

Promoting students' informal inferential reasoning through arts-integrated data literacy education

Structured abstract

Purpose

Arts-integration is a promising approach to building students' abilities to create and critique arguments with data, also known as informal inferential reasoning (IIR). However, differences in disciplinary practices and routines, as well as school organization and culture, can pose barriers to subject integration. We describe synergies and tensions between data science and the arts, and how [these can](#) create or constrain opportunities for learners to engage in IIR.

Design/methodology/approach

[We co-designed and implemented](#) four arts-integrated data literacy units with 10 teachers of arts and mathematics in middle school classrooms from four different schools in the United States. Our data include student-generated artwork and their written rationales, and interviews with teachers and students. Through maximum variation sampling, we identified [examples from our data to](#) illustrate disciplinary synergies and tensions that appeared to support different IIR processes [among students](#).

Findings

Aspects of artistic representation, including embodiment, narrative, and visual image; and aspects of the culture of arts, including an emphasis on personal experience, the acknowledgement of subjectivity, and considerations for the audience's perspective, created [synergies and tensions that both offered and hindered](#) opportunities for IIR (i.e., going beyond data, using data as evidence, and expressing uncertainty).

Originality/value

This study answers calls for humanistic approaches to data literacy education. [It contributes an interdisciplinary perspective on data literacy that complements other context-oriented perspectives on data science. This study also offers recommendations for how designers and educators can capitalize on synergies and mitigate tensions between domains to promote successful IIR in arts-integrated data literacy education.](#)

Keywords

Arts-integration, data literacy, data science education, middle school, classrooms, co-design, informal inferential reasoning, interdisciplinary learning, STEAM

Introduction

Youth live in a society abundant with data, in which data-based arguments frequently support journalism and advocacy, but are also accompanied by risks of misinformation (Tandoc and Kim, 2022). Increased access to, and use of private and public data have led to a shift in mathematics education from emphasizing developing students' understanding of core statistical concepts and skills related to measures of central tendency and percentages, toward developing students' informal inferential reasoning (IIR) about data (Franklin & Bargagliotti, 2020). IIR is defined as "the way in which students use their informal statistical knowledge to make arguments to support inferences about unknown populations based on observed samples" (Zieffler et al., 2008, p. 44). This reasoning includes making sense of data and data patterns in terms of their real-world context and implications, raising questions about the data-based inferences and uncertainty, using data as evidence for claims and predictions, and making generalizations that extend to broader contexts and populations (Ben-Zvi et al, 2015; Franklin & Bargagliotti, 2020; Pfannkuch, 2007; Makar & Rubin, 2018; 2009).

Informal inferential reasoning can provide middle grades students with a critical foundation for engaging data literacy. While formal statistical inferential reasoning requires an understanding of complex statistical concepts that middle school students do not typically have, informal inferential reasoning can provide an entrypoint and pathway toward formal statistical reasoning for students with a range of formal statistical mathematics backgrounds (e.g., D'Ignazio and Klein, 2020; O'Neil, 2016; Pangrazio and Sefton-Green, 2022; Perez, 2019; Wild and Pfannkuch, 1999). Moreover, IIR's focus on generalizing to real-world contexts can invite students to reason about their personal and community connections to data and the implications of these data for themselves and society.

Data reasoning—whether formal or informal—is interdisciplinary: it requires one to draw upon knowledge and practices from multiple disciplines to create meaning from context (Briggs, 2002, 2023; Madison, 2002; Radke et al., Rubin, 2005, 2022; Scheaffer, 2001). For example, in interpreting and predicting numerical patterns of species decline across various continents, learners need to draw upon knowledge and skills from mathematics, biology, social studies, and environmental science, to make data-based claims that require an understanding of the human and environmental factors and for the mathematics and statistical approaches to gathering and modeling patterns in the data. Middle grades students face challenges in drawing on the knowledge across multiple disciplines required for IIR. Typical school-based approaches to teaching about data tend to take place in mathematics classes that foreground mathematical processes often lack opportunities for learners to appreciate the sociopolitical and cultural contexts of data necessary to fully reason about the implications of the statistical patterns that they identify (Bhargava et al., 2015; Philip et al., 2013; Rubin, 2021; Wolff et al., 2016).

The case for data-art inquiry

Integrating data science with arts has the potential to foster students' IIR, as these disciplines share practices of exploring, sensemaking, critiquing, and communicating about issues (Table 1). These disciplinary intersections create possibilities to engage students who might not otherwise engage in mathematics, and to reinforce learning across these shared

practices. While the arts consist of a broad spectrum of creative activities, we define arts as a set of practices that involve the creation of an artifact—written, visualized, sonified, or performed—for the purpose of self-expression. Especially in contemporary art, artistic expression tends to be valued by how it situates personal experiences within broader societal issues, thus offering social commentary, and evoking emotional reactions of audiences by both connecting to an audience's experiences, and revealing otherwise untold perspectives (Bevan *et al.*, 2019). Thus, data-art inquiry is an arts-based approach to inquiry that involves using artistic practices and forms to represent patterns in data—and in some cases, to generate data—with the goal of evoking audiences' emotional responses to issues (e.g., Jordan, 2009; Miebach *et al.*, 2022).

Data-art inquiry can build IIR practices and disciplinary knowledge, and broaden engagement in data literacy. It draws on arts-based inquiry approaches that center critical and reflective practices (Blumenfeld-Jones, 2016; Halverson, 2021), that and offer opportunities to humanize data science education (D'Ignazio and Klein, 2020; Lee *et al.*, 2021) by encouraging an awareness of the subjectivity inherent in data generation and communication, and of the personal and societal consequences of that subjectivity (D'Ignazio, 2017; Friel *et al.*, 2001; Lee *et al.*, 2022; Pfannkuch *et al.*, 2004; Sorto, 2006). The creative aspects of artistic expression in arts-based inquiry can generate new and innovative approaches to visualizing, interpreting and sharing data-based claims (Aslan *et al.*, 2014). Arts-integrated data literacy education can also broaden inclusion of learners by providing alternative, personally relevant, and equally valid ways of engaging with data (Bhargava *et al.*, 2015; Conner *et al.*, 2017; Radke *et al.*, 2023; Stone, 2022). With both data and art recognized as tools for advocacy and social impact, data-art inquiry can support more learners to participate in social discourses (Fam *et al.*, 2018; Henriksen, 2018; Meijias *et al.*, 2021; Shapiro, 2022).

Table 1. Alignments in inquiry practices between data science, the arts, and data-art inquiry, adapted from Bevan *et al.* (2019)

	Data Inquiry Practices	Arts Inquiry Practices	Data-Art Inquiry Practices
Goal	To inform through conveying objective information on an issue.	To evoke an emotional response from an audience.	To communicate data in a way that evokes action with data.
Explore	Identify a question. Determine what data, and how to collect it to answer that question.	Identify an issue of artistic worth by reflecting on one's personal experiences in relation to global ones.	Identify a problem or question using data to reflect on one's personal experiences in relation to global ones.
Make meaning	Use statistical and other analytic processes to answer the question.	Expand one's perspective on the issue through immersion, observation, and experiences.	Use formal and informal inferential reasoning, combined with subjective experiences, to answer the question

			or describe a perspective in relation to a broader pattern or trend.
Critique and communicate	Interpret data and infer implications for people impacted. Use conventions for building objective arguments from evidence.	Use aesthetic strategies to create an artifact that expresses a message. Step away to determine how it resonates with personal feelings and understandings of the issue.	Convey a perspective or argument on an issue based on data. Use aesthetic strategies to evoke an emotional reaction from audiences.

Data-art inquiry for informal inferential reasoning

The arts can support the three interrelated processes of IIR (Makar and Rubin, 2007): (1) *Going beyond the data* to make generalizations about a population (e.g., predictions, parameter estimates, claims) (Ben-Zvi, Gil and Apel, 2007; Curcio, 1987; Rossman, 2008); (2) *Using data as evidence* for those generalizations; and (3) *Expressing uncertainty* about those generalizations. Arts-based data literacy approaches present opportunities for *going beyond the data* by encouraging learners to contextualize data by making connections between data and their personal or local ecologies. Learners' personal knowledge of a data set's history or the situation it references can shape engagement with that data (Lee *et al.*, 2021), and sometimes, personal knowledge is required because the data are about their families, their communities, or even their own bodies (e.g., Kahn, 2020; Lee and Dubovi, 2020; Van Wart *et al.*, 2020). Arts-integrated data literacy approaches also broaden opportunities for *using data as evidence* to substantiate generalizations, as it widens the landscape of what may be considered useful, valid evidence (including qualitative, not just quantitative evidence), as well as the ways in which evidence can be represented and aesthetic goals such representations may have (i.e., evoking a certain emotion). These opportunities can offer alternative entry points to understanding and working with data that may help engage more learners. Finally, arts integration offers unique opportunities for *expressing uncertainty* about generalization, as they can surface the inherent subjectivity in the collection, interpretation, and use of data in argumentation.

Disciplinary cultures

Disciplinary practices arise from unique disciplinary cultures. When creating discipline-integrated learning experiences, it is crucial to acknowledge the intersections of these cultures. By *culture*, we refer to the personally- institutionally- and domain-shaped values, reflected in a domain's accepted methodologies for generating knowledge, and in the practices and routines for teaching within a domain (Warren *et al.*, 2020). Culture also shapes the forms and ways of using *representations*, that is, the domain-specific standards and expectations for what counts as, and how to represent knowledge, evidence, and argument.

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3 The culture of data science values both technical skills needed to make valid data-based
4 claims from large data sets as well as visualization and storytelling practices that can engage
5 non-experts with data findings (Wolff et al., 2016; Yau, 2013). Typical data visualizations map
6 measurable variables onto graphic elements (e.g., line, space, color, shape) to highlight
7 quantitative patterns and trends across a population. In contrast, the culture of arts education
8 values reflection on personal or shared lived experiences, observation of qualities and patterns
9 of one's chosen subject, and expression of multiple perspectives (Winner *et al.*, 2020; Halverson
10 and Sawyer, 2022). The varied media and approaches to creating artworks encourage new
11 approaches to the expression of abstract ideas, emotions, memories, and stories, which are not
12 as expressible in numbers. Arts-based practices such as *close looking*, *self-reflection*, *critique*,
13 and *exhibition*, can also cultivate IIR practices by encouraging learners to attend to details that
14 might otherwise not be seen, and to make mindful choices about how to express ideas. Through
15 such practices, students can come to re-see familiar ideas from new perspectives; to reason
16 about the roles of context and perspective in shaping the meaning and implications of data; to
17 explore questions about, and uncertainties in data; to consider how aesthetic strategies can
18 evoke particular audience reactions to data claims; and, by presenting their work to external
19 audiences, to see how data and the arts can allow them to contribute their perspectives to
20 broader societal discourses. Thus, the integration of data science and the arts offers
21 opportunities to mutually strengthen practices of analysis and communication in both domains,
22 challenging learners to use data to generalize their personal experiences, while also
23 representing the social and environmental context and implications of their data-based claims.
24 However, tensions can also emerge as students attempt to create data-art that satisfies the
25 values of each discipline.
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33 Cross-domain synergies and tensions

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35 In spite of its benefits, there are also many hurdles to integrating arts and data literacy in
36 formal learning environments, including challenges of teacher preparation, and of the availability
37 of time and resources necessary to support cross-domain co-design and instruction (Campbell
38 *et al.*, 2021). In response to these challenges, arts-integration falls along a spectrum, where on
39 one end, the arts is used in service of mathematics and statistical learning goals (e.g., design a
40 poster to communicate survey findings); and on the other, the arts and data literacy are fully
41 integrated such that values and practices of each are mutually supportive of the other's learning
42 goals (Mejias *et al.*, 2021). At this latter end of the spectrum, students may learn values and
43 practices not just *within* a discipline, but *through* a discipline, and ultimately transfer these to
44 other contexts and domains (cf. Halverson and Sawyer, 2022).
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47 Extending our previous work on data-art inquiry learning (Authors, DATE), this current
48 study considers how the cultures of arts and data science, including their values and
49 representations, intersect to produce the disciplinary synergies and tensions that either create
50 or constrain opportunities for students' IIR. Figure 1 illustrates how we conceptualize arts and
51 data science practices and representations to be uniquely shaped by the disciplinary cultures in
52 which they are embedded; and how we propose synergies and tensions to emerge from the
53 intersection of these cultures. This conceptualization builds on Mejias et al.'s (2021) notion of
54 arts-integrated STEM—in which we include data science—as mutually instrumental and
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pedagogical. More specifically, our view of data-art inquiry is one in which the learning goals of each of data science and the arts have equal weight; and moreover, contribute to advancing learning both within and across their disciplinary boundaries. At the same time, we recognize that such disciplinary alignments are not always feasible in practice. Thus, we refer to *synergies* as the realization of epistemic alignments between data science and the arts (e.g., exploration, sensemaking, critiquing) (cf. Bevan *et al.*, 2019; Blumenfeld-Jones, 2016; Tygel and Kirsch, 2016), such that they are mutually supportive of their shared learning goals. Meanwhile, *tensions* refer to the failure to realize epistemic alignments such that one domain's goals become overshadowed by the other.

With a focus on supports and constraints for IIR, this study asks:

How do the synergies and tensions at the intersection of data science and the arts support or constrain opportunities for students' engagement in IIR practices, including "going beyond data," "using data as evidence," and "evaluating and expressing uncertainty about generalizations"?

By examining IIR in terms of disciplinary synergies and tensions, this study aims to describe the opportunities and challenges of arts-integrated approaches to data literacy instruction. Our findings contribute to theoretical conceptualizations of data literacy learning and of integrated disciplinary learning, as well as practical recommendations to guide educators and designers of similar learning experiences.

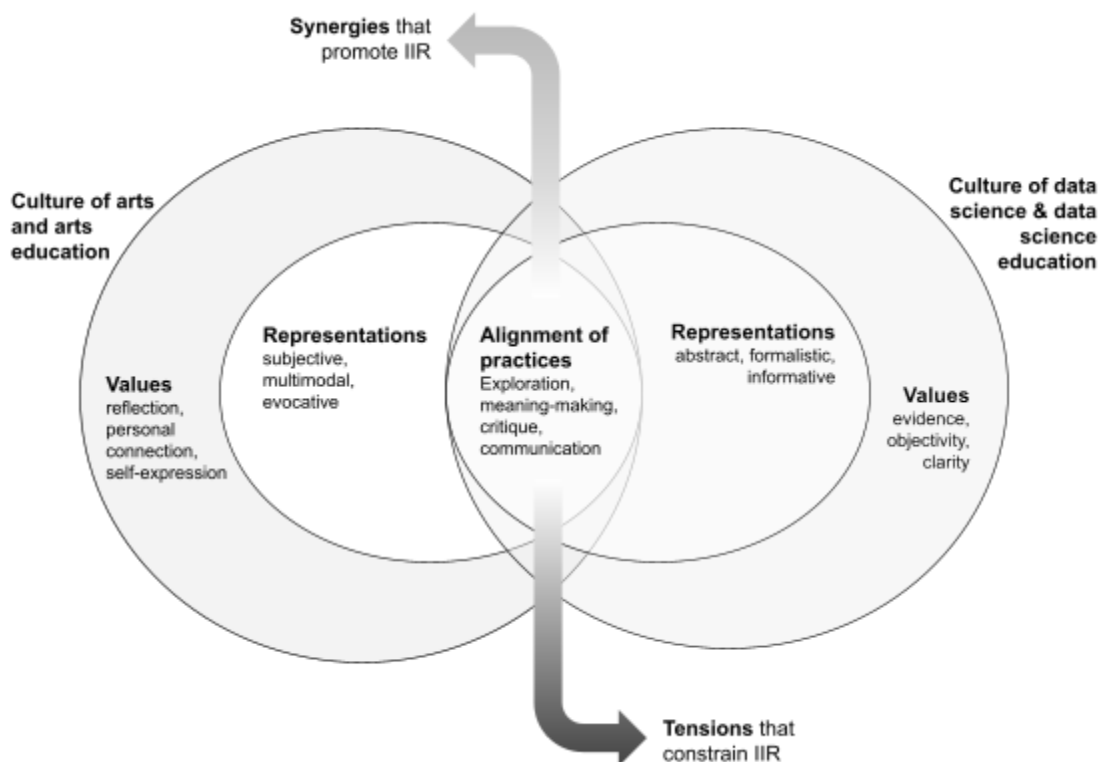


Figure 1. The intersection of arts and data science cultures can create synergies or tensions that promote or constrain IIR.

Methods

Participants and context

The co-authors of this study include faculty and graduate students, who are team members of a project funded by the National Science Foundation (NSF) to promote middle school students' data literacy learning through the arts. At the time of writing our proposal to the NSF, we recruited 10 teacher participants to co-design the project's curriculum with us: Two teachers from each of four schools (1 public charter, 1 private, and 2 public schools, across three states in the United States). These teachers were recruited from among our personal and professional networks, based on their expressed interest in teaching across disciplines by incorporating data science literacy into their arts curricula, or vice versa. The teachers were experienced in their subject domains, with 5-10 or more years of classroom teaching experience, but all were new to co-design and to arts-integrated data literacy education. The four schools served diverse student populations that varied from 2-65% white and 25-95% non-white students, and 40-86% in economic need as defined by eligibility for free and reduced price lunch. Each of the classrooms in which we implemented the units included 15-30 students.

Unit designs and implementation

In school-specific teams that each included at least one math, one arts teacher, and two researchers, we co-designed and supported teachers' enactment of four units (1 unit/school) with integrated arts and data literacy learning goals (Table 2): *Dance*, *Photoessays*, *Comics*, and *Collages*. Except for *Dance* (whose teachers had made alternative curriculum commitments), we supported a second iteration and enactment of each unit in the subsequent year of our collaboration, and include data from those second implementations in our current analysis.

The four unit designs emerged from our co-design process with teachers, in which we sought to align our larger project's overarching goal to address data literacy learning goals through the arts with each teacher's curriculum goals, student interests, and classroom resources. The resulting units ranged from 2 weeks to 1 semester long. While they varied according to teachers' circumstances, we ensured that each unit shared the following features, based on our conjecture that they would promote students' engagement in IIR through the arts: (1) A driving inquiry question grounded in a personally- and socially-relevant issue; (2) a student-generated or public dataset to enable students to use data respond to the driving question; (3) a prompt to use an artistic medium to communicate a claim or perspective based in a critical interpretation of data; (4) a prompt for students to write an artist's statement to explain the data-based claim, and to rationalize their artistic choices. These common elements and the variations that emerged as teams identified overarching questions, datasets, and artistic forms and materials) provided an opportunity to examine how and the extent to which data-art inquiry engaged students in IIR.

More specifically, in a *Dance* unit, students choreographed and performed dances that communicated a claim developed based on their examination of graphs on various socio-economic and environmental issues (labor, gender inequality, environment). In a

Photoessays unit, students used photography and creative writing to personalize and critique standard indicators of community health. In a *Comics* unit, students created graphic narratives, in which they reflected on how their personal friendship experiences related to their findings from a grade-wide survey on friendship, as well as PEW Research data on Teens and Technology. In a *Collages* unit, students created collages from found digital imagery to represent their personal time use in relation to findings from the American Time Use Survey ([bls.gov/tus](https://www.bls.gov/tus)). For further details of the unit designs and implementation outcomes, see Authors *et al.*, (DATE).

Table 2. Brief descriptions of the four data-art inquiry units.

Unit	Description
Integrated subjects <i>School</i>	
<i>Collages</i> ELA Math <i>Public urban school</i>	How can we use collage to make data-based arguments about personal time use? Students critiqued informational texts and analyzed public data about time use, and produced digital collages with found imagery to communicate arguments about what their own personally-collected time use data says about them.
<i>Comics</i> Visual Art Math <i>Public urban school</i>	How can we use comics to reflect on our own friendship experiences in relation to others? Students analyzed graphs of their own and their peers' responses to a survey about friendship beliefs and experiences (e.g., Which best describes you?: I can count on my friends when things go wrong. I find it easy to make friends, etc.). They created digital comics to convey personal reflections about their own experiences in relation to their class data.
<i>Dance</i> Dance Math <i>Suburban charter school</i>	How can dance be used to communicate meaning behind data? Students interpreted data visualizations on issues of their choice (e.g., employment, environment, addiction), then choreographed dances to communicate about those data and their inferred implications.
<i>Photoessays</i> ELA Visual Art Math <i>Private urban school</i>	How can we use photography to engage critically with public data around the question: 'What contributes to a healthy neighborhood'? Students critiqued existing indices of healthy places, then used photography and creative writing to document and convey their personal perspectives on indicators of the health of their own communities.

Data sources and analysis

Our research data include (1) post-implementation interviews with each of the 10 teachers. These 1-2 hour-long semi-structured interviews focused on eliciting teachers'

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3 reflections on the challenges and successes of the units, their observations of student learning,
4 and their ideas for improving the unit. (2) Teacher-generated artifacts, including presentation
5 slides, exit tickets, and written post-class reflections. (3) Student-generated artifacts, including
6 their data artworks and artist statements (e.g. Figures 1-4). (4) Interviews with 3-4 focal students
7 per implementation, which asked students to reflect on their processes and artistic decisions,
8 and to explain the connections between their artworks and their interpretations of the data.
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10 To develop our analytic framework, our research team engaged in a process of
11 collaborative qualitative data analysis, which prioritizes the integration of multiple diverse
12 perspectives—both those of individual team members, and of different theoretical stances—into
13 the interpretation of data (Schielke et al., 2009). This process recognizes the value of
14 consensus among multiple team members as an indicator of reliability in data analysis, which
15 can be as robust as inter-coder reliability among two researchers, and more robust than if an
16 idea were advanced by a single researcher (Morrow, 2005). We chose this approach because
17 the aim of our analysis was to test the limits and possibilities of an emerging framework, and not
18 to make claims of representativeness, for which conventional approaches to, and measures of
19 interrater reliability (e.g., blind independent coding and Cohen's Kappa) would have otherwise
20 been better suited.
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24 To ensure reliability in our analysis, we divided our larger team of researchers into
25 subteams, which each led analyses of data gathered from implementations of individual units.
26 Each researcher served on two subteams. We vetted and developed ideas through iterative
27 cycles of independent analysis by subteams, and discussion among our large team. To ensure
28 the inclusion of each team members' perspectives, we initially wrote individual memos shortly
29 following the implementations of the units. These were written in a shared document, structured
30 with prompts that we had designed to elicit our ideas on the challenges, opportunities, and
31 distinct data-art practices we each observed in our work with participating teachers and students
32 (see Authors, DATE for the prompts). These memos served to initiate our ongoing subteam and
33 whole team discussions as we first analyzed implementation-specific data, then synthesized
34 across those findings to develop our current, broader conceptualization of the role of the arts in
35 data literacy education.
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38 The results presented here come from our iterative subteam and whole team
39 discussions of our entire project data set. From these data, we followed a purposive sampling
40 approach called maximum variation sampling (Etikan *et al.*, 2016) to identify examples from
41 students' work to demonstrate aspects of our framework. Rather than attempt to describe a
42 representative student experience, this approach seeks examples that are most illustrative of a
43 framework, both by showing the ideal, and the non-ideal experiences. In doing so, this analytic
44 approach helps to define and test the utility of a framework for explaining a phenomenon.
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47 For this study, we nominated examples of student work that either illustrated students
48 successfully, or less successfully, going beyond data, using data as evidence, or expressing
49 uncertainty, as defined by Makar and Rubin's (2007) framework for IIR. Through further
50 discussion among our whole research team, we identified the aspects of data-art integration that
51 appeared to support or hinder IIR. We particularly sought to define these aspects in terms of
52 tensions and synergies created at the intersection of disciplinary cultures and their traditional
53 representations, and to use these to explain how they supported or hindered students' IIR. An
54 example of successful IIR created by a disciplinary synergy is one in which students articulated
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3 an IIR practice through an artistic practice (e.g., making aesthetic choices that would evoke an
4 emotional response to a data claim). An example of a less successful IIR is one in which
5 students' engagement in an arts practice was at the expense of their effective engagement in an
6 IIR practice (e.g. students abandoning attempts to make artistic choices based on accurately
7 conveying a data claim, in favor of what they personally find to be aesthetically appealing).
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9 After identifying these examples, we compared them in terms of the unit designs that
10 supported their creation, the classroom context of the unit's implementation, the students'
11 personal experiences in creating those examples, as relayed to us by their teachers. This final
12 step allowed us to elucidate the potential role of the context of our implementations in shaping
13 the disciplinary synergies and tensions, and the IIR we observed in students.
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15 Notably, some of the examples we identified demonstrate various synergies and
16 tensions across multiple aspects of our framework. For instance, one example may at once
17 illustrate students using aesthetic representations and integrating their personal experiences
18 (two data-art practices that we identified in our analysis) to convey a particular emotional tone in
19 communicating data-based predictions as they "go beyond the data." The fact that one data-art
20 practice can facilitate more than one IIR practice indicates the many opportunities that data-art
21 inquiry offers for engaging students in IIR.
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24 Likewise, the same example might at once illustrate both a disciplinary synergy that
25 facilitates an IIR practice, even as it illustrates a tension that constrains a different IIR practice.
26 Such overlaps in practices are expected—and welcome—in interdisciplinary work (Reynante et
27 al., 2020). Moreover, the fact that one data-art practice can potentially illustrate many kinds of
28 IIR is indicative of the various learning opportunities that data art inquiry offers engaging
29 students in IIR.
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31 For clarity, we limit the presentation of our results to those examples that, in our
32 estimation, best illustrate the most distinct affordances and challenges of data-art inquiry for
33 supporting IIR. We also include these examples because they contribute to the whole of our
34 results by illustrating the range of different data-art inquiry approaches and outcomes observed
35 among our student participants.
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38 Results

39 Here, we describe examples from across our data, selected to best illustrate disciplinary
40 synergies and tensions as they promoted or hindered IIR. For a synthesis of our findings, see
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Table 3. Disciplinary synergies and tensions that promote or hinder IIR practices (Makar and Rubin, 2007).

IIR Practice	Contributions of the arts to data literacy learning	
<p>Going beyond data by making generalizations, explanations, predictions about populations, mechanisms, or contexts that are broader or different than the sample of collected data.</p>	<p>Synergies</p> <ul style="list-style-type: none"> + Generalizations are informed by personally and locally relevant experiences, and used to reason about the meaning of data, and its social and environmental implications. + Construct claims by connecting lived experiences to aggregated data. + Artistic forms (e.g., image, narrative, movement, embodiment) and techniques can concretize and center context and social and environmental implications of data (in contrast to abstract representational forms). 	<p>Tensions</p> <ul style="list-style-type: none"> - Challenges arise with expressing local/personal perspectives that are in discourse with broader patterns evident in the data. - Domain differences exist in valuing subjectivity vs. objectivity, and in the kinds of data and claims considered to be more/less valid. - Domains differ in the place that personal and social issues have in learning.
<p>Using data as evidence by representing data and explaining data reasoning.</p>	<p>Synergies</p> <ul style="list-style-type: none"> + Data include qualitative as well as quantitative values (e.g., numbers, text, images). + Artistic approaches enhance ways to generate, communicate, and represent data. + Artistic materials and forms center context and embodiment in data representations 	<p>Tensions</p> <ul style="list-style-type: none"> - Challenges relate to simultaneously representing and balancing both 'local' and 'global' perspectives of data through the materials of specific art forms. - Students must navigate multiple disciplinary ideas about what counts as evidence and what priorities should drive representational choices.
<p>Expressing uncertainty by qualifying generalizations with probabilistic language.</p>	<p>Synergies</p> <ul style="list-style-type: none"> + Arts component allows for emphasis on engaging with multiple perspectives or data stories throughout data inquiry. + Acknowledge and represent the non-neutral nature of data inquiry and visualizations. + Uncertainty can be visualized and embodied through artistic characteristics as well as through language. 	<p>Tensions</p> <ul style="list-style-type: none"> - Conventions for mapping meaning onto artistic representations are not pre-determined as they tend to be in conventional data representations, which can present challenges in choosing and interpreting representations. - Allowance of subjectivity in both the creation and interpretation of data-art can lessen creators' control over their message.

How disciplinary synergies promoted IIR

Going beyond data: Contextualizing data through visualized or performed narratives

The narrative or performative art forms of dance, comics, photo-essay, and collage, each offered unique affordances for supporting students in *going beyond data*. In the *Dance* unit, one group of students choreographed a dance based on a line graph visualizing e-cigarette use among teens. The students used their body positions to create an embodied quantitative comparison between two groups and choreographed their movements to represent how the data changed over time. However, the students also went beyond describing data by physically representing the likely outcome of using e-cigarettes: The dance ended with all students laying still and lifeless on the floor. Thus, dance offered a physical language with which students could both describe a numerical trend and narrate the possible health impacts on teens.

In the *Photoessays* unit, one student composed a series of photographs that highlighted construction as a potential contributor to lower air quality in her neighborhood (Figure 2). After selecting air quality data from a public map-based data visualization tool and making a scatterplot to explore the relationship between air quality and average life expectancy, the student *went beyond the data* by using photography to highlight a potential explanation of lower air quality observable at the street level of her neighborhood. To construct her photo-essay, she chose to photograph a construction site she passes everyday to school. Her series used patterns to represent the frequency of exposure she experiences in her daily routines and her broader claim about the prevalence of construction in her neighborhood over time. In her artist statement, she explained her compositional choices, such as framing, use of line, and repetition, to “shine light on these neglected endangerments” and “show my perspective of seeing construction in my daily life.” This example demonstrates how data storytelling through photography can help students to contextualize quantitative patterns in their personal experiences, and to communicate potential explanations for those patterns.



Students' artist statement: “I grew up with the thought that construction is usually the cause of traffic. While that's true, I wasn't told much more about the dangers of it. Other than the worsened transportation, most sites go overlooked until a building or bridge is officially created and advertised. With construction being the normality in this borough, the damage it causes lives in a shadow behind 'more important' issues. Construction isn't deemed to be important to many people, yet causes decreased air quality that is capable of damaging lungs and increased harsh sounds that contribute to noise pollution. My goal for this photo series was to shine light on these neglected endangerments.

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Everyday, to and from school, I pass by a bridge that is constantly under construction and next to it, a building that is in the works of being finished. I realized that I never really paid much mind to it because it's normal for places to be under construction. No harm can come from it, in fact we are gaining a better bridge and building, right? Then I thought more about it and came to a conclusion that although it looks like not much damage is occurring, there is always more than meets the eye. We aren't able to see the air quality changing, but it does. The average microgram per cubic meter of fine particulate matter is 7.2 where I live. Then we passed by cranes and drills that I used for capturing the noise that came from construction. It is also important to have greenery in a healthy neighborhood and the places that are a great opportunity for this are being occupied with being the home to construction materials.

Throughout my journey of creating my photo essay, I tried to focus also on what was visually appealing. I used the bridge lines to divide parts of my pictures. Construction sites use a lot of bright orange cones and blockers that I wanted to incorporate in my photos to add color. I took the pictures in my car and used the window frame to show my perspective of seeing construction in my daily life."

Figure 2. This students' photo-essay uses photography techniques and verbal narrative to connect her lived experiences to aggregated data, and to spotlight an environmental issue in her neighborhood.

In the *Comics* unit, one student created a comic using the online comic-creation platform, Pixton, to reflect on issues teens experience related to friendship, such as bullying on social media. The student selected data about how often students in their class experienced drama on social media from a class-wide survey completed at the beginning of the unit. Their comic (Figure 3) introduces this issue by showing an interaction between three friends: Two boys notice that their other friend is sad and discover that he was bullied on social media. The two boys respond empathetically through their dialogue and gestures. However, one of the boys researches this issue further, finding a statistic about bullying on social media. The character *goes beyond the data* by using this statistic to alleviate his friend's pain, pointing out how the statistic shows that a lot of other teens have experienced a similar kind of bullying and that it is not an isolated event. Drawing on data enabled the friend to not only individually express empathy but suggest that there is a broader population of their peers who would likely empathize with this experience. In this case, the strategy helps the friend distance himself from the negative experience and re-engage in social media with a new perspective. This connection between the use of data to reflect on how one might manage their emotions was not just enacted through comic narratives, but in the way student authors reflected on their reasoning process. For instance, one student shared:

"This made me see that I'm not the only one that's struggling and it's okay because there's still kids that are going to find it easy and they're going to know how to become your friend properly. It shows that basically everyone has a little bit of trouble for the most part and I'm not alone when it comes to how I view making friends."



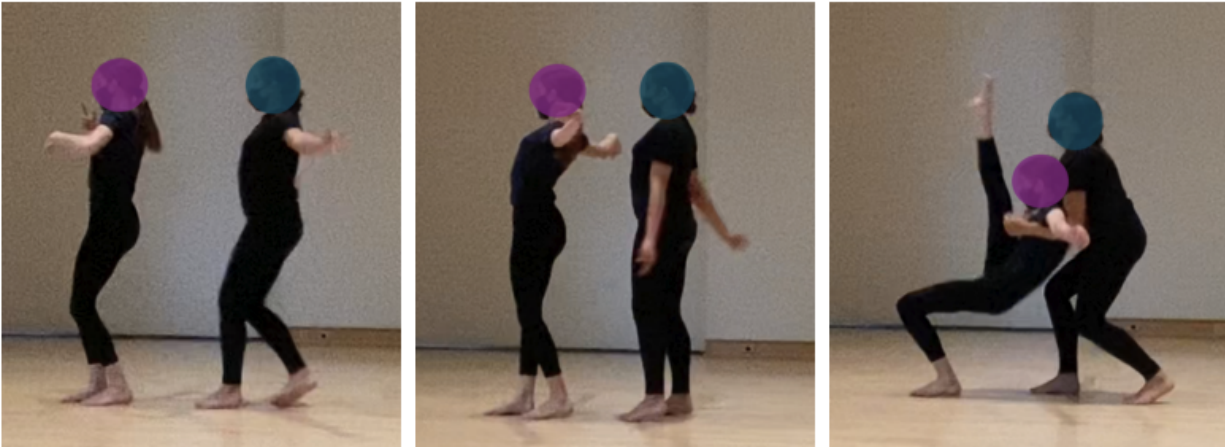
Figure 3. One student's data comic on online bullying and frequency of drama.

Using data as evidence: Representing data in context through composition and movement

Integrating art and data challenged traditional disciplinary ideas about what kinds of data (e.g., numbers, text, photographs) count as evidence and how to communicate data as evidence. In the *Photoessay* unit, students shuttled between taking photographs and engaging in statistical inquiry (i.e., asking statistical questions, analyzing data, and visualizing data) to investigate social and environmental issues in their neighborhood. Photography motivated students to reason about different types of data (i.e. qualitative and quantitative data) at different levels of aggregation (e.g., street vs. neighborhood) to construct data stories. Furthermore, artist statements which accompanied artworks in presentation, enabled students to reflect on their lived experiences and how reasoning about data, in some cases, shifted their perspectives. As one student remarked:

"I never really paid much mind to it because it's normal for places to be under construction. (...) Then I thought more about it (...) We aren't able to see the air quality changing, but it does. The average microgram per cubic meter of fine particulate matter is 7.2 where I live..."

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3 An arts-integrated approach to data visualization also offered unique ways to
4 contextualize data. For example, in the *Dance* unit, students choreographed dances that not
5 only compared groups along categorical variables but physically embodied features of these
6 groups (e.g., movements like those of a bird or a fish). In one dance, students contextualized
7 human's exploitation of animals through a "trust fall" (Figure 4): One dancer, embodying
8 animals, falls into the arms of another dancer, embodying humans, as a metaphor for animals'
9 reliance on—and thus need to trust—humans to help them to survive. As one student explained,
10 using dance to both represent and interpret statistical ideas, "made us look at the graphs in a
11 different way. Like at all angles to figure out what is the best view we can get of this graph to
12 make movements to help others understand what is happening."
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31 **Figure 4.** Two students doing a "trust" fall in their final performance of their choreography, based
32 on their examination of an animal population graph.
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36 Expressing uncertainty: Critically engaging with how data are produced and 37 used 38

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40 Students demonstrated engagement with the inherent uncertainty of informal inferences
41 by raising critical questions about generalizability and by representing multiple perspectives on
42 data or possible data stories. In the *Comics* unit, for example, one student created a comic that
43 reflected on class-wide data on a survey item, "*How easy or hard it is to make friends?*" (Figure
44 5). The main character is a comic book version of herself speaking directly to the readers, and
45 engaging with potential uncertainties in the data by reflecting on her own friendship history. She
46 notes that all her friends were made at such a young age that she cannot remember what it was
47 like to make new friends. She wonders whether her experience "matters" in how to interpret the
48 survey result given these potential unaccounted variables ("when and how you met your
49 friends," and people's abilities to recall those experiences) and questions whether the data is
50 generalizable for her. In this example, the dialogic, character-centric format of the comic,
51 facilitated this students' personal reflection on the data, encouraging her use of personal
52 experiences to identify hidden variables and question the validity of the survey data.
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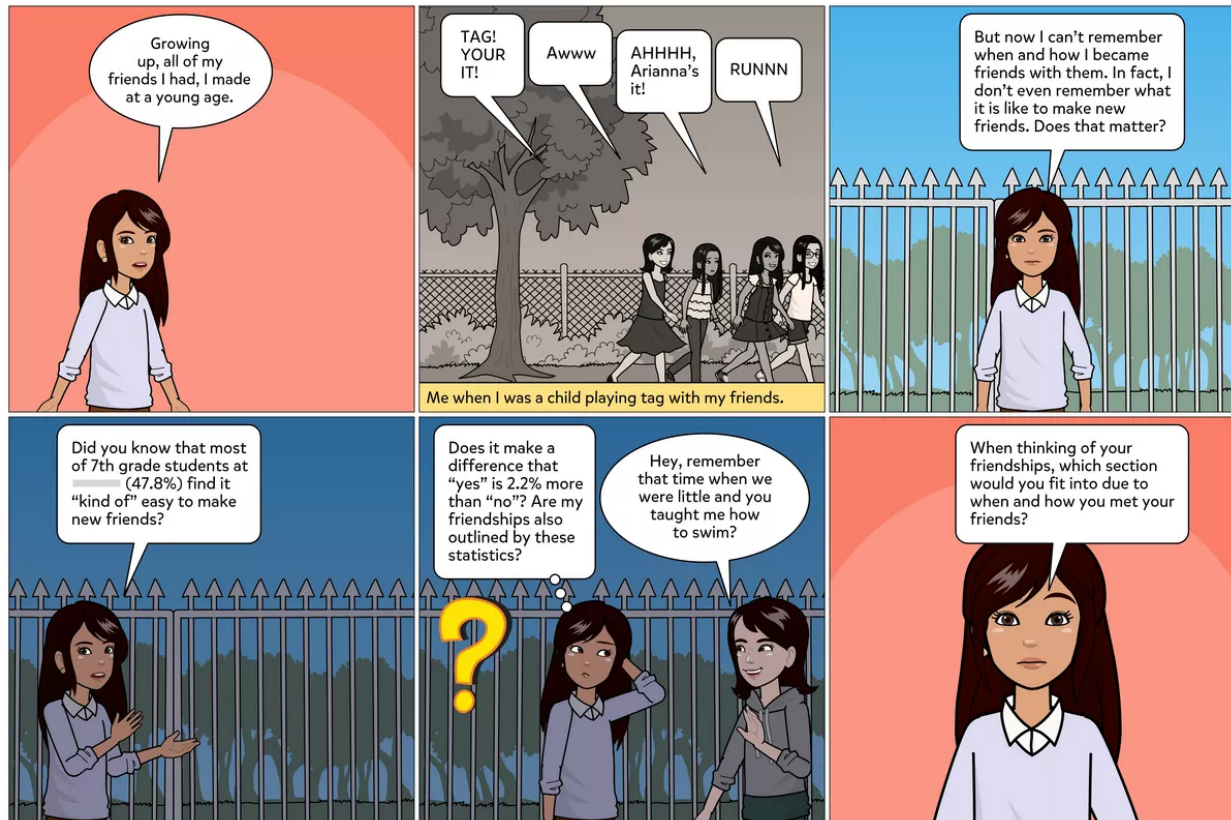


Figure 5. Example of a comic made by a student from the *Comics* unit.

In the *Collages* unit, students created collages to represent how teens spend their time and how time use impacts their well-being. The whole class engaged with uncertainties inherent in making informal inferences about a population (i.e. teens) from a sample (i.e., class-wide data) by asking questions such as “how would this data look different for students living in California?” Notably, planning visual associations between time use and wellbeing in making their collages surfaced students’ own assumptions about how they see themselves and others (Figure 6). For instance, one student challenged claims that people have agency over their time use, positing that time use among youth is less of a choice than it is for adults. Another student reflected on how assumptions about people based only on their time use can misrepresent who they actually are, and limit their possibilities for growth. Such discussions led students to question what other data might be needed to best reflect who and why a person is who they are.



It worked well for him, because he knew the reason why we were making it he knew that it had to be based in rooted in data, his own data, how do I spend my time, how does it make me feel...
-ELA teacher



Life Is A Road - Which Side Will You Travel?

"She changed her argument halfway through the second day and she was like maybe as we get older these things become a choice, like you don't always have to engage in the things that make you feel depleted and sad and you know all those things are still going to be there, but maybe it becomes a choice."
-ELA teacher

Figure 6. Two student-created collages alongside reflections on their work shared by their teacher during the post-implementation interview.

How disciplinary tensions constrained IIR

Going beyond data: Missed opportunities to integrate disciplinary practices

While there were many promising ways that art and data science synergized to support IIR, there were also ways that these domains created tensions that constrained IIR. Leveraging art to contextualize patterns, consider implications, and draw connections to students' lived experiences required shuttling between domain-specific practices and routines that were part of different classroom cultures. However, some students demonstrated over-reliance on either artistic or mathematical practices and values common in their classrooms. In the first iteration of the *Collages* unit, for example, we had initially planned for concurrent ELA and Math classes to engage students in complementary perspectives on data from the American Time Use Survey (bls.gov/tus). However, unforeseen testing requirements disrupted this schedule so that students first completed an ELA-only unit, then a Math-only unit, using the same focal dataset. As a result, discussion of big ideas about data (a typical practice in ELA), and support for graphing and data analysis (typical practices in Math), were contained in separate classrooms,

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3 rather than integrated. When students in the Math class began to question the relevance of data
4 to their lives, teachers, lacking preparation to facilitate these critical discussions, missed
5 opportunities to help their students go beyond the data by, for example, examining the role of
6 sampling in informal inferences or the social implications of potentially under-representing some
7 groups of people. On the other hand, while such questions were explored in ELA, the discussion
8 of data remained broad and conceptual rather than tied to a specific data set and analysis.
9

10 Another type of constraint emerged from teachers' concerns about facilitating discussion
11 around social issues. In the comic unit, for example, teachers were concerned about the kind of
12 discussions and personal reflections that might emerge from exploring the topic of friendship.
13 One consequence was that data on some variables (such as cyberbullying and race) were left
14 out of the data set, and in turn, from the data visualizations students analyzed. Ultimately,
15 students spontaneously addressed topics of cyberbullying and race in their comics,
16 demonstrating the personal relevance of these issues to their lives, but also showing how
17 neglecting these variables limited the kinds of informal inferences students could make about
18 them. While the art teacher felt comfortable connecting disciplinary concepts to personal
19 experiences, the math teacher was prompted to adjust her pedagogical approach, and shared,
20 "I felt like it was just a positive experience for me because I don't always get to talk to them
21 about, you know, things that are more relatable."
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25 Furthermore, the integration of personally-relevant data also introduced tensions in how
26 to reconcile personal experiences with broader trends, and the impact of such connections on
27 broader claims that can be made. The ELA teacher of the *Collages* unit, for instance, noted in
28 her post-implementation interview that many of her students "weren't creating collages based on
29 data [from the American Time Use Survey, or sampled from their personal time use]. They were
30 creating collages in an attempt to send some kind of message about teenagers in their lives,
31 and how they spend their time and how they feel." While this in itself is a valuable endeavor, in
32 an arts-integrated IIR learning context, it also demonstrates the need to engage students with
33 models of data-art that effectively integrate both personal and broader experiences evidenced in
34 data.
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39 Using data as evidence: Missed opportunities to connect artistic choices to 40 a broader narrative based on data

41 [Differences between data science and the arts in terms of the kinds of evidence valued in](#)
42 [arguments, were especially apparent in the *Collages* unit. When her math teacher colleague](#)
43 [dropped out of the study, the ELA teacher led both the math and the ELA components in a](#)
44 [second implementation of this unit.](#) Students collected self-reported data about how they spent
45 their time over the prior week (i.e., activities, time on task, mood) and collectively created three
46 data visualizations of time spent engaging in different kinds of activities (i.e., leisure, work,
47 outdoor time). While the ELA teacher supported students in identifying data points, clusters, and
48 patterns in a data visualization intended to be used by students as evidence of their claims, she
49 generally prioritized categorical data and descriptive analysis, typical of common ELA activities,
50 such as identifying evidence in news articles. Thus, students received less support in engaging
51 with more formal mathematical concepts and practices, such as representing proportions and
52 distributions. Their collages reflected this emphasis by communicating broader themes of their
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3 investigation, but lacking numerical representations or explanations. There were thus missed
4 opportunities to engage with critical perspectives about data using the affordances of collage to
5 integrate images, text, and numbers.
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7 These different disciplinary priorities were also reflected in students' tendencies to allow
8 aesthetic preferences, rather than data, to drive their artistic decisions. A student in the *Dance*
9 unit, for example, reflected: "We wanted to do (dance) movements that didn't always go with the
10 graphs," but instead, "just kinda looked cool." Students also negotiated tensions between
11 embracing subjectivity, which tends to be valued in the arts; and conveying clear messages,
12 which tends to be valued in data science. For some students, audience considerations were
13 central to supporting their representational choices. For example, in the *Dance* unit, as students
14 planned how they would create embodied representations of the data, they questioned and
15 examined the perspective of the audience, including how the audience would interpret and
16 engage with their dance and the information they were communicating, as well as the feelings
17 that they wanted them to experience. One student reflected on their data dance creation
18 process, sharing:
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22 "Some pieces we did change because when I was choreographing the dance, I like
23 knew what was happening and what it was supposed to represent, but we really had to
24 think about... how to make it easier to understand for those who haven't watched it a
25 bunch of times"
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28 This example demonstrates the challenge for students to communicate claims clearly in a
29 medium that is so open to interpretation. Yet at the same time, this example shows how
30 students recognizing the possibility for multiple interpretations, and desiring to balance these
31 with a clear message, assumed the perspectives of an audience to critique their own work, and
32 to inform refinements to their representational choices.
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35 While some students across all four implementations successfully realized this
36 disciplinary synergy, and could connect aesthetic values, art elements, composition strategies,
37 and stories to informal inferences, others struggled. For instance, in the *Collages* unit, the
38 messages in some students' artworks primarily emphasized the emotional consequences of
39 time use and only weakly incorporated data-based evidence. Meanwhile other students'
40 artworks only superficially commented on things that they liked and disliked. In these cases,
41 students' familiarity with typical art class collage and self-portrait assignments may have led
42 them to overlook the prompt to use these to connect data to a claim.
43

44 In the *Photoessays* unit, some students relied too strongly on feeling "inspired" to take
45 pictures, missing other opportunities to connect images with quantitative data about their
46 neighborhoods. One student reflected on this tension between inspiration and using
47 photography as a form of inquiry in his artist statement: "I was ready to go outside and find
48 some inspiration to create a story of some kind with my pictures, but as big as my neighborhood
49 park is, there was only one thing that made me inspired to take pictures..." The final
50 photo-essay demonstrated the result of not addressing this tension. The essay begins by
51 discussing statistics on access to parks and the student's process of inquiry, but shifts abruptly
52 to a more poetic, conceptual analysis in order to explain and justify the photographs the student
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3 was “inspired” to take. While the essay explores a clear theme, the overall message and
4 informal inference is ambiguous and not fully supported by data.
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6 7 Expressing uncertainty: Grappling with uncertainty in both data and art

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9 In recognizing the inherent uncertainty of informal inferences, students are ideally challenged to
10 ask questions about how data are produced and used (e.g., who collected the data, for what
11 purpose, what is not represented by that data?) instead of disregarding data that does not align
12 with their lived experiences or citing inferences as neutral, objective facts.
13

14 In the *Comics* unit, for example, some students identified gaps in their class data set,
15 highlighting variables such as race and other aspects of identity as important for understanding
16 how teens make friends and for reasoning about the statistical interpretations within their data.
17 When explaining their certainty regarding the data, one student responded:
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20 “I feel like [the survey should consider] bullying and maybe something close to
21 friendships with how you make the friendship in life when it works out. For example, if
22 you’re maybe a person of color it could be difficult for you to make friends, or if you have
23 a disability or reasons why you might be excluded or reasons why you might not feel like
24 you can make friends.”
25

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27 Thus, students identified gaps in available data (e.g., the absence of data on race), which
28 introduced uncertainty about their inferences. They questioned whether it was possible to make
29 valid informal inferences with the dataset without being able to explore how patterns in the
30 aggregate might differ by student background. In turn, students struggled to use the Comics
31 format to both convey a clear inference, while also conveying their uncertainty about it.
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34 35 Discussion

36 37 Data-art inquiry practices and instructional recommendations

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39 We sought to explore how integrating data science and the arts enabled or constrained
40 opportunities for students’ IIR. Often, traditional graph-based representations accompanied by a
41 verbal narrative are adequate to support in IIR. Yet, we argue that arts-integration prioritizes a
42 humanistic perspective on data that allows students to incorporate the personal and contextual
43 knowledge necessary for IIR (Bhargava *et al.*, 2015; De Veaux, *et al.*, 2022; Gebre, 2022;
44 Madison, 2002; Philip *et al.*, 2013; Rubin, 2005, 2021; Scheaffer, 2001; Steen, 2001; Vance *et al.*,
45 2022; Wolff *et al.*, 2016).
46

47
48 Below, we posit four data-art inquiry practices observed to support or constrain students’
49 engagement in IIR, along with instructional recommendations for amplifying the synergies, or
50 addressing the tensions observed between domains.
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52 53 1. Use visual or performed narratives to contextualize data relationships

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3 While students' used narrative to engage successfully in certain aspects of IIR, some
4 students struggled to integrate data science ideas, such as uncertainty and evidence, into a
5 narrative form.
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7 In terms of promoting IIR, we observed how narratives offered structures for elaborating
8 on the context of data (Zohar & Nemet, 2002), and for communicating generalizations,
9 explanations and predictions with data. For instance, in the *Comics* unit, students used narrative
10 structures of conflict to explain the expected and apparent messages in the data; and
11 concretized abstract data relationships through relatable examples (e.g., social interactions
12 among characters). In the *Dance* unit, students made intentional decisions about how to
13 re-represent relationships observed in graphs using time, space, movement, music, and
14 dancers' roles; and moreover, how these elements of dance would impart an emotional quality
15 to those relationships portrayed, effectively communicating their evaluation of their real-world
16 implications. In the *Photoessays* unit, one student proposed a relationship between low air
17 quality observed in public city data, and the abundant local construction observed in her
18 neighborhood, captured in her photo series. Such examples are notable because of how
19 contextualizing data can support informal inferences, the understanding of real-world
20 applications of statistical concepts such as multivariate analysis (Makar et al., 2011; Pfannkuch,
21 2011); and can also seed discussions of what further data investigations could be conducted to
22 test hypotheses.
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26 At the same time, narratives tend to afford telling a singular or limited set of
27 perspectives. Conversely, a conventional data-based argument describes aggregated
28 perspectives apparent in data patterns and trends. We aimed for learners to embrace both the
29 single and aggregate perspectives. However, achieving this balance was challenging,
30 particularly as students were still navigating the constraints and affordances of specific artistic
31 materials and forms.
32

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34 *Recommendations.* Contextualizing data in narrative can be a powerful way to
35 concretize abstract ideas about data, but it can also lead students to focus on individual stories
36 instead of aggregate data patterns. Curriculum designs can help learners to take advantage of
37 narrative to support contextualization of the data by offering templates of narrative structures
38 and techniques for communicating about data, and a discussion of their limitations. These
39 templates might scaffold strategies for integrating single and aggregate perspectives, comparing
40 among contrasting perspectives, and juxtaposing complementary datasets. For example, Bach
41 et al. (2018) identifies design patterns for data comics, which use features such as panel order
42 and layout for data-driven storytelling.
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45 46 **2. Draw on personal experiences to engage with uncertainty in relating local to global 47 data**

48 In this data-art inquiry practice, learners go beyond the data to grapple with issues of evidence
49 and certainty in relation to their personal experiences (D'Ignazio & Bhargava, 2016; Gutiérrez et
50 al., 2020). In the *Photoessays* unit, learners localized their investigation of a data topic in a
51 familiar context (their neighborhoods), and used their experiences living in those neighborhoods
52 to identify gaps in data that contribute to its uncertainty. Meanwhile, *Collages* students, reflecting
53 on their own and others' time use, wondered about the degree to which people have agency in
54 the activities they choose. This led students to question the certainty with which global
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3 conclusions could be drawn about time use data, a theme that ultimately appeared in some
4 students' artworks.
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6 While an arts-based approach to data can support engagement with bigger ideas in data
7 science, such as uncertainty, it also risks leading students to overemphasize subjective and
8 personal experiences at the expense of grounding their ideas in data. For example, some
9 *Collages* students developed artworks about how they would like to spend their time, rather than
10 to communicate data about their current time use. Such examples resonate with other literature,
11 which finds that contextual information in statistical problems can sometimes mislead students,
12 causing them to magnify their personal experiences relative to aggregated data-based evidence
13 and broader patterns in data (Konold, et al. 2015; 1997; Lee and Wilkerson, 2018).
14

15 *Recommendations.* Curriculum designs might support students' reasoning about local
16 and global data by guiding their reflection on how their personal experiences relate to these
17 data. Such guidance might involve prompts to consider how variations between local and global
18 patterns might correspond to concepts of sample representativeness and sample variability
19 (Rubin, 1991). This guidance might also support learners' appreciation of the implications of
20 uncertainty in such data. For example, students might be prompted to use their personal
21 experiences to identify missing or "counter-data" (D'ignazio & Klein, 2020), to consider how
22 these gaps contribute to the certainty with which conclusions about these data can be drawn,
23 and how they contribute to misrepresentation of the populations described by the data
24 (D'ignazio and Klein, 2020; Lee et al., 2022). In this manner, students' personal experiences
25 might begin conversations about the significance of data at a societal level.
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30 **3. Use aesthetic representations to elevate emotion in communicating about data**

31 In this data-art inquiry practice, learners are intentional about using their data art to emphasize
32 the lived experiences of the people reflected in the data. Students in our study used
33 characteristics of their artistic media, such as collaborative choreography in *Dance*, and
34 interactions among characters in *Comics*, to represent the human dimensions of data even as
35 they communicated statistical ideas, such as uncertainty, trends, and group comparisons. These
36 dimensions enabled learners to convey emotions through how their characters felt in the
37 *Comics*, and within how the message was conveyed in the choreographic choices in *Dance*.
38 This practice resonates with a data feminism principle that d'ignazio & Klein (2020) call
39 "elevating emotion."
40

41 However, artistic data representations can conflict with data-driven choices. These
42 tensions can become more pronounced when disciplines differ in what counts as evidence and
43 what priorities should drive representational choices; and when learners shift from using
44 canonical data representations, which have established conventions for symbolizing ideas about
45 data, to imagining novel artistic representations to both communicate data ideas, and to elevate
46 emotion. For example, some *Dance* students chose particular dance moves because of their
47 aesthetic appeal, not because they would serve a data-based argument. Similarly, some
48 *Photoessays* students sought to collect certain photos that were visually interesting, even
49 though they were unrelated to the subject of their data; and some *Collages* students chose to
50 include certain imagery in their collages because these were related to the broader theme of
51 their investigation not because they illustrated any pattern interpreted in their dataset.
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Recommendations. One recommendation for supporting learners in adopting this data-art inquiry practice is to establish clear criteria for what counts as evidence with respect to the values of each domain. These criteria could be illustrated with models to demonstrate various ways that artistic media can be used to communicate particular arguments with data. Students could examine professional examples of data art in terms of the perceived effectiveness of different techniques at conveying data claims and evoking particular emotions, and use these as inspiration for their own data artworks. Templates of common techniques might also be provided, which students could modify according to their own goals.

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Another recommendation is to incorporate the writing of artist statements. Artist statements are used by artists for self-analysis, but also to convey to audiences their intentions, approaches, and reasoning (Fallon, 2019). In our study, students additionally used artist statements to describe how they analyzed and interpreted their data, the data-based argument that they aimed to convey, and the impact they intended to have on their audiences through their artistic choices.

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Finally, assessment strategies should be devised early during unit planning, with consideration for what disciplinary, interdisciplinary, or transdisciplinary learning goals are intended, and for what would be satisfactory evidence that learners have achieved those goals (Gao, et al., 2020). Artist statements can be useful assessment artifacts, as they reflect students' reasoning and understanding in ways that are implicit in their final products. Artist statements also monumentalize the process of data art creation, and so address criticisms that STEAM overlooks the importance of the creative process in favor of the final product (Perignat, 2019).

31 **4. Use audience considerations to reflect on the non-neutrality of data**

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In this data-art inquiry practice, learners use their audiences' likely interpretations to refine their artistic choices. This exercise can prompt reflection on the inherent subjectivity of both art and data. It can also encourage recognition of how, through messaging, data can be used and misused in arguments. For instance, students in the *Dance* unit put themselves in their audience's shoes to help evaluate the clarity of their message, and to iterate on their choreography accordingly. In the *Collages* unit, students reflecting on the stated purpose and application of public time use data, proposed that agency over time use may be different among teens than among adults, so that arguments based on time use will be more or less valid, depending on the audience to whom they are intended to apply. Recognizing the non-neutrality of data is especially relevant as youth increasingly encounter complex social issues that require reasoning about data, and understanding it from multiple perspectives (Gutiérrez et al., 2020). Data science and the arts invite different degrees of subjective interpretations and critical questioning of data-based evidence.

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Recommendations. Peer critique can support learners in this data-art inquiry practice. Critique is a discussion format through which groups of artists reflect on peer (or professional) work. Critique can be used to analyze and learn from artistic choices. It can also allow artists to test whether their choices are having the desired audience impact. By observing an audience's reactions to, and interpretations of a message, learners can determine whether the perspectives and stories they intended to convey are apparent to others. Critique can furthermore be a

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3 valuable opportunity for formative feedback, as learners can use audience feedback to iterate
4 on, and refine their artwork (Hetland et al. 2015).
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6 7 Theoretical contribution

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9 This work connects to several existing theories and frameworks in data science
10 education that similarly seek to expand on learners' informal inferential reasoning skills. One
11 notable connection between a data-art inquiry approach and a feminist approach to data
12 science (D'ignazio & Klein, 2020), whereby art can serve as a means for personal
13 self-expression and for wrestling with issues of subjectivity. By elevating emotion and
14 embodiment, rethinking binaries and hierarchies, and considering contexts—each of which are
15 principles of data feminism—the data-art inquiry approach has learners engage in IIR in ways
16 that emphasize the power relations inherent in the generation and use of data. Concurrently, the
17 data-art inquiry approach joins other efforts to take more humanistic approaches to data
18 science. Data-art inquiry practices may serve as a way to collapse the distance between what
19 Wilkerson & Lee (2021) describe as the personal and cultural layers of data practice. Students'
20 taking on artistic approaches to visualize data can further challenge disciplinary values in data
21 science, which in contrast, have historically minimized the value of context, emotion, and
22 subjectivity. Lastly, a data-art inquiry approach connects with Halverson's (2021) notion of
23 learning *in* the arts (e.g., learning about pottery in a pottery class) and learning *through* the arts
24 (i.e. learning about Ancient Greek culture and mythology in a pottery class). Our findings
25 suggest that, at least with an already interdisciplinary field of reasoning such as IIR, it is worth
26 not only considering how students might learn about data “in: and “through” the arts, but “in
27 synergy with” the arts.
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33 Limitations and future work

34 Variation in support for interdisciplinary instruction

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36 This research is limited in several ways. First, we were limited to selecting our examples
37 based on those for which we had the most complete information in terms of documentation of
38 students' process and final artifacts, teachers' reflections on their observations of those
39 particular students, and/or post-unit interviews with the students.
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42 This variation in quality and completeness of our data is in part due to contextual
43 variations between participating schools. Indeed, opportunities in arts-integrated data inquiry are
44 shaped by conditions of their implementation (Damşa *et al.*, 2019). The synergies and tensions
45 we observed varied across contexts, which differed in terms of the resources including time,
46 technology access, and incentives or disincentives, that can support cross-domain teaching and
47 learning. For example, the *Dance* school already prioritized interdisciplinary student-led project
48 based learning, had existing routines for teacher collaboration, flexibility in the curriculum for
49 teachers to coordinate across their classes, and traditions for celebrating students'
50 interdisciplinary work in a community-wide exhibition. Meanwhile, the other schools differed in
51 the degree to which teachers were held accountable to standards, and struggled to find time to
52 co-design and coordinate their classes. Support for interdisciplinary instruction also differed
53 between subject areas, with math classes tending to get priority access to laptops, and the arts
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3 classes tending to have more flexibility in what content could be covered. Unexpected testing
4 requirements and unreliable technology access interrupted our implementation plans, requiring
5 us to make on-the-fly curriculum adjustments, such as paper-based versions of previously
6 planned digital data visualization activities
7

8 As Vess and Linkon (2023) state, interdisciplinary education, while valuable for both
9 teachers and students, often requires significant institutional reform to be effective. The
10 challenges in implementation that we observed echo Power and Handley's (2019) research,
11 which identifies barriers to interdisciplinary instruction to similarly include curriculum inflexibility,
12 regulatory limitations with regard to classroom space and course scheduling, and lack of
13 resources and administrative support. However, Power and Handley also identify facilitators of
14 interdisciplinary instruction, including motivated and qualified instructors, spaces conducive to
15 interdisciplinary collaboration, and institutional goals and individual recognition for
16 interdisciplinary efforts.
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19 Future research might therefore explore ways to create subject-integrated curriculum
20 that is flexible and adaptable to contexts that differ in terms of administrative support, school
21 priorities, and teacher preparation. Future work could additionally explore different approaches
22 to disciplinary integration that may be more or less feasible in different contexts, such as
23 boundary crossing, which the intersection between disciplines is used as a site for
24 transformation, where students can develop new and unexpected ways of doing and thinking
25 (Vereijken et al., 2023). This future work might also explore how to best prepare teachers across
26 subject areas and schools that are differently resourced and supported, to teach arts-integrated
27 data literacy in ways that build on their own and their schools' assets. As Power and Handley
28 (2019) In such efforts, it is important to be mindful of the barriers and facilitators of
29 interdisciplinarity (Power & Handley, 2019).
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33 Generalizability to other arts contexts 34

35 Another limitation is our small sample size, which reduces the generalizability of our
36 findings to other teachers and learners. Future research might consider how arts-integrated data
37 literacy instruction might take place in other learning contexts, such as schools with different
38 student demographic and/or achievement profiles, contexts both in and out-of-school; by
39 teachers with different preparation; and in institutions with different disciplinary cultures and
40 resources.
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42 A related limitation is that this study focused on the integration of data literacy into just
43 three arts contexts: visual arts, dance, and English Language Arts. As well, our units largely had
44 students engage with aggregated data and data visualizations, and not with raw data. Future
45 research might test the applicability of our framework to other arts and arts-related learning
46 contexts, such as filmmaking and journalism. Similarly, future work might more systematically
47 explore the potential value of various other curricular approaches to data-art inquiry, such as
48 offering students existing datasets vs. having them generate their own; having them work with
49 raw data vs. aggregated data; and encouraging their creation of artwork based on an inference
50 from data, vs. artwork that concretely maps symbols to individual data points. It is possible that
51 such further research may uncover new data-art practices not captured by this current study.
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Conclusion

Drawing on different disciplinary values and practices can promote more humanistic data literacy education. This study has implications for research, design, and practice in the context of interdisciplinary learning more broadly, and in data literacy education more specifically. Given the barriers to cross-subject integration in classroom settings, establishing a robust conceptualization of arts-integrated data literacy learning will guide curriculum designs that build on each discipline's unique affordances to ensure that the learning goals of each are reciprocally supportive (Mejias et al., 2021), and help teachers and researchers to better recognize and support data literacy learning at the intersection of domains.

Differences in the cultures of domains in subject-integrated learning environments can either foreground or background epistemic (mis)alignments. Educators and curriculum designers might support students in navigating the epistemic misalignments between data science and the arts so that these misalignments do not remain tensions that hinder, but might become synergies that support learning opportunities.

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