPLE: Take Screenshot. Come find me, i will give you 10 Bear Paws.! →ending - luck > 0.71:	You got a Common Pet				
~ rare_pets += 1 <font color="6C3483"> YOU GOT A MYTHICAL! - luck &gt; 0.61:</font>	Welcome to egg hatching simulator				
<pre>~ rare_pets += 1 You got a <font color="D68910"> Legendary! - luck &gt; 0.3:</font></pre>	What egg do you want to hatch?				
You got a <font color="3498DB"> Rare Pet. - else: You got a <font color="000000"> Common Pet</font></font>	Uncommon				
} > intro	Rare				
ending ==== If you made it to this, the Ending you are the luckiest person ever. The chances of hatching this were 1 in 1,000 (I think)	Legendary				
Props to you!!!!! ################################	SEASONAL Harvest				
elp About For Teachers					

Figure 1. A screenshot of Unfold Studio, showing zdev's story "Egg Hatching Simulator."

The code excerpt in Figure 1 generates a random number between 0 and 1 and then cascades through cases to determine which pet the player receives. If the random number is above 0.999, the player sees "Soo, this is the secret pet. You got an <h2>Electric Shock.</h2> This is not meant to be in the game yet. If you hatch this and have proof EXAMPLE: Take Screenshot. Come find me, i will give you 10 Bear Paws.!" The story then redirects to the ending, which outputs, "If you made it to this, the Ending you are the luckiest person ever. The chances of hatching this were 1 in 1,000 (I think)...... Props to you!!!!! **\*\*\*\*\*\***." This text would indeed be shown as output one time in a thousand. Therefore, this text is likely intended to be read by peers who choose to read the game's source code in addition to playing. Important computational concepts are expressed and framed in the context of speaking to an audience of gamer-programmers, as insiders in-the-know. In positioning the player as being extremely lucky ("1 in 1,000"), zdev makes a probabilistic assertion grounded in a fairly complex code structure, and does so in an interactional context which positions him as an authoritative explainer and the reader as an interested colleague. In the rest of this paper we argue that these literacy interactions, in which students are positioned as authors and as audience, were the basis for a kind of computer science meaning-making for and with others. We explore two research questions:

- 1. Is participation in interactive story-based literacy associated with computer science learning grounded in a cognitive framing?
- 2. If so, is this association mediated by individual student practice in writing their own stories?

#### **Methods**

In this study, we compare two approaches to analyzing students' learning: via a summative, cognitive-based assessment of a student work artifact, and via students' participation using their interaction with others' stories as captured in the app's activity logs. We also conduct static program analysis of the content of students' stories.

#### Summative assessment

At the end of the unit, each student submitted a portfolio of their two best stories: one that showed off their technical skills and one that showed off their storytelling skills. In this paper, we consider only the technical skills submission. These stories were assessed according to a rubric (see Table 1). Students were familiar with the rubric from in-class activities and from feedback on drafts. The technical skills rubric emphasized two concepts: flow and state. These objectives correspond to the *K-12 CS Framework*'s Algorithms and Programming concepts of "Control" and "Variables" (2016). The distribution of students' scores on this assessment (flow and state combined) was roughly normal, with a mean of 4.22 and standard deviation of 2.01.

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Level	Flow criteria	State criteria	
Advanced (4 points)	Meets criteria for Proficient AND use of flow adds meaning to the story. Uses an advanced flow control structure.	adds meaning to the story. Uses an adds meaning to the story. Uses at least one	
Proficient (3 points)	Uses diverts correctly and meaningfully to control story execution.	Uses variables (either built-in or declared) to keep track of something in the story and using it to change what happens in the future.	
Basic (2 points)	The use of flow might be based closely on another story. The use of flow might "check the boxes" but not have much effect on the story. May include minor errors in usage.	The use of state might be based closely on another story. The use of state might "check the boxes" but not have much effect on the story. May include minor errors in usage.	
(1 point)	Does not meet criteria for Basic.	Does not meet criteria for Basic.	

# Literacy events

We operationalize literacy events as actions taken by users in the process of reading and writing stories, as well as browsing, searching, following other users, and commenting on stories. In this study, we consider only those literacy events in which one user views, loves, or forks (makes a copy of) another user's story. These interactions feature two important, reciprocally-connected roles, those of author and audience. As described in the background, we view these as important learning opportunities within a literacy place grounded in, but extending beyond, the classroom. Each literacy event can be considered as a link in a bipartite network of authors and stories. We define a user's author score as the number of literacy events in which another user interacted with one of the user's stories. Similarly, a user's audience score is the number of literacy events in which that user interacted with a story written by another user. Figure 2 shows a histogram of participants' author and audience scores.

Thirty of the fifty study participants have author scores of zero because they chose not to make any of their stories publicly visible to their peers. (While this group wrote fewer stories on average than authors with positive author scores, they still wrote an average of 8 stories.) Note that the sums of all author and audience scores are not equal because these scores consider interactions with all Unfold Studio users. Some participants wrote stories which became popular on the site beyond the classes involved in this study, and they were occasionally inspired by stories written by external authors. For example, a student at another school wrote a story in which the player walks through an imagined monument to LGBTQ heroes from history. Several students referred to this story as influencing their own planning and writing.

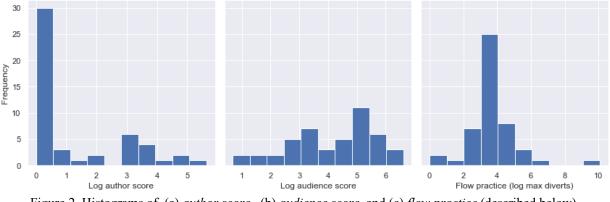


Figure 2. Histograms of (a) author score, (b) audience score, and (c) flow practice (described below).

#### Stories

Finally, we consider the content of students' interactive stories, which are the primary artifacts created on Unfold Studio. Over the course of the unit, the 48 authors participating in the research wrote 640 stories. In this study, we conduct static program analysis of the code from the final state of each story. (The left pane in Figure 1 shows an

excerpt of a story's code.) Following a common strategy of counting syntactic elements which map to concepts (e.g. Brennan & Resnick, 2012; Fields, et al., 2016), we count the use of syntactic elements which correspond to flow and state, the two primary content knowledge goals of the unit.

We chose to count the number of diverts in each story as a measure of practicing flow. An interactive story can be visualized as a directed graph, where each knot, or chunk of textual content, is connected to other knots by edges. Each divert (->) implements an edge, so the number of diverts in a story corresponds to the number of edges in its story graph. We defined a students' *flow practice* score as the logarithm of the maximum number of diverts in any of an author's stories. (Using the sum across an author's stories would be artificially inflated when authors repeatedly forked their own stories, and using an average would be artificially deflated for authors who made numerous throwaway stories for notes or to test out constructs.). We conducted a similar analysis for stories' use of state which will be reported in a subsequent publication.

### Results

Our first research question asks whether there is an association between participation in the literacy place, either as author or as audience, and performance on the summative assessment. Using standard OLS regression, we found a statistically-significant association between both author and audience scores and summative performance. Plots of these associations are shown in Figure 3 and regression tables are shown in Table 2. We additionally tried several models including measures of students' prior interest and experience with Computer Science and English/Language Arts (using the survey from Proctor & Blikstein (2019)). These covariates both had statistically-significant associations with summative performance. However, when they were added to the models shown in Figure 3 and Table 2, author and audience scores remained statistically-significant and their coefficients did not change much. Therefore, we do not include these covariates in the following results.

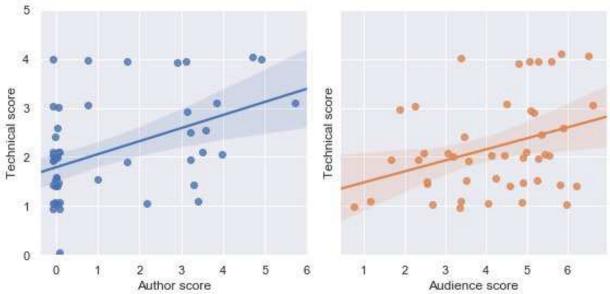


Figure 3. Regression plots showing association between summative technical score and (a) *author score* and (b) *audience score*. Shaded bands indicate standard error of the model's intercept and coefficient.

Figure 3 shows the positive association between technical score and both author score and audience score. Students who participated more in the literacy place, as authors and as audience, tended to have higher scores on the summative assessment of Computer Science content. *This suggests that writing for an audience, as well as participating as an audience of others' work, was associated with better performance on the technical summative assessment.* There was a substantial correlation between author score and audience score ( $r^2 = 0.36$ ), which explains the collapse of model (3) in Table 2 due to collinearity. In other words, students with high author scores were reasonably likely to also have high audience scores. Intuitively, this is not surprising, as we hypothesize that these are reciprocal, dialogic relationships.

Table 2: Regression table for summative technical score (\*: p<0.1; \*\*: p<0.05; \*\*\*: p<0.01)

Author score	0.241*** (0.081)		0.170* (0.101)
Audience score		0.202** (0.092)	0.083 (0.115)
Constant	1.797*** (0.163)	1.317*** (0.407)	1.601*** (0.432)
Observations	49	45	45
adjusted r^2	0.139	0.079	0.117
Residual Std. Error	0.937 (df = 47)	0.914 (df = 43)	0.895 (df = 42)
F Statistic	8.773*** (df = 1; 47)	$4.780^{**}$ (df = 1; 43)	3.918** (df = 2; 42)

# Mediation by story content

Having found an association between literacy participation and summative score, we further hypothesized that this association was mediated by the content of authors' own stories. Our intuition was guided by cases like zdev's, where authors either read and were inspired by other stories, or where authors were motivated by potential readers to make their stories technically sophisticated, elegant, and/or understandable. (Several authors published stories which served as tutorials, for example explaining to their peers how and why they should use variables in their stories.) The *flow practice* and *state practice* variables capture the extent to which authors used these concepts in their stories. Due to space constraints, we restrict our mediation analysis to *flow practice* as potentially mediating the association between *author/audience score* and summative technical score.

Following Baron & Kenny's (1986) method for mediation analysis, we show that the association between *author/audience score* and summative technical score is significant, that the association between *author/audience score* and *flow practice* is significant, and that effect size for *author/audience score* is reduced when *flow practice* is added to the model. We used bootstrap significance testing as implemented in the R mediation package (Tingley, Yamamoto, Hirose, Keele, & Imai, 2014), using the default value of 1000 simulations. The results, shown in Table 3, indicate that *flow practice* significantly mediates both relationships. Almost half (0.464) of the association between *author score* and summative technical score was mediated by *flow practice*, as was almost three quarters (0.721) of the association between *audience score* and summative technical score. This corresponds with the Vygotskian intuition that social practices are internalized through performance.

	Author score	Audience score
Average causal mediation effect	0.0982***	0.1512***
Average direct effect	0.106	0.0464
Total effect	0.205***	0.1976**
Proportion mediated	0.464**	0.721**

Table 3. Analysis of flow practice as mediating the association between author score and summative technical score, and audience score and summative technical score. (\*: p<0.1; \*\*: p<0.05; \*\*\*: p<0.01)

# Discussion

In this paper, we have shown that literacy participation, as an author and as audience, was associated with better cognitive performance on a summative assessment of Computer Science content. Furthermore, we showed that both associations were mediated by *flow practice*, a measure of students individually engaging with computer science concepts in their own stories. These results demonstrate how quantitative assessments of learning, based on cognitive and sociocultural framings of learning, can be put into dialogue. In addition, the results also support our broad hypothesis that a literacy-based approach to introductory Computer Science can be an effective learning environment. *The fact that these results were not substantially affected by the inclusion of covariates measuring* 

students' prior interest in Computer Science and writing suggests that this approach could be particularly effective for broadening participation in computing practice. Indeed, in the exit survey (not analyzed here), numerous students related that they had not expected to enjoy programming.

Even though these associations remain when controlling for prior interest in Computer Science and English/Language Arts, it is possible that we have missed hidden variables accounting for both students' participation and their scores on the summative assessment. Moreover, we have so far only provided a sketch of an argument for these results' external validity. Our next steps will involve rigorous qualitative analysis showing that the measures used here accurately describe students' experiences of participation and learning.

In the course of this analysis, we developed *author score* and *audience score* as measures of participation in the classroom literacy place. The results show alignment between a traditional cognitive (or competency-based) measure of learning, and two measures based on students' participation in a community of computational practice. In future research, we intend to center participation in a community of practice as a primary form of learning, producing quantitative measures which can be held up against cognitive assessments. The challenge then will be to justify that the participation, the community of practice, and participants' enacted identities are legitimate forms of Computer Science. We do not envision a reconciliation or unification of cognitive and sociocultural approaches (e.g. Billett, 1996); rather our goal is to highlight the tradeoffs of each approach and possibly displace cognitivism as the default presumed to be most legitimate. Social learning analytics combined with qualitative analysis will be invaluable tools in this task, as they will provide a high-granularity view of the nature of students' practice. It seems likely that *author* and *audience scores* are a coarse view on emergent dynamics in students' trajectories of participation; our future research will further explore these dynamics.

### Conclusion

As K-12 Computer Science continues to develop and mature, we need dialogue between multiple theoretical framings of learning. However, if this research is to impact policy and practice, we also need ways of measuring and evaluating research based on these different framings. In this paper, we present evidence for a literacy-based approach to introductory Computer Science education, as well as an example of how research framed in terms of literacy could integrate quantitative assessments of learning based in multiple theoretical frames.

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