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Reasoning about data in elementary school: student strategies and strengths when reasoning with multiple variables

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ABSTRACT
The need for data literacy is an increasingly pressing priority in society, but most of the work in data-centred education has focused on developing skills at the middle school, secondary, and post-secondary levels, with little attention on the potential for engaging elementary-aged students in reasoning with and about data. This paper reports findings from a foundational study to explore the natural strengths, skills, and strategies that upper elementary students bring to reasoning about data-centred problems. It was the first phase of a project that aimed to design and test activities to promote data literacy among upper elementary students. Clinical interviews with students in grades 3, 4, and 5 centred on a series of non-mathematical data 'scenarios' designed to elicit students' reasoning about data without requiring them to manipulate or interpret tabular or graphical representations. The findings indicate that young students were able to reason about multivariate problems and were particularly adept at thinking critically about the data sources and evidence in the data. The findings indicate that students bring foundational strengths that can inform the development of curricular interventions, as well as stimulate further research into the early stages of students' development of data literacy.

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Introduction

Data literacy has become essential to an ever-broadening array of professions, as more careers and fields require the ability to work with, interpret, and think critically about a variety of types of data (Association of American Colleges and Universities [AACU], 2011; National Academies of Sciences, Engineering, and Medicine [NASEM], 2018; ODI, 2016). Innovations in data collection and infrastructure technologies in scientific research are making increasingly large, and complex data sets more immediately and widely available. The potential for rapidly expanding access to such data is transforming how we live and work, and at a minimum, there is a need for every person to be a skilled

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reader and critical consumer of data (Kastens et al., 2015; Louie, 2022). Given the importance of data literacy, educators and scholars recognise the need to identify and develop in students the skills needed to think critically about and work productively with data (Engle, 2017; Kastens et al., 2015; Wolff et al., 2016).

To date, much of the work in data-centred education has focused on supporting middle and high school students in learning about content through work with large, complex, and/or professionally collected data sets (e.g. Gold et al., 2015; Kochevar et al., 2015; Rubin, 2021; Vahey et al., 2012). With the exception of research of statistical reasoning (discussed below), there has been relatively little exploration of data literacy development with elementary-aged students. Although some early efforts to incorporate data-centred learning experiences in early grades have found ways that these students can develop and refine key skills for thinking about and working with data (English, 2012; Wolff et al., 2015), this remains a relatively big gap in the educational research landscape.

Frameworks of data literacy

As a relatively new area of exploration, there is no clear consensus of a single framework for data literacy or its underlying skills; instead, a number of frameworks have emerged. One perspective of data literacy draws upon statistical education literature, which has long studied the development of students' statistical reasoning (Ben-Zvi & Garfield, 2004; Konold et al., 2015; Konold & Higgins, 2002). Rubin's (2020) recent review of this literature positions five well-researched statistical literacy concepts as essential components of an emerging data literacy framework, including contextualising data, considering variability, aggregate views, visualisation for sense-making, and drawing inferences.

Others have taken a broader lens, looking at data skills used across the life cycle of an inquiry. This includes statistical literacy and extends to skills of engaging in scientific inquiry with data (e.g. problematising, planning, collecting or acquiring data, constructing explanations, and evaluating explanations), as well as data management skills and ethical considerations (Herschel & Miori, 2017; ODI, 2016; Wolff et al., 2016). A related perspective emphasises data literacy needing to include skills for grappling with the complexity and 'messiness' of data, particularly the types of big data that are increasingly available and of concern in discussions of data science education (Erickson, 2022; Kjelvik & Schultheis, 2019). From this perspective, data literacy requires the ability to work with large amounts of multivariate data (including more data than are necessary to answer a given question), grappling with their complex properties, and actively selecting, organising, and manipulating data to answer questions. This definition emphasises the need for computational thinking and computer science skills.

Several scholars have proposed integrating these frameworks to position data literacy at the centre of a Venn diagram representing the intersections of mathematical or statistical skills, computational thinking or data science skills, and disciplinary content knowledge (Conway, 2011; Finzer, 2013; Kjelvik & Schultheis, 2019). A critical attribute of this integrated framing is placing content understanding as a key piece of data literacy, highlighting the importance of applying knowledge about the subject matter and data's context in order to effectively identify and evaluate relevant data, interpret patterns within data, and draw conclusions (Figure 1(a)).

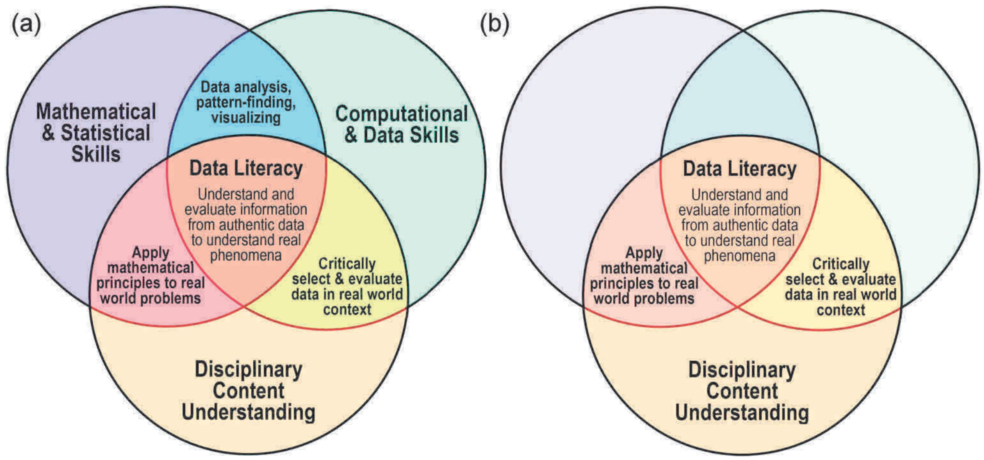

Figure 1. (a) Full integrated framework of data literacy (adapted from Kjelvik and Schultheis (2019) and Finzer (2013)); (b) Focused framework used for this study.

Adapting the integrated data literacy framework for elementary grades

We needed to further adapt this integrated data literacy framework, which was designed to encapsulate the full spectrum of adult-level skills of data science, for our inquiry into foundational data literacy skills in young students. We grounded our research in a narrowed version of the framework to account for the fact that young students are still mastering fundamental mathematical concepts (CCSSI, 2010). Our adaptation (Figure 1(b)) focused on the data literacy skills that intersect with subject area content understanding, while de-emphasising specialised mathematical knowledge and computational abilities. This focused framework minimised emphasis on the mechanics of collecting, manipulating, or processing values contained in data or data representations, while maintaining a focus on skills that involve thinking about data as ways of characterising objects and events in the natural world and of connecting scientific phenomena with data that represent them. Further, for application within a science classroom, considering data literacy skills as they intersect with disciplinary understanding was a promising approach for academically meaningful explorations that teachers would find relevant to their goals (and curriculum standards) for science education.

This narrower framing does not neglect quantitative reasoning but emphasises applying broad mathematical principles to real-world problems using critical thinking and logic (Kjelvik & Schultheis, 2019), without relying on precise mathematical operations or familiarity with rational numbers. Similarly, this framing does not neglect computational and data skills (the third element of the framework) but focuses on skills of evaluating and thinking critically about data collected by someone else, for example, assessing the source of data, understanding their limitations, and recognising what data can and cannot tell you about phenomena of interest (Rubin, 2021), rather than skills of data manipulation for quantitative pattern-finding. We posit that students can, and should, be developing the foundational skills of this narrower framework to combine content understanding, quantitative thinking, and data-centred reasoning from early in their schooling. Through this lens, educators would benefit from greater understanding of how students use and reason with and about data when they are relieved from both the demands for mathematical computation and decoding the symbols and graphic language of data representations. This understanding could inform the development of curricular interventions, as well as stimulating further research directions about the early stages of students' development of data literacy.

Creating non-mathematised problems to elicit reasoning

Our research aim was to explore the reasoning skills that elementary students apply, unassisted, to engage with complex, open-ended problems involving familiar and concrete representations of data – images, photographs, objects – rather than mathematical, symbolic, or graphical representations of data. As students in early grades are still learning mathematics and conventional graphic representations of data (Konold et al., 2015; Lehrer & Schauble, 2004), data-centred tasks that rely on mathematical understanding or conventional data representations could mask students' actual abilities by implicitly requiring mathematical literacy. We wanted to understand young students' underlying abilities to reason about contextualised data in their environments (e.g. Engle, 2021; Gopnik, 2012), disentangled from abilities to read or manipulate conventional data visualisations and representations. This was a first stage in a larger research and development project that aimed to develop classroom activities and supports to engage young learners to build data literacy skills by working with professionally collected (rather than student-collected) data.

Therefore, our research question was: What analytical thinking approaches do students spontaneously use when making meaning from data presented through familiar representations and with minimal adult scaffolding? Based on the literature, we identified three key attributes of data problems that would allow students to demonstrate their natural strengths, proclivities, and limits when it comes to reasoning through complex data. These attributes guided our development of research stimuli to maximise access to students' data-centred reasoning.

Reducing the potential influence of a mathematical literacy barrier

Research has shown promise in developing young students' abilities to make sense of the relationship between observed phenomena and identifying a quantitative measurement that would operationalise that phenomenon for inquiry. To date, this success has largely relied on students designing their own inquiry, variables, and measurement strategies (Lehrer & English, 2018; Manz, 2018). Because we were interested in young students' abilities to make sense of data collected by *others*, we wanted to consider that a lack of some fundamental mathematical literacy could obfuscate otherwise comprehensible relationships if data were expressed primarily by numbers. This issue pointed to the need for data problems that did not represent data with traditional science or mathematics representations, but presented students with data that represented the underlying phenomenon directly, concretely, and in familiar formats. We anticipated exploring students' responses to conventional, quantitative representations of data in a subsequent study.

Problems without clear answers

Data literacy requires the ability to reason through complex variables, conflicting information, limitations of the data source or collection method, and draw interpretations that address uncertainty and consideration of many potential solutions or interpretations (Erickson, 2022; Finzer, 2013). Research has shown that children as young as three can accurately isolate causally relevant variables in a multivariate problem when the problem has a single correct solution (Goddu & Gopnik, 2020), so it was important that the data problems we presented to students introduce complexity and uncertainty regarding potential solutions – qualities which have also been shown to encourage students to engage in reasoning and argumentation (Manz, 2014).

Grounding problems in accessible contexts

Students are more likely to persevere at data-centred investigations when they are able to connect to and find personal relevance in the work (Vahey et al., 2012; Wolff et al., 2019). This study was focused on Earth science data, which connects to many aspects of the natural world that children can observe and experience, such as weather, stream flow, and erosion; it is also a relevant content area for curricula in upper elementary grades in the United States (NGSS Lead States, 2013). Moreover, such phenomena lend themselves to data questions that can reveal complex, multivariate systems and relationships that manifest in highly familiar, observable ways within the natural world, even for young learners.

Method

We used the attributes described in the above section (i.e. reducing mathematical literacy barrier, creating problems without clear answers, and grounding in accessible contexts) to develop a series of data scenarios, representations, and an interview protocol to guide one-on-one conversations with students about their interpretations of the data and accompanying reasoning. First, we identified rainfall as an Earth science phenomenon that met the criteria of being complex and multivariate, as well as familiar, observable, and relevant to students. Rainfall is a phenomenon that students encounter regularly (particularly in the Mid-Atlantic region of the United States) and would have experienced its many variations – in intensity, duration, and interaction with objects in the physical world (e.g. when rain hits a roof, overhang, or tree the surface diverts the rain and can keep people or objects underneath dry or drier than if they were uncovered).

Second, we represented data in formats familiar to students, using a set of images, labelled with non-technical language to introduce each new variable in the scenarios. Independent variables included *intensity of rainfall* (photographs of rain events at several intensities, labelled as heavy, medium, or light); *duration of data collection event* (labels of half hour, 1 hour, and 2 hours); and *interaction of rainwater collector with the physical world* (photographs of an empty drinking glass placed to collect rainfall on pavement, on soil, and under branches of a bush). Rather than represent the dependent variable (amount of rainfall collected) quantitatively (as with a graduated cylinder or rain gauge), it was represented by photographs of the same drinking glass with water at different levels (low, medium, high). Images used in the student tasks are shown in Figure 2.

Figure 2. Images and labels used with students during interviews.

The interview probed students' thinking as they were presented with a series of four scenarios, which asked them to apply their knowledge of rainfall to the provided photographic data related to rain intensity, rain duration, and placement of the glass to collect rain. The first scenario asked students to match levels of water (dependent variable) with only one independent variable, intensity of rainfall. This was used to verify that students were able to reason through the fundamental conceptual relationship between rain intensity and rain capture. The interview then presented a sequence of three multivariate scenarios (outlined in Table 1), which gradually increased in complexity, introducing new

Table 1. Details of the four scenarios and variables presented to each student.

Scenario	Each child's rainfall collection conditions (independent variables in the scenario)			Question (dependent variable)
	Anne	Bobby	Cara	
1: Intensity	• Light Drizzle	• Steady Rain	• Heavy Rain	With everything that we know from these pictures, which child do you think collected which glass of water? (low, middle, high)
2: Intensity & duration	• Light Drizzle • One hour	• Steady Rain • Two hours	• Heavy Rain • Half hour	
3: Intensity & collection site	• Light Drizzle • Glass set on pavement	• Steady RainGlass set under a leafy bush	• Heavy Rain • Glass set on soil	
4: Intensity, duration, & collection site	• Light Drizzle • One hour • Glass set on pavement	• Steady Rain • Two hours • Glass set under a leafy bush	• Heavy Rain • Half hour • Glass set on soil	

independent variables with conflicting effects on the dependent variable (e.g. high intensity rainfall occurring for the shortest amount of time). Scenario 2 asked students to consider rain intensity with rainfall duration. Scenario 3 asked students to consider rain intensity with the site chosen for rainfall collection. Scenario 4 asked students to consider all three independent variables together. Because data were not quantified, the scenarios allowed for multiple paths of reasoning about possible interactions of the independent variables in drawing conclusions about the dependent variable. In addition, the scenarios provided an opportunity to consider uncertainty and articulate limitations of the data provided.

Participants

Forty-five students, evenly distributed across grades 3, 4, and 5, participated in the study. The students were drawn from three partner schools, each located in a different school system in the Mid-Atlantic region of the United States. Two were rural schools (School A and School B) and one was an urban school (School C). Ultimately, 14 interviews were conducted at School A, 15 at School B, and 16 at School C.

Procedure

Each student participated in a one-on-one, clinical interview process with a researcher. Because our interests lay in the reasoning students spontaneously brought to the tasks, interviewers focused on eliciting student thinking processes, including their struggles. Interviewers were careful not to include any instruction or scaffolding during the interview. For example, if a student made a statement that was factually incorrect, the interviewer agreed and encouraged them to explain their reasoning without redirection or indication that their understanding or reasoning may have been flawed. This approach is helpful to prompt students to engage in an ongoing process of reasoning, rather than simply doing things 'the right way' (Miller et al., 2018). Similarly, students would occasionally ask the interviewer questions or seek additional information about the images or scenarios. For example, asking about what was beyond the frame of the picture or if something/someone interfered with the glasses. When this occurred, the interviewer could clarify but did not provide additional information; instead, the interviewer probed further to understand the thinking behind the question, specifically how the student thought the information could help them make a decision.

Each interview took between 10 and 20 min, during which the student was presented with the four scenarios about three fictional children who had collected rainwater in glasses at their homes. In introducing each scenario, the researcher presented the student with photographs and/or labels showing different data to consider (Figure 2). With each scenario (Table 1), the student was asked to arrange the images to match the amount of water collected (dependent variable; low, medium, and high) with a child (Anne, Bobby, and Cara), based on the images of their rainfall collection conditions (independent variables). While the scenarios did not include values or measurements, they did incorporate concepts of relative quantity – within variable sets there was a maximum, a minimum, and an intermediate level. This allowed us to observe some degree of quantitative reasoning without requiring either mathematical computations or decoding of data representations that were likely to be beyond most students' experience level.

Analytic approaches and coding

The interviewer audio recorded the conversation and took observational notes about students' sorting behaviours and choices within each scenario. Because our goal was to understand how students reasoned about variables related to a familiar phenomenon, our approach to analysis of the transcripts and notes was qualitative. We developed a system to code data with two lenses to address two distinct lines of inquiry: (1) Level of reasoning demonstrated within each scenario (2-4) and (2) Specific reasoning strategies applied at any time in an interview. The former reflected our primary interest in learning more about the range of complexity in reasoning abilities among students, and the latter reflected our secondary interest in the presence and qualities of several specific reasoning strategies that emerged, such as efforts to mathematise the problem or critically question data sources. However, each of these lenses required a different system for coding data; each is described in the following sections.

Coding with lens 1: reasoning levels

A major focus of analysis was on characterising the range of students' analytical reasoning abilities within the multivariate scenarios. To this end, we developed a rubric that would capture more of the nuance of students' success and struggles than a rubric that focused only on an outcome's presence (e.g. not at all, a little, more, or a lot) and support a systematic categorisation of the level of complexity demonstrated by the data of students' reasoning. Rubric development was guided by both the literature about the use of rubrics in education (Popham, 1997; Stevens & Levi, 2013) and our own prior use of rubrics to assess data literacy skills in an undergraduate setting (Sickler et al., 2021). After an initial review of the data, we identified three evaluative criteria to characterise the level of complexity exhibited in students' reasoning: (a) number of variables considered, (b) coherence of articulated reasoning, and (c) consistency between students' sort of the photographs and verbal reasoning. Using these criteria,

Table 2. Description of coding criteria within the rubric for level of reasoning displayed, applied to each student's entire student reasoning per scenario (scenarios 2–4).

Complex Reasoning	Approaching Complex Reasoning	Univariate Reasoning	Minimal Reasoning
• Reasoning shows student considered multiple variables in their choices. • Articulates how they 'connected the dots' between the evidence sources and their choices. • Sort and reasoning are consistent with one another.	• Reasoning shows effort to consider multiple variables but is not fully successful (see below). • Struggles to explain how they 'connect the dots' between variables or use interpretations beyond the available evidence to arrive at answer. • Sort aligns with stated reasoning.	• Does not meaningfully consider a second (or third) variable. • Clearly states how the one variable matters to their answer. • Sort aligns with stated reasoning.	• Struggles with all components of task. • May mention multiple variables, but consideration isn't clearly articulated. • Struggles to explain thinking; reasoning is unclear, wandering, and/or contradictory. • Reasoning and sorts may not match.

we examined the data to create concrete definitions of four levels of reasoning, based on what was observable in the data, shown in Table 2. (Note: Table 4, in Results, includes student quotations that illustrate each level of reasoning). We then worked to refine the rubric and its definitions to assure it both reflected the data and could be used reliably to independently code our corpus of interviews.

The rubric was applied three times to each interview, once per multivariate scenario (i.e. scenarios 2-4). The rubric considered the totality of the students' reasoning and responses to a single scenario. Because each student considered three separate scenarios, each was considered an instance of reasoning and coded for the level of complexity shown. This approach reflected the reality that students could display different levels of reasoning in response to different scenarios.

Our analysis of these levels was descriptive, intended to examine the relative frequency of the levels of reasoning across all instances of reasoning in the sample (n = 135 [45 students x 3 scenarios]). For further exploration, we examined the range of levels of reasoning exhibited within an individual student's interview (n = 45), including how many students exhibited complex reasoning in at least one scenario and how many students exhibited minimal reasoning in at least one scenario of the interview. We also considered how reasoning abilities varied, depending on the number of independent variables in a scenario (n = 90 instances of reasoning for the two, two-variable scenarios and n = 45 instances of reasoning for the one, three-variable scenario). Finally, we explored how reasoning was distributed across the three grade levels included in the study (n = 45 instances of reasoning per grade level). These explorations were descriptive, conducted to inform our interpretations of the aggregate findings and point to potential areas for further research; they should not be construed as conclusive comparative analysis.

Coding with lens 2: analytical thinking strategies

Our second interest was looking for evidence of instances when specific types of analytical thinking strategies emerged in students' verbalised thinking. We used a generalised inductive approach (Thomas, 2006), in which the topics to explore were guided by the objectives of the larger curriculum development project that this research was meant to inform, but the final set of categories and code definitions were developed inductively based on students' behaviours and talk as they worked through the scenarios. The final code book of analytical thinking strategies identified four overarching categories: (a) Connecting data to experience; (b) Thinking critically about evidence; (c) Analytically addressing complexity; and (d) Other strategies used to manage complexity. Within these high-level categories, sub-codes were created to describe the specific strategies and skills exhibited.

Coding process

To test the reliability of the coding system, two researchers engaged in four iterations of independently coding two transcripts per iteration and comparing for inter-rater reliability, until the target of 75% agreement between coders was reached. After each iteration, researchers met to compare coding and discuss discrepancies; disagreements were used to revise the codebook and rubric. For transcripts coded during this process, the researchers agreed upon a final consensus coding after resolving discrepancies. Once the threshold of reliability was reached, each remaining transcript was coded by one researcher. To further bolster reliability, during independent coding each researcher flagged any excerpts where they felt there might be ambiguity in applying the codebook; the two researchers then met to discuss each flagged excerpt to ensure agreement and consistency on the application of the codebook. With this final stage of consensus coding, we sought to mitigate the risk of subjectivity of a single coder when the verbalisation of reasoning was not clear-cut by working collectively to ensure we consistently applied scores.

Results

All students in the study easily made the correct matches for the first scenario, confirming that they readily understood the basic principle that greater rain intensity produces more water falling from the air and reaching the ground. Because the first scenario was designed to check this assumption, it was not coded for level of reasoning.

Levels of reasoning

We examined students' level of reasoning from several angles. First, we identified the frequency with which each level was observed across all 135 instances of reasoning in the sample. Then we disaggregated the data to explore the range of reasoning levels exhibited by an individual student across the three scenarios, whether the reasoning levels were different between two-variable and three-variable scenarios, and any variation in reasoning by grade level.

Levels of reasoning observed overall

Across all 135 instances of reasoning possible (3 scenarios x 45 students), Complex Reasoning was the most commonly observed, accounting for 41% of all coded instances of reasoning (Table 3). Students demonstrating Complex Reasoning showed they were able to consider multiple variables, compare them against one another, make a choice based on the information provided, and explain their thinking in a consistent way. This group reflected the most sophisticated level of reasoning we observed among student participants. Somewhat less sophisticated reasoning was reflected in the Approaching Complex Reasoning level, in which students exhibited some elements of Complex Reasoning, but did not

Table 3. Frequency distribution of reasoning levels displayed across all instances of student reasoning in scenarios 2–4.

Level of Reasoning Demonstrated	Instances of Reasoning Coded to Level (n = 135)	
	Count	Percentage
Complex Reasoning	55	41%
Approaching Complex Reasoning	24	18%
Univariate Reasoning	35	26%
Minimal Reasoning	18	16%

articulate how they connected all of the variables in their thinking. Eighteen percent of all instances of reasoning about the three scenarios fell into this level.

Univariate Reasoning was the second most common level of reasoning observed (26% of all instances). In these cases, students focused on a single variable they considered to be most important or easiest to understand and did not address other, contradictory variables in their explanations of their sorts. A small subset of responses (16% of all instances) were coded as reflecting Minimal Reasoning, in which students were not able to articulate or explain their sorting choices. Examples of all four categories of reasoning are presented in Table 4.

Range of reasoning levels used by individual students

When examining reasoning exhibited by individual students, the overall pattern is similar, but not identical, to the aggregated patterns across every instance of reasoning. Of the 45 individual students interviewed, 64% used Complex Reasoning at least one time in the interview. However, only six students maintained Complex Reasoning through all

Table 4. Examples of students' responses to Scenario 3: Rain intensity & collection site

Level of Reasoning	Example Excerpt from Coded Transcripts
Complex	*Student's final sort: Bobby: lowest, Anne: middle, Cara: highest* Interviewer: What makes you think those are the matches now? Student: Because Anne had it out in the open, so did Cara and she had the heavy rain. So more rain would be coming down and Bobby had the glass covered by leaves so not much would get into the glass. … Because if you're going to put it under like a tree, it wouldn't get much water in it because it's covered by it and like it would go beside it where the tree isn't covering.
Approaching Complex	*Student's final sort: Anne: lowest, Cara: middle, Bobby: highest* Student: *[Pointing to Anne as the lowest]* [Anne] is still the same [as Scenario 2]. Because right here, it's not that hard, she said. So, it's light rain, that's what Anne said. Interviewer: OK. What about Bobby and Cara? Who do you think got more now that we know where they put their glass? Student: Bobby. Because Bobby put it in the leaves in the centre because maybe … Why did he put the cup inside the leaves? Maybe because the leaves get wet so it gets more … And then the leaves put it in the water so and then it makes it bigger … . And then it went drop, drop, drop. And then it rained hard and then it went faster and then it stopped here.
Univariate	*Student's final sort: Bobby: lowest, Cara: middle, Anne: highest* Student: [Bobby] had the least, because of the leaves. The leaves around cup, the glass. And this cup, this glass, there was no space for the water to go in there. And this [Cara's placement] was like maybe it was a lot of trees around there so it would fill the cup to the middle.
Minimal	*Student's final sort: Anne: lowest, Bobby: middle, Cara: highest* Interviewer: *[After introducing the scenario]* Do you think that would change which glass do you think came from which place? Student: Probably. *[Long pause.]* Interviewer: What do you think is making it hard to decide? Is there something tricky about it? *[Student nods.]* Yeah? What do you think is tricky about it? Student: That they're different. They're all in different places and I can't think about which one should go where or if they're fine.

three scenarios. On the other end of the spectrum, 36% of students showed Minimal Reasoning at least once during the interview; but only four students (9%) showed this level of reasoning in more than one scenario. Most students showed a range of reasoning abilities across their interview.

Differences in reasoning in relation to increasing number of variables

During interviews, students sometimes expressed uncertainty, and even frustration when asked to reason about variables that did not yield a clear and definitive solution to the task of assigning water levels to the children in the scenarios. Anecdotally, these affective responses were especially strong during the final scenario, which asked students to consider all three independent variables together. In examining the levels of reasoning exhibited, however, the overall frequency of Complex Reasoning demonstrated within the three-variable scenario (38% of 45 instances) was only slightly lower than it was within the two two-variable scenarios (42% of 90 instances; see Table 5) despite students' affective acknowledgements of the challenges they were encountering. At the same time, the frequency with which students demonstrated Approaching Complex Reasoning actually increased with the additional complexity (from 14% of instances to 24% of instances). The frequency of Univariate Reasoning dropped dramatically from 32% to 13% when students were asked to reason about all three-variables simultaneously (scenario 4), however there was also an increase in the proportion of students who showed Minimal Reasoning, struggling to articulate reasoning at all when three variables were introduced.

Range of reasoning across grade levels

Students in fourth and fifth grades tended to use Complex Reasoning at a higher frequency than third grade students and, overall, the fourth and fifth grade students tended to show similar patterns of reasoning. Conversely, third graders displayed Minimal Reasoning at a much higher rate than the older students, as well as higher rates of Univariate Reasoning (Table 6).

Analytical thinking strategies

Students in the study exhibited a variety of specific, verbalised strategies for thinking analytically with and about the data or for dealing with the problems' complexity, regardless of the level of complexity they demonstrated in their reasoning. Below we provide descriptive results of how frequently students demonstrated strategies in the four coded categories: (a) connecting data to content knowledge; (b) thinking critically about evidence; (c) analytically addressing complexity; and (d) other strategies used to manage complexity.

Table 5. Frequency distributions of levels of reasoning demonstrated by students, comparing reasoning during two-variable scenarios and the three-variable scenario.

	Percentage of Instances of Reasoning Coded to Level	
Level of Reasoning Demonstrated	Two-Variable Scenarios (n = 90)	Three-Variable Scenario (n = 45)
Complex Reasoning	42%	38%
Approaching Complex Reasoning	14%	24%
Univariate Reasoning	32%	13%
Minimal Reasoning	11%	24%

Table 6. Frequency distributions of levels of reasoning demonstrated by students, comparing reasoning exhibited by grade level of the student

	Percentage of Instances of Reasoning Coded to Level		
Level of Reasoning Demonstrated	3rd Grade Students (n = 45)	4th Grade Students (n = 45)	5th Grade Students (n = 45)
Complex Reasoning	22%	49%	51%
Approaching Complex Reasoning	11%	27%	16%
Univariate Reasoning	38%	16%	24%
Minimal Reasoning	29%	24%	9%

Connecting data to content knowledge

Just under half (49%) of the 45 students in the study made spontaneous statements during their interviews that indicated they were drawing on prior knowledge and experiences in thinking about the data and problems posed in the scenarios. Most often, these connections between prior knowledge and current tasks showed students were drawing upon science concepts and practices they thought might be relevant to the problem, such as the effects of evaporation and climate (e.g. differences in rainfall between a forest or an arid climate) or designing experiments. These connections came up regularly across students in all three grades. Connections that relied solely on personal experience were less frequent, and primarily expressed familiarity with the different types of rain shown (e.g. 'That's May rain').

> Student: And then the heavy rain is like where it's raining, where it's a lot, a lot of precipitation that could actually cause a flood.

> Student: Because in Anne's [picture], it looks like it's a very hot place and I don't think water is really going to fall. So I thought it was like the lowest [amount]. … And for Bobby, … when I see the leaves, maybe it's a forest and probably a lot of rain comes here, so that's why it's at the top.

Thinking critically about evidence

Students' responses were coded as demonstrating critical thinking when they questioned or critically evaluated aspects of the data and scenario as it was presented, including pointing out specific visual evidence within images to support an inference, asking clarifying questions about data collection or images, or identifying other information that would help them draw a conclusion. Critical thinking occurred in more than half of the interviews overall (56%) and was seen at all three grade levels, but we observed critical thinking most often among fourth graders interviewed.

Students most often demonstrated critical thinking with respect to placement of the glass, often by paying close attention to visual evidence in the images, asking questions, and reasoning about how rainfall at different intensities might interact with the data collection position. For example, a common observation was commenting on or asking about shadows students noticed in Cara's photo of the glass placement (see Figure 2). Students inferred that these shadows might indicate a tree being overhead (but not visible in the photograph), which could influence the amount of rain caught by the glass. This inference would factor into their decisions about the amount of water Anne, Bobby, and Cara collected. Another example of critical thinking involved students considering a range of ways the leaves over Bobby's glass (Figure 2) could interact with the rainfall. Some students concluded that the leaves would block much of the rain and result in a lower collection total while others developed hypotheses of how the force of the rain might interact with the leaves differently to allow some or more water to pass through the barrier into the glass.

More than 1 in 5 students (22%) expressed critical thinking about the measurement of water in the glass (the dependent variable). The range of critical interpretations students posed primarily focused on disputing the amount of rain captured (e.g. that heavy rain would produce far more volume than any of the options), but isolated students observed the three glasses may not be identical or identified better receptacles for collecting rainfall data.

> Interviewer: But you're saying. . . you think that [Cara's glass] would be even fuller [than shown]? Why is that?
>
> Student: Because, [when] it's heavy rain, it rains a lot. I've even had where it's almost a flood … I feel like [the glass] would be overflowing.
>
> Student: I would put out a bowl. Maybe … a medium size, like bigger bowl like that, like the one you use for cooking. Because this [glass] is only that big, but the bowl's top could be that *[hand gesture]* big, so it would collect more.
>
> Interviewer: Oh. So, you'd get something with a wider opening?
>
> Student: Because they looked like they got pictures [of the glasses used] from different angles, but it might be the same spot [where the photo was taken]. … Well some [of the glasses] might be smaller.

Analytically addressing complexity

Across the entire corpus of data, we observed students engaging in several different strategies that appeared to help them manage the complexity of the data in the scenarios. These efforts also signalled the development of foundational analytical thinking skills of data literacy.

Deductive sorting. Deductive sorting was the most common, explicit strategy we observed students using; over 40% of students in the study called upon this strategy at some point in their interview. We coded students' decision-making process as deductive sorting when they described deconstructing the problem into smaller pieces so they could make one 'easy' placement at an extreme end of the sort, and then focus on the more difficult task of reasoning through the remaining two matches. Both their explanations and their physical interactions with the materials suggested that making the placement they were most sure about simplified the problem by narrowing the problem to two sets of variables to compare.

> Student: Cara would still have the most. The heavy rain will drip down the whole bottle and it's in the middle of the place and it's not somewhere between here. [Bobby's glass] is hiding. So, [Cara's glass] has a better chance of hers having the most.
>
> Interviewer: Okay. So Cara, we think, has the most. You sound real confident about that. Who do you think got more water in their glass, Bobby or Anne?
>
> Student: Bobby's would slip out of the cup. I think it's Anne's. … Yeah, if you put it near shelter it wouldn't fill up anything. And if you put it in the middle of the place, it would fill up something.

> Interviewer: Were there any that were harder to decide between?
>
> Student: Bobby and Anne's. Because light rain is light, and there's not as much rain, and light rain doesn't last as much. And rain does last as much, but the placing that [gives] shelter for you. So, it's just going to all slip out of there because of the leaves. And Cara, she's in the middle of the place, and then the whole thing would be way fuller.

Mathematising the problem. A few students (6 of the 45 students interviewed, or 13%) approached the non-numeric (photographic) data by trying to mathematise the problem in some way. Typically, these students either attempted to attach units of measurement to the data or tried to quantify the problem itself. Efforts related to the latter included talking about the problem using mathematical terminology (e.g. rate or measurement) or asking the researcher for quantitative information about the variables (e.g. 'If you could tell me how many inches fell per hour'). None of the third-grade students in this study used this strategy, while roughly one in five fourth- and fifth-grade students were observed trying to mathematise the problem.

> Student: If I was trying to measure all of these things … I think I would take at least a side of a centimetre ruler and measure how much rain we got.
>
> Interviewer: So you want more precise measurements of how much water is in each cup.
>
> Student: Mm-hmm [affirmative]. I would also write down how much rain there was and make estimates each time it rains and say, 'Oh, there's heavy rain, we're probably going to get about so-so inches or centimetres.'

Acknowledging uncertainty. The scenarios presented students with thought-provoking puzzles without clear answers, and we looked within interview transcripts for evidence of how students talked about uncertainty. Only a few students, primarily fifth graders, articulated a clear awareness that the problems as presented did not provide them enough or precise enough data for them to offer a definitive solution. This articulation of uncertainty was observed in only seven (16%) of the 45 interviews. These thoughtful expressions of uncertainty were distinguished from comments expressing struggle with the problem or uncertainty that their placement was correct. Such comments did not as clearly demonstrate an awareness of the uncertainty inherent in the data or relationships between variables.

> Student: I mean Bobby, [his glass was out for] like two hours. [Cara] is only half an hour. So maybe once you switch around … who knows? But it could be the same, there's a possible chance.

Other strategies to manage complexity

While the scenarios were challenging for most students, many students interviewed expressed verbally that the tasks pushed them both cognitively and affectively to manage the challenge, such as this example.

> Student: I need to look at the picture. It's hard. I'm trying to think. … I'm looking at this one [Anne] and I'm saying light rain, but it rained for one hour. And [for Cara] it's heavy rain and it rained for a half hour, so I'm like, oh my God, it's heavier rain. But it would fill up a lot quicker. … It's complicated.

In addition to the analytical strategies discussed above, a smaller subset of students brought other strategies to manage the complexity, which were not as aligned with skills of data literacy. A relatively small proportion of students (16%) dealt with the challenge of conflicting variables by attempting to make the problem easier by rearranging the independent variables (rather than the dependent variable) to align all of the data along their low, medium, or high categories. Another approach was used by 13% of the students, who came up with explanations that went beyond the data presented or their content knowledge to (often imaginatively) explain away difficult variables. Examples included asserting that a glass had tipped and spilled water, bugs got in the glass, and other unsupported assertions of data collection problems.

> Student: *[About Bobby's placement]* That's a dumb spot. Because it's covered by everything. And there's also too many animals on there.
>
> Interviewer: So it's covered by all the leaves and animals. What about animals?
>
> Student: Insects. Because like worms are on this stuff, I don't watch to touch that glass after they touched it. And [the glass] stayed there for a year.
>
> Interviewer: Oh, those bugs might have crawled all over it while it was down there.
>
> Student: Yeah, it looks like it's been there for years.

Discussion

This study adds to a relatively small research literature about elementary students' data literacy skills writ large (Cui et al., 2023; English, 2012; Shreiner, 2019; Wolff et al., 2015). Like these studies, it paints an optimistic picture of the cognitive assets that young students bring to tasks calling on data literacy. The majority of students in this study, irrespective of grade level, were able to make claims, use evidence, and articulate their reasoning in response to complex, multivariate problems when using non-quantified, commonplace data. Our exploration by grade level suggests that higher-grade students may be somewhat more adept at achieving complex levels of reasoning than those in third grade; although we still saw that most third grade students were able to productively take on the task to some degree. As with prior work that introduced activities and discussions that centred on empirical uncertainty (Manz, 2018), using complex data visualisations to solve problems (Wolff et al., 2016), or modelling data from a story to answer new questions (English, 2012), our findings suggest that elementary aged students demonstrate the capacity to reason about complex and sometimes ambiguous data. As part of this growing literature base, this study suggests that offering young students the opportunity to engage in reasoning about data involving situations that are both familiar and complex is not only possible, but could be a stepping stone to expanded and more quantitative reasoning with data.

The study also found that the introduction of three independent variables prompted a divergence of reasoning abilities with fewer students applying univariate reasoning, implicitly showing awareness that a single variable explanation was insufficient for the complexity of the problem. But with awareness of that complexity, it seemed to become difficult for some students to reason through independently at any level.

These trends suggest that children's ability to coordinate multiple variables is, in part, subject to cognitive-developmental constraints (Case & Griffin, 1990; Fischer, 1980), and is a promising area for further research.

Because we were interested in learning about the intellectual assets and approaches that students access on their own, our data cannot address the question of whether early-grade students like those in our study would be able to employ the complex and sophisticated reasoning strategies of their higher-grade peers within a more scaffolded, instructional context. However, prior research has suggested that through intentionally designed instructional strategies, careful facilitation by an educator, and opportunities for discussion, elementary students are able to be successful at thinking critically about empirical uncertainty (Manz, 2018), scientific argumentation (McNeill, 2011), and use of data lenses (English, 2012), for example. Alongside this prior work, it seems likely that, with classroom scaffolding and data problems like those used here, an even broader range of students would be able to employ more complex reasoning to make sense of the scenarios in educational practice.

Also of note, many of these students spontaneously demonstrated data literacy practices by thinking critically about the nature of the data they were working with, asking thoughtful questions about the data, and methods of collection. When asked to reason about familiar phenomena using non-mathematised data, students showed a willingness and ability to think about the limitations of the data and to identify information that might help them arrive at a better supported solution, as they freely asked the interviewer for more information about the variables, data collectors, or context of the data collection scenarios. Students searched images for visual evidence to inform and support their reasoning, connected it to their knowledge of phenomena related to rainfall, and applied their understanding of the world to generate a better-supported solution. This paralleled findings of elementary students' abilities to recognise and discuss the importance and differences of investigative design decisions, when faced with scenarios of empirical uncertainty (Manz, 2018); both our study and Manz's work indicate that elementary students can think critically and discuss the sources, validity, and meaning of data, if they are given the opportunity. Developing the capacity and the disposition to engage in such practices is fundamental to data literacy, and this study's evidence was very encouraging for the value of including more data exploration in early grades.

Most students gamely persevered in working towards a solution to each scenario, even as some indicated that they were challenged by the problems posed. Nonetheless, their processes of reasoning demonstrated a wide range of analytically grounded strategies for problem-solving and reasoning with data, such as breaking the problem into smaller pieces, trying to mathematise the data, or to address some of the inherent uncertainty in the task. The strategies they spontaneously employed reflect young learners' cognitive strengths, which could potentially be activated more purposefully by elementary science educators. This suggests a promising starting point for designing data literacy experiences that would encourage and scaffold accessible routines for managing, evaluating, and making sense of data. Anecdotally, many students' language and behaviour during the interviews made clear that they experienced the scenarios and interview as an enjoyable challenge to puzzle through. In contrast to being experienced as a routine, step-by-step process, it provided an engaging mystery and latitude for creative problem-solving. These are likely important attributes to consider for future data-centred lesson design.

In addition to identifying seeds of foundational data practices and dispositions that could be further leveraged through instructional interventions, the strategies we observed in this study point to an implicit awareness in many students that they needed evidence to support a conclusion. For example, students who commented on uncertainty implicitly acknowledged the need for more or different evidence, even if they could not articulate what evidence they needed to draw a conclusion. Similarly, students' careful analysis of visual evidence within photographs was in service of finding further information that could ground a working theory about which child would have collected more (or less) water. The students in our study demonstrated the capacity to activate the three key areas of our data literacy framework (Figure 1), searching for ways to gather qualitative information about the phenomenon (applying content knowledge) and/or the data collection tools and methods (computational/data skills) to ground and support their determination about the relative amounts of water (quantitative reasoning).

Conclusions

The focus on educational and curricular interventions to promote data literacy has filtered down to K-12 education from collegiate and post-collegiate efforts to train students for future careers (Kochevar et al., 2015; NASEM, 2018). This top-down approach has largely been step-wise, in which gaps identified in needed knowledge or skills at one grade band (in this case, data literacy knowledge, practices, and dispositions) have become the focus of research and intervention at the band below. While there is logic to this approach, it invariably leaves the learning of elementary students to the end, and thereby misses an opportunity to add a bottom-up approach that can help ensure that young students are prepared for the more sophisticated disciplinary thinking in later schooling by having learning experiences to develop familiarity with, grounding in, and dispositions of data literacy.

This study was part of a broader body of research aimed at learning how best to integrate data literacy skills into K-12 classrooms (e.g. Gold et al., 2015; Kastens et al., 2015; Vahey et al., 2012; Wolff et al., 2019). This work is all relatively new and is still in the process of developing both conceptual and empirical foundations, especially with regard to the early development of such skills. It is telling that most of the published data literacy education research has been conducted at the middle school, high school, and college levels. As Manz has articulated about elementary science curricula, 'the default assumption … is that the easiest entrée to scientific practice is to ask students to engage in highly simplified investigations' (2018), where they are not encountering the authentic complexities and uncertainties of scientific investigation or working with data. Our finding that students in grades 3–5 were able to apply their knowledge of phenomena to understand and reason about data problems suggests that the integration of data literacy activities into elementary science classrooms is both possible and is potentially a productive approach to developing foundational data literacy skills and practices. Our findings suggest that complex reasoning about data – even multivariate data – is well within the capabilities of upper-elementary grade students. The specific analytical thinking skills we observed, including connecting data to real-world events, thinking critically about evidence, acknowledging uncertainty, and mathematising the problem, are all important aspects of achieving overall fluency in making meaning from data.

In order to initially understand what students were capable of, these data scenarios intentionally removed the potential barrier of students' limited mathematical, statistical, and/or computational experience or skills. A next step would be to explore how well students are able to interpret and/or reason from conventional representations of data, like those traditionally created from professionally collected geoscience data, to find avenues for merging students' natural reasoning abilities with their strengths and limitations when dealing with professionally collected science data.

This research also points to the need for educators and instructional designers to experiment with instructional strategies and stimuli that leverage the students' assets and strengths for thinking about data, while avoiding bogging down exploration with introduction of mathematical, statistical, or graphical knowledge that is beyond their school experience. For data to be practically incorporated into an elementary science curriculum, it will need to work with students' existing strengths and math skills. This study identified several attributes of a data problem or task that have promise for the design of future curricula, including focusing on an open-ended problem that can lead to multiple plausible conclusions; working with a familiar (or already studied) phenomenon that requires no additional content instruction to engage with the data; and a series of problems that progressively increase in complexity, letting students build on their past thinking and reasoning as data become more complicated.

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