

UC Davis

UC Davis Electronic Theses and Dissertations

Title

Exploring Data-Rich Pedagogy and Data Fluency in K-12 Science Educators

Permalink

<https://escholarship.org/uc/item/49k2x1cg>

ISBN

9798276023519

Author

Ostrom, Tracy Ann

Publication Date

2025-12-06

Peer reviewed|Thesis/dissertation

Exploring Data-Rich Pedagogy and Data Fluency in K-12 Science Educators

By

TRACY A. OSTROM

DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Education

in the

OFFICE OF GRADUATE STUDIES

of the

UNIVERSITY OF CALIFORNIA

DAVIS

Approved:

Cynthia Passmore, Chair

Alexis Patterson-Williams

Ron Cohen

Committee in Charge

2025

Table of Contents

ABSTRACT.....	III
CHAPTER 1 - INTRODUCTION.....	1
CHAPTER 2 – DATA SCIENCE IN K-12 EDUCATION: A STUDY OF EDUCATOR PROFICIENCY IN DATA FLUENCY AND DATA-RICH PEDAGOGY USING NASA ASSETS.....	4
CHAPTER 3 - EXAMINING DATA-RICH PEDAGOGY IN MIDDLE SCHOOL SCIENCE EDUCATORS	45
CHAPTER 4 - THE EFFECTS OF PROFESSIONAL DEVELOPMENT AND ONE-ON- ONE SUPPORT IN DEVELOPING DATA-RICH PEDAGOGY AND DATA FLUENCY IN MIDDLE SCHOOL SCIENCE EDUCATORS.....	86
CHAPTER 5 – CLOSING REMARKS	131
APPENDICES.....	138

Abstract

In a data-driven age, K–12 science education must evolve to foster data literacy among learners. This goal relies heavily on educators’ ability to integrate authentic data experiences into instruction. This two-part study first investigates the level at which educators practice data-rich pedagogy in their science classrooms and their ability to make sense of data when connecting to science content areas. An additional study then investigates how structured professional learning and one-on-one mentoring can enhance educators’ data-rich pedagogy (DRP) and data fluency (DF). Over the course of 2 years, data were collected from K–12 science educators in both studies through surveys, interviews, and classroom observations.

Results reveal a notable discrepancy between educators’ perceived proficiency with data and the depth of their classroom integration of data-rich practices. Although participants demonstrated enthusiasm for using a variety of data resources available to them through National Aeronautics and Space Administration (NASA) and Global Learning and Observation to Benefit the Environment (GLOBE), they reported challenges, including limited time, insufficient formal training in data science, and constrained curricular flexibility. Professional learning opportunities—particularly individualized mentoring—proved highly effective in helping educators understand how to navigate data resources while developing data-rich strategies. Also, when educators made sense of data sources through their interactions with data, they advanced their development of data fluency. This resulted in greater educator confidence in delivering data-centric lessons, providing learners with data literacy skills, and using data more iteratively and intentionally with them.

Both studies identify the gap in the literature on the critical role of sustained, targeted professional development in bridging the gap between educators’ intentions and enactment of

data-rich instruction. Perhaps this gap in educational science research exists because scaling such professional learning models remains challenging yet essential for preparing preservice and in-service educators to empower learners with the data literacy skills needed to engage in authentic scientific inquiry and problem-solving now and to better prepare them for post-secondary education. One of the overarching contributions of this study, absent from the field, is new knowledge on how to help science educators develop a variety of data-rich practices and advance their data fluency by demonstrating the connections among DRP, DF, and PD. Simply put, these studies address the “how to” of integrating data to support science content learning and data skills in learners, rather than merely relying on the principles that identify them.

Keywords: data, data science education, data literacy, data fluency, data-rich pedagogy

Chapter 1 - Introduction

The motivation for this research arose in 2020, during the height of the COVID-19 pandemic. As classrooms shifted to online learning, professional development also evolved. A district in the Bay Area asked me to host a webinar for K–12 science educators on engaging learners with science through distance learning. I focused on data, especially on numerous COVID-19 data-related news articles. My goal was to demonstrate to educators how to utilize COVID-19 data with their learners in a way that aligns with science practices. During the webinar, I explained how data helped learners understand the district’s decision to implement distance learning. They could also use the data to illustrate its impact on health choices, scientific research, and even public policies. The one-hour webinar revealed that science educators had limited experience in using and interpreting data for science content learning. Their exposure to data was mainly limited to “cookbook labs.” I then decided to explore further how data are used as tools in science education by identifying specific data connections within Next Generation Science Standards (NGSS) Science and Engineering Practices, along with references to modeling and collecting evidence in NGSS Performance Expectations. I wanted to determine whether educators were unaware of these data connections to state standards or unsure about how to teach with data.

This led me to deliver a data-focused webinar to a group of GLOBE educators I was already contracted to work with. The response was nearly identical. The GLOBE educators had experience engaging their learners in data collection, but they struggled to analyze and interpret the data as outlined in NGSS. As a result, their ability to interpret COVID-19 data for their learners was also limited. For the rest of the school year and the following year, I focused on providing professional support to help educators develop their learners’ awareness of the role

data plays in science education. These experiences fueled my passion for understanding data-rich pedagogy and using it as a tool in science education. At 59, I returned to school to earn a PhD, gaining deeper knowledge of data science education and exploring educators' ability to meaningfully incorporate data into their classrooms. In 2021, there was very little research on data integration in K–12 science education. I aimed to change that by researching to benefit both educational research and science teaching.

I quickly realized I needed a wider perspective on how science educators use data tools with their learners. After receiving a three-year fellowship through the NASA Solicitation and Proposal Integrated Review and Evaluation System (NSPIRES), I studied educators' proficiency in data integration within NASA's Science Activation Program, which is part of the Science Mission Directorate, along with their partners. This study and the results are presented in Chapter 2. After completing this study, it became clear that science educators primarily develop their understanding of data-rich teaching and data fluency through their educational experiences rather than through formal professional development. This study laid the groundwork for my additional research. I wanted to explore more deeply how educators use data as a tool in their classrooms after receiving formal professional support.

During the 2024-2025 school year, I collaborated with five middle school science educators, each with different teaching backgrounds, to explore how they use data in their classrooms. The study included five group professional learning sessions on data-rich teaching strategies, along with individual mentoring. I was curious about how these support measures influenced educators' progress and confidence levels in implementing data-rich lessons and supporting their data fluency. I observed these educators implementing data-driven practices and provided them with real-time feedback throughout the year. I also interviewed them at the end of

the year and asked them to evaluate their progress in DRP and data fluency using two continuums I developed. These continuums required educators to self-assess their DRP level and data fluency at the start and end of the school year. Results from this year-long study are presented in Chapters 3 and 4. Chapter 3 focuses on how these educators implemented data-rich practices with their learners, and Chapter 4 examines the impact of the professional learning and mentoring on their DRP and data fluency.

The following three chapters examine how to enhance educators' ability to integrate data into middle school science classrooms, thereby supporting science content learning and increasing educators' data fluency. Chapter 2 focuses on the first study with NASA-supported educators, and Chapters 3 and 4 focus on the research design and results of collaborating with five middle school science educators. Chapter 5 identifies my positionality and the limitations of both studies. Overall conclusions on the completed research, its contribution to educational research, and its implications for advancing data-rich practices and data fluency among science educators are also presented.

Chapter 2 – Data Science in K-12 Education: A Study of Educator Proficiency in Data Fluency and Data-Rich Pedagogy Using NASA Assets

Table of Contents Chapter 2

TABLE OF CONTENTS.....	4
ABSTRACT.....	5
INTRODUCTION.....	6
TERMINOLOGY	8
FRAMEWORKS.....	10
RESEARCH QUESTIONS.....	14
METHODOLOGY	15
STUDY RESPONDENTS.....	24
FINDINGS.....	27
DATA ANALYSIS	36
DISCUSSION	37
CONCLUSION & NEXT STEPS.....	38
REFERENCES.....	40

Tables and Figures Chapter 2

Table 2-1 – Alpha (Reliability) Values.....	19
Table 2-2 – Science Activation Partners Represented by Survey Respondents.....	24
Table 2-3 – IDEAS for Science Learning Survey Item Statistics.....	27
Table 2-4 – Domain 1 Responses from Formal Educators by Grade Level.....	28
Table 2-5 – Domain 2 Responses from Formal Educators by Grade Level	30
Table 2-6 – Domain 3 Responses from Formal Educators by Grade Level	32
Table 2-7 – Training That Shaped Educators’ Data Fluency	33

Table 2-8 – Summary of Data-Rich Pedagogy from Interview Data.....	34
Figure 2-1 – Core Components of Educator Data Integration and Fluency.....	7
Figure 2-2 – Educational Setting (Location) of Survey Respondents.....	25
Figure 2-3 – Distribution of Experience of Survey Respondents.....	26
Figure 2-4 – Grade Level of Learners from Survey Respondents.....	26

Abstract

As data science and data technologies advance, K-12 science education must keep pace to foster data literacy among learners. We rely on educators to accomplish this lofty data goal. I completed a study that examined the resources, practices, and professional training used by educators working with the National Aeronautics and Space Administration’s (NASA’s) Science Activation (SciAct) group in the Science Mission Directorate, in collaboration with partnering organizations, to develop their data fluency and data-rich practices. The study, conducted over 2 years, analyzed 158 K-12 educator survey responses on data fluency and data-rich practices, as well as 18 interviews with educators with varying teaching experience and grade levels.

Despite high self-reported confidence in understanding how to use data to support science content learning, the findings revealed a disconnect between educators' perceived data proficiency and the actual integration of data-rich instructional strategies. The reason for this disconnect may be twofold. First, most educators reported a lack of formal training in data science, relying instead on previous educational or work experiences in data practices. Second, educators reported that time constraints and the extensive science content hindered the iterative, deeper integration of data practices. Interview data highlighted that while educators value data and frequently use NASA visuals and other resources in the classroom, few could articulate the learner impacts of these pedagogical practices.

As a result of this study, I have identified the critical need for targeted professional development to bridge the gap between data-driven aspirations and actual practices. This form of educator professional learning has the potential to empower educators to effectively develop and use data as a tool to enhance science content learning and improve learners' data literacy skills.

Keywords: data, data science education, data literacy, data fluency, data-rich pedagogy

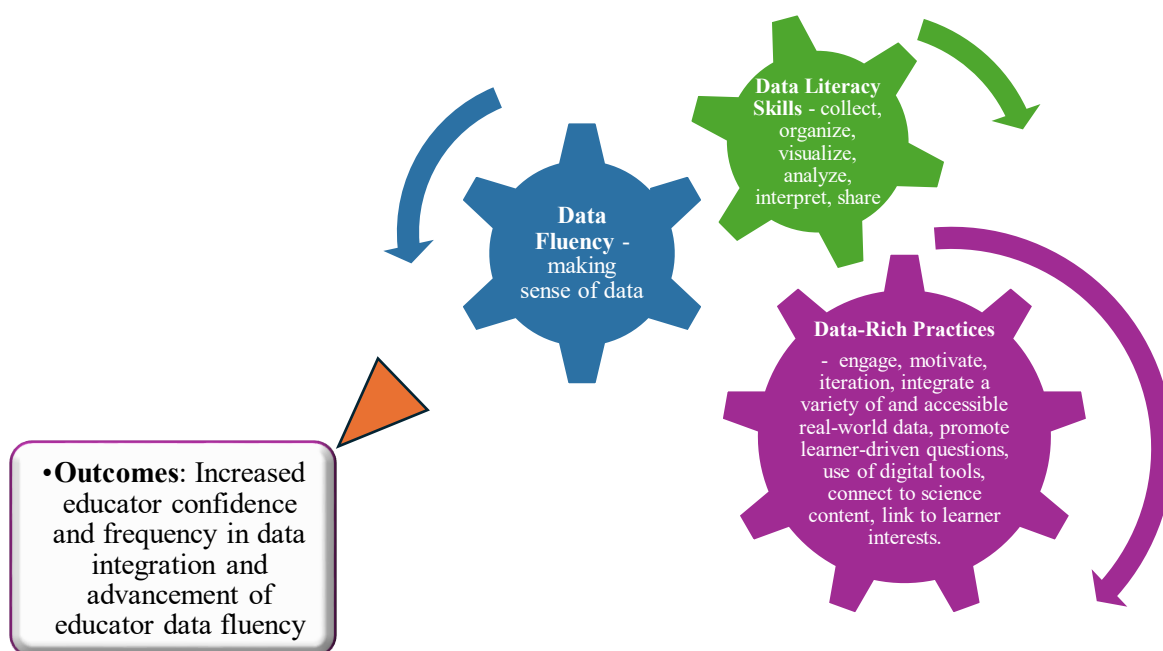
Introduction

Data and its associated technology significantly influence our daily decisions, including political choices, health risks, living conditions, and food preferences. Understanding how data are used in society and making sense of data is a valuable skill. Data helps us survive in the fast-paced world of technology, but it also enables us to thrive and contribute to positive changes in our communities (Schultheis & Kjelvik, 2019; Wise, 2020). Simply put, data is an informational tool that can lead to greater knowledge and improved decision-making (Rowley, 2007).

But understanding data integration in K-12 educational settings is not easily measured or understood. Data science courses have expanded significantly in post-secondary education over the past few decades. A recent internet search found at least 135 colleges and universities in the United States offering data science courses or degrees. The increase in data science education at the college level underscores the importance of promoting data literacy in K-12 science education (Gould et al., 2016; Wolff et al., 2016). Understanding data-rich practices, learner-centered data skills, and educator data fluency in K-12 classrooms is a core construct that this paper will address. Figure 2-1 illustrates how these data components, such as skills, practices, and fluency, support an increase in educator confidence in data integration and the advancement of data fluency. When educators scaffold various data-rich pedagogical strategies with their learners and engage in this iterative process throughout K-12 education, learners are better

equipped to think critically about data, develop data-centered analytical skills, and are more prepared to understand and solve real-world issues in their communities and globally (Kjelvik & Schultheis, 2019).

Figure 2-1 Core Components of Educator Data Integration and Fluency



Some researchers recommend that science educators adopt blended approaches to incorporating data into various traditional pedagogical strategies (Lee & Wilkerson, 2018). These blended approaches prepare learners to acquire and use different data skills in their learning. However, how educators perceive the blend of data literacy skills and practices within their educational contexts remains unclear. This research will investigate the level and types of data integration practices science educators currently employ with their learners. It will also examine how science educators perceive their level of data fluency and how that perception influences their data-rich practices. Understanding educators' current data-rich practices will contribute to the field of educational research by confirming existing support tools or proposing new tools to help educators acquire and implement data in their classrooms.

Terminology

Data and Data Science

The term 'data' originated from a tradition of research on numeracy and, later, 'statistical literacy' (Gould, 2017). Data consists of raw, unprocessed facts that require context and analysis to become useful. Data transforms into information when processed, organized, and interpreted to add meaning and value (Jain, 2025).

Stanford Professor Victor Lee acknowledges that “data science” can take on different meanings depending on the author's perspective and purpose (Lee, 2025). Lee provides a brief history and various viewpoints on how social scientists, mathematicians, and programmers perceive the use and purpose of data science. However, from a K-12 education perspective, Lee outlines the fundamentals of data science as the ability to reason with and utilize data (Lee, 2025). Data Science Education K-12 (DSE K-12) asserts that “*data is and all of the ways [learners] should think about and frame [data] as a concept and tool.*” (<https://teachingdatak12.org/concept>).

Data Literacy vs. Data Fluency

Numerous efforts have been made over the years to define data literacy; most agree that it is, at a minimum, an essential skill encompassing the ability to read, express, and understand data (Bauder, 2021). It most often describes learners, workers, and voters who need to develop “information literacy” to become fully functional citizens in the emerging “Age of Data” (Bauder, 2021). Kristin Hunter-Thomson, an author, presenter, and founder of Dataspire.org, defines data literacy in the context of K-12 education. She describes it as the ability for learners to think critically and ask questions about what they are learning and why it matters. Specifically, she highlights data literacy skills such as collecting, organizing, visualizing,

interpreting, analyzing, and sharing—core components of data science education

(<https://www.dataspire.org>).

Once we lay the foundations of data literacy in education, we can better understand why it is essential to acquire data skills. “Data Fluency” is the “ability and confidence to make sense of and use data actively” (Wong et. al, 2024). Making sense of data requires educators to provide learners with data-rich experiences, enabling them to interpret scientific news, make informed decisions, vote knowledgeably, and manage both personal and business choices (Yarnall & Ranney, 2017; Gould, 2017; Oppenheimer & Edwards, 2012). As colleges and universities expand their programs to include more data science courses, a need is likely to emerge for K-12 educators to provide learners with the necessary background to succeed in university data science curricula.

Data-Rich Pedagogy

WestEd’s team of researchers is perhaps the leader in educational exploration of data-rich strategies. They have carefully aligned data-rich strategies with proven teaching strategies. Their alignment has focused on learner-driven outcomes in teaching. Specifically, they developed and defined principles of data-rich pedagogy that support all learners in their development towards data fluency (WestEd, 2025).

As we progress in an increasingly data-driven world, effectively understanding, analyzing, and communicating data will remain a critical skill for everyone. Educators who struggle to incorporate data skills into their classrooms can blend various data-rich pedagogical strategies with science content pedagogy. This blended strategy goes beyond mere knowledge and literacy skills; it encompasses knowing when, how, and why to use data to explore science (or other) topics and for specific purposes, such as solving problems, understanding phenomena,

and communicating ideas grounded in evidence (WestEd, 2025). While educator practices are clear and carefully thought out, the classroom implementation methods for these practices remain unclear and will be examined in this research study.

Frameworks

Data Fluency

Integrating data science into K-12 science education lays the groundwork for developing learners' data skills. As these skills emerge throughout elementary and secondary education, students can engage actively with data, deepening their understanding and application while cultivating 21st-century skills such as critical thinking and problem-solving.

It is clear that in educational settings, learners advance in their mastery of data and science skills and related content knowledge when educators have a firm grasp of the content they are teaching (Banilower, 2018; Darling-Hammond et al., 2017). However, defining the framework for educator data fluency acquisition and competency is not straightforward. Few educational studies have focused on supporting educators in developing data fluency. This lack of professional learning opportunities challenges educators to gain data fluency and impart data literacy skills to their students. Without professional learning to support data fluency, educators often rely on personal experiences that may not effectively prepare their learners (Pratt, 2002; Gulamhussein, 2013; Banilower, 2018).

Emerging research provides educators with the tools to enhance their data fluency and understand the tools necessary for integrating data into their classrooms. A qualitative study titled "Towards a Theoretical Framework for Data Fluency Teaching and Learning in Middle School STEM," conducted by WestEd, examined the development of data fluency skills in eleven

experienced educators. These educators collaborated with a WestEd team to design and implement data-rich lessons in grades 6–9 mathematics and science classrooms (Wong et. al, 2024). The project's broader goal was to develop a Data Fluency Framework for Teaching and Learning, which describes the knowledge and skills educators need to support learners in their data fluency. The 2024 study findings emphasized the need for professional learning among in-service K-12 educators. The study also highlighted the critical data fluency skills educators require:

- a broad exposure and understanding of a variety of data types and representations,
- ability to emphasize the roles humans play in all activities connected to data,
- ability to choose and understand the tradeoffs between primary and secondary datasets,
- capacity to include data activities for learners that are both meaningful and feasible,
- desire to use data to support science content goals,
- capability to select technologies that support specific instructional purposes and learning goals, and to include habits of mind (such as skepticism, imagination, and curiosity) that shape how learners approach data.

While these data fluency characteristics in educators empower learners with the tools needed to understand and effectively use data as a resource for science content instruction, do all educators have the same interpretation of data fluency? Is the understanding of data fluency as common as **Pedagogical Content Knowledge (PCK)**? Can PCK and data fluency be described as specialized knowledge that educators use to make a subject understandable to their learners, blending a teacher's understanding of the subject matter with their knowledge of how to teach it effectively—including proven strategies and accommodations for common learner

misconceptions? This research will examine data fluency among science educators and report on their interpretations and perceptions of their data fluency.

Data-Rich Pedagogy

Understanding a data-rich pedagogy framework may be a more straightforward task than defining educators' data fluency. It starts with grasping effective, NGSS-aligned science pedagogy. A comprehensive survey tool was developed by Hayes et al. to assess the alignment of instructional practices with NGSS goals (Hayes et al., 2016). Focusing just on the instructional practices of this survey tool, simple modifications can be made to demonstrate how data pedagogy can be integrated with science teaching strategies. The five instructional practices are modified (in italics) to include data science terminology, resulting in a blend of both data and science instructional practices:

- Empirical Investigations – asking questions [*that can be answered with data*]; determining what needs to be observed, collected, analyzed, and interpreted,
- Interrogation [*of the data*] – asking who and how evidence is [*data are*] collected, what types of evidence [*data*] are gathered,
- Explanations and Variability – focusing on modeling, argumentation, constructing explanations, analyzing, and interpreting evidence [*data*]
- Visualizations and Communication – focusing on scientific discourse on making sense [*of the data*] through visual representations
- Culture and Knowledge – connecting community languages, cultures, and knowledge with real-world science to bridge science epistemologies and learner experiences [*with data*].

There is a clear connection between effective science teaching practices and the use of data in science education. As the inclusion of data in K-12 science education continues to grow in prominence and depth, so do the principles of data-rich pedagogy. The following seven principles of data-rich pedagogy were published from WestEd’s *Boosting Data Science Teaching and Learning in STEM (Data Fluency)* Project (WestEd, 2025):

- Data-rich learning is accessible to all learners. Data-rich classrooms employ the principles of universal design and culturally sustaining pedagogies to support all learners in developing their data fluency.
- Data-rich learning is learner-driven. Data-rich instruction promotes the use of data for purposes that matter to learners by empowering them to become “data detectives,” to question and explore data stories for themselves, and to develop productive habits of mind such as perseverance and curiosity.
- Data-rich learning uses a variety of datasets. Datasets foster learners’ imagination and curiosity, enabling them to find and explore questions that are meaningful to them and engage in data science practices such as cleaning and transforming messy data for authentic purposes.
- Data-rich learning encourages a healthy skepticism. Data-rich classrooms utilize scaffolds or routines to evaluate data sources, interpretations, and representations, preparing students to be critical consumers and ethical producers of data.
- Data-rich learning strengthens content knowledge. Data-rich classrooms provide opportunities for learners to engage with data that is interesting, relevant, and potentially surprising, thereby stimulating interest and supporting the content goals of the learning.

- Data-rich learning utilizes the power of digital tools. Technology provides opportunities to find and access a wide range of datasets, generate displays, manipulate values, and communicate insights about data that aren't possible with paper and pencil.
- Data-rich learning draws on learners' personal, historical, and cultural contexts. Interacting with and using data that are contextualized, personal, historical, or culturally meaningful to learners offers opportunities to explore socio-cultural impacts.

As research and data-driven practices evolve to provide better opportunities for enhancing learners' data skills, additional educational research is needed to assess educators' current data fluency and data-rich practices. I proposed to fill this gap under the auspices of the NASA Solicitation and Proposal Integrated Review and Evaluation System (NSPIRES). I conducted a study exploring data-rich pedagogy and data fluency among science educators working with NASA and its partnering organizations in the SciAct group within the Science Mission Directorate.

Research Questions

This study addresses a gap in the research regarding educators' data fluency and their implementation of data integration into their curriculum. Specifically, this study will answer:

- What are the perceptions of data fluency of formal and informal educators?
- What are the examples of data-rich pedagogy, including those that utilize NASA data assets, in educational settings?
- How often do educators integrate data-rich pedagogy in their educational settings?

Research Objectives

The study objectives are to:

- Determine educators' perception of their data fluency in K-12 educational settings,
- Identify specific strategies that support data integration in classrooms,
- Gain a deeper understanding of data practices through educator interviews,
- Assess how and how often NASA data assets are incorporated in K-12 educational settings to support science learning,
- Explore challenges in practicing data integration in K-12 education.

Gathering this information from targeted educators has a far greater reach than NASA and its SciAct partners; it will provide academic researchers a glimpse into educators' perceptions of their data fluency and data-rich practices. With this information, educational communities can build and/or expand their training to meet the needs of evolving data practices and advance educators' data fluency.

Methodology

This study employed a mixed-methods approach to answer the research questions. It was conducted from spring 2023 through fall 2024 and consisted of two distinct phases. Phase I involved a quantitative survey designed to understand how educators perceive data fluency and data-rich practices in their educational settings. The survey used a 7-point Likert scale (strongly disagree-1, disagree-2, somewhat disagree-3, neutral-4, somewhat agree-5, agree-6, strongly agree-7). Qualtrics was used to record survey responses, and the final survey is included as Appendix A. The survey was distributed to K-12 formal and informal educators currently working with NASA SciAct partners. There are possibly over 2,000 formal and informal

educators involved with NASA SciAct partners annually (NASEM, 2020). If the survey was sent to all estimated 2,000 educators, 234 responded to at least part of it, resulting in a response rate of approximately 12 percent. Data analysis shows that about 31 percent (74) of respondents who started the survey did not go past Section 1. The reason for this is unclear, but responses to the open-ended question in Section 2 suggest that educators' time constraints are likely a factor. Despite the high number of incomplete responses across sections, the respondents who completed part or all of the survey represent the intended study population.

The second phase of the study, Phase II, took place from fall 2023 to summer 2024. This phase involved one-on-one interviews with 18 educators to deepen understanding of data-rich practices and how educators develop data fluency. The interview consisted of three sections. First, each educator was asked to discuss the factors that influence their data fluency. The second section focused on the types of data-rich pedagogy used in their educational settings, including a discussion on how such pedagogy impacts learner outcomes. The third section looked at how often data is integrated into their academic environments. Educators were not matched with their survey responses. The interview guide is provided as Appendix B.

Survey Development

The survey was structured with three sections. Section 1 contained a question asking respondents to identify their SciAct partner. The first seven survey items focused on the educators' perceptions of their data fluency (Domain 1), the following 10 items focused on a variety of data-rich pedagogical practices (Domain 2), and the third set of 5 items focused on the frequency of integrating data-rich practices into their curriculum (Domain 3). Section 2 of the survey asked respondents to answer one open-ended question: "What challenges do you face in using NASA Assets in your educational setting? Please be as specific as possible." This question

was used to determine potential barriers educators face in using data-rich practices. Section 3 of the survey included questions on educators' experience, learners' grade level, and other school demographics. This section was embedded as the third section of the survey to ensure respondents did not lose steam after it and did not neglect to complete the survey on data fluency and data-rich practices.

It was essential to create a survey that met the study's intended objectives; therefore, a content alignment study was performed to ensure the survey items aligned with and represented the study's focus.

First Survey Alignment

The first content alignment study was based on designing a survey with reliable questions (providing consistent measures in comparable situations) and valid (answers correspond to what they are intended to measure) (Fowler, 2009). The initial survey was administered to seven subject-matter experts (SMEs) in data literacy and science instruction. The SMEs were asked to align each item to a domain and assign a relevance score to each item. This alignment testing also ensured a consistent message, style, tone, and voice across all survey sections and that each domain was adequately addressed. The initial survey contained 46 items, rated on a 7-point Likert scale from strongly agree to disagree strongly. The results of the first content alignment study showed that fewer than 50% of the items were aligned with the intended domains.

Second Survey Alignment

Based on the results of the first content alignment study, the survey was reduced from 46 to 22 items. Many items were rewritten to eliminate double meanings and vagueness. The domains of the survey were also rewritten and finalized to better align with the research questions:

Domain 1: *Assessment* of Data fluency in formal and informal educators. This domain determines an educator's view of their data fluency.

Domain 2: *Perception* of data-rich pedagogy. This domain is designed to determine how educators integrate data into their instructional practices.

Domain 3: *Emphasis* on data-rich infusion instructional practices. This domain determines how often educators infuse data into their instructional practices.

The second content alignment study was conducted with a different group of seven SMEs, of whom six were practicing K-12 educators. An additional middle school educator volunteered to conduct a think-aloud on the revised survey. The think-aloud was a form of validity testing that asks potential respondents to read through a study and discuss how they interpreted the questions and arrived at their responses (Wilson, 2019). The main objective in using the think-aloud technique was not to judge the outcomes of a participant's cognitive process but to explore the performance process (Lundgrén-Laine and Salanterä, 2010).

All SMEs completed the second content alignment study and matched at least 90% of the items to the intended domain, thereby validating that the survey items addressed the research construct. Throughout the content alignment studies, data fluency leaders in the field, Dr. Leigh Peak from Gulf of Maine Research Institute, Kristin Hunter-Thomson of Dataspire, and Kirsten Daehler from WestEd, collaborated on the survey, and Dr. Rachel Connolly from Massachusetts Institute of Technology Media Lab reviewed and provided input on the final survey items. All of these collaborators are SciAct partners or directly involved with SciAct partners. Once finalized, the UC Davis Institutional Review Board (IRB) prepared the survey for approval. IRB deemed the study exempt.

Survey Item Response Theory Analysis

A polytomous Item Response Theory (IRT) model provided a unified and comprehensive analysis of the interaction between survey respondents and various response categories within IRT (de Ayala, 2022; Desjardins, 2018). Two polytomous models were used to evaluate item responses. The first is the Rating Scale Model (RSM), where all items (or groups of items) share the same rating scale structure. In this model, the distances between the difficulties of adjacent outcomes remained consistent across items (de Ayala, 2022; Desjardins, 2018). The second model evaluated is the Partial Credit Model (PCM), in which each item has a unique rating scale structure (de Ayala, 2022; Desjardins, 2018). The IRT analysis of the survey responses validated that the questions achieved the intended outcome regarding their ability to measure an educator's assessment of their data fluency and data-rich practices, the latent construct.

Reliability Check of Survey Items

A reliability check was also performed on the survey response dataset. Knowing the reliability of each item was beneficial because it indicated the overall consistency of the item scale and survey responses in measuring the underlying latent construct or the observed scores generated by the IRT models (de Ayala, 2022). The alpha scores for Section 1, Domains 1, 2, and 3 are below. Cronbach's alpha of .70 and above is considered good, .80 and above is better, and .90 and above is best (Koretz, 2009). The data in Table 1 show alpha greater than .90 for each item, indicating that the survey items had excellent reliability.

Table 2-1: Alpha (Reliability) Values

Question by Domain	Raw Alpha	Standardized Alpha¹
D1-Q1	.94	.95
D1-Q2	.93	.94
D1-Q3	.93	.93
D1-Q4	.93	.93
D1-Q5	.93	.93
D1-Q6	.93	.93
D1-Q7	.93	.94
D2-Q1	.96	.96
D2-Q2	.96	.96
D2-Q3	.96	.96
D2-Q4	.96	.96
D2-Q5	.96	.96
D2-Q6	.96	.96
D2-Q7	.96	.96
D2-Q8	.96	.96
D2-Q9	.96	.96
D2-Q10	.96	.96
D3-Q1	.95	.95
D3-Q2	.95	.95
D3-Q3	.95	.95
D3-Q4	.94	.94
D3-Q5	.95	.95

NOTES

Domain 1 (D1– Q1-7) – Educator’s data fluency

Domain 2 (D2– Q1-10) –Practices of data-rich instruction

Domain 3 (D3– Q1-5) – Frequency of data-rich instruction integration

Dimensionality of Survey Items

Dimensionality, i.e., checking model assumptions, was extremely important as it ensured that the items and item responses were consistent with the latent trait construct.

Unidimensionality checks (Scree Plot and Parallel Analysis) were performed on the dataset. The Scree Plot displayed eigenvalues as a function of the analyzed factors and showed a downward curve (Yong and Pearce, 2013). Based on the Parallel Analysis, the data suggested that the number of factors assessed in the survey is 1 (Glorfeld, 1995). The Scree Plot test also showed eigenvalues leveling off at one or less, suggesting that a one-factor analysis is appropriate for this domain and supporting unidimensionality.

Interview Questions

In Phase II of this study, educators who completed the survey were invited to participate in a follow-up interview. Interviews were designed to capture how educators developed their data fluency and the specific data-rich pedagogies they used with their students. A total of 36 educators who completed the IDEAS survey and volunteered for an interview were contacted for a 45-minute session. Twenty-two educators responded to the request. Four of these educators were located internationally, and their interview data were excluded from this study. Key questions reflecting on data fluency and data-rich practices posed during the interview were:

Section 1: Educator Data Fluency

- Describe your data fluency (ability to make sense of data)?
- What types of professional development or training involving data did you experience?
- What aspects of your training or experiences supported your ability to make sense of data?
- How did your teaching experiences inform your understanding and use of data as a tool for learning science content?

Section 2: Data-Rich Pedagogy and Learner Impact

- What did data-rich pedagogy entail in your educational setting?
- How do you characterize your use of data? For example, did the data learners measure or obtain from secondary sources?
- What learner outcomes did you expect when integrating data into your classroom?
- Do you believe these outcomes were achieved by incorporating data or data-rich pedagogy?

- Do you believe that your learners' attitudes toward data changed through the use of data? If so, in what ways?

Section 3: Frequency of Data Integration

- How often do you integrate data into your curriculum?
- What challenges made it difficult to embed data into your subject area?
- How do you believe data supports scientific content for your learners?

Data Coding

The free-response questions in Section 2 of the survey and the interview data were manually analyzed and coded. No automated tools or software were used for this analysis. Before starting the coding process, notes and transcripts from all interview sessions were reviewed. The interview sections were organized into broad categories using initial codes relating to the research questions: 1) data fluency among educators, 2) data-rich pedagogies (learning accessibility, learner-driven, use of data sets, data skepticism, content knowledge, digital tools, learner contexts), and 3) the frequency of data integration. After organizing the interview questions into these categories, I analyzed the responses pertaining to each question and chunked them into bins. For question 1, the bins were high, medium, and low confidence levels based on (self-identified) proficiency in data fluency. As I reviewed my notes and transcripts on data fluency, I employed constant comparative methods to identify additional topics relevant to the research questions (Glaser, 2008). For instance, when educators provided responses related to factors influencing data fluency, they were grouped into additional bins that supported their response: attending NASA professional development, participating in STEM-related professional development outside of school, engaging in STEM-related professional development provided by the school or district, and relying on undergraduate or graduate

experiences—this additional chunking (organization) of the data responses provided context for educator responses to their data fluency.

For question 2, the bin organization was more complex. The responses were first organized into one of the seven data-rich pedagogy strategies described by the educator. However, the educators' strategies often overlapped. So, I also created additional bins that combined data-rich strategies. For example, one educator reported using a data practice to support science content, but she also indicated that the visual she selected was accessible to all levels of her learners. Therefore, I redefined the bins as single or multiple strategies and reorganized educator responses about their data-rich pedagogy accordingly.

For question 3, the organization of the responses is again quite straightforward. Educator responses regarding the frequency of data-rich practices were grouped into the following bins: daily, weekly, more than once per month, monthly, and less than monthly. A few (4) educators mentioned that their practices changed from the first semester to the second semester. For example, one educator reported using more data-driven practices in the first semester but less frequently in the second semester. In these cases, I recorded the frequency of data practices as the semester when they integrated data more often.

Additional interview questions were used to examine the reliability of educators' responses towards data-rich strategies. For example, I probed educators by asking them about the intended learner outcomes when using data-rich practices. I organized their responses into bins. These bins were: state standards, scaffolding, modeling, reinforcement, and engagement. This type of probing question was intended to establish the credibility of educators' responses regarding data practices, but their responses were difficult to categorize because they overlapped so much, leading to simple confirmation of data-rich practices rather than a rationale for each

practice. The detailed organization of interview responses, combined with the survey data results, yielded a comprehensive analysis of educators' positions and the development of data fluency, including examples and the frequency of their data-rich pedagogy.

Study Respondents

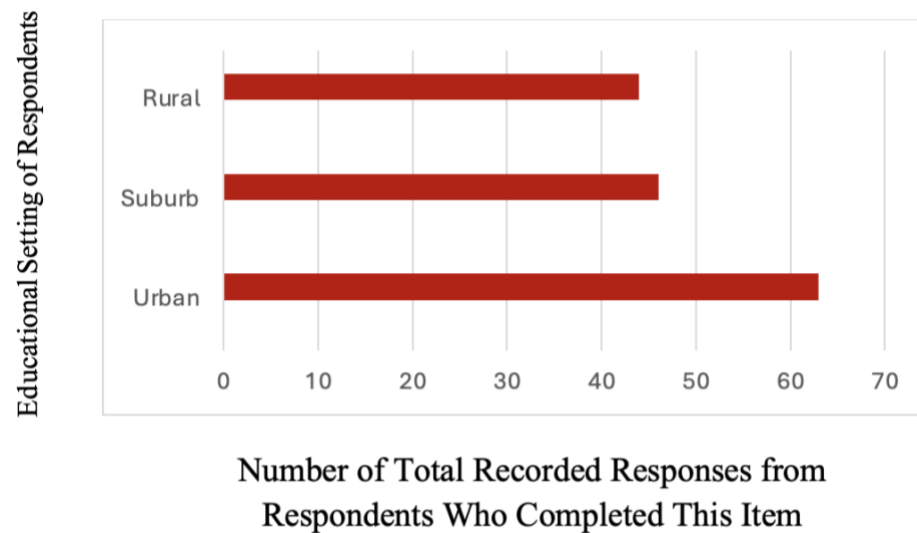
The first question in the survey asked respondents to identify their SciAct partners. Respondents did not represent all of the operating SciAct Partners. The overwhelming majority (46%) of respondents receive support from Astronomy Activation Ambassadors and GLOBE Mission Earth. Approximately 10% of respondents were unsure as to which SciAct Partner they were aligned with. Table 2 shows the representation of SciAct Partners for respondents who completed Section 1 of the survey. SciAct partners omitted from the table had no survey respondents as of August 5, 2023.

Table 2-2: Science Activation Partners Represented by Survey Respondents

AREN/GLOBE	4.43%	7
Astronomy Activation Ambassadors	24.68%	39
Earth to Sky	1.90%	3
Eclipse Soundscapes	0.63%	1
GLOBE Mission Earth	20.25%	32
Growing Beyond Earth	0.63%	1
MIT Media Lab	0.63%	1
Museum and Informal Education	1.90%	3
NASA Earth Science Education Collaborative (NESEC)	6.96%	11
NASA Heliophysics Education Team	0.63%	1
NASA's Neurodiversity Network (N3)	2.53%	4
NASA's Universe of Learning	0.63%	1
NASA @ My Library	1.27%	2
National Institute of Aerospace	4.43%	7
Night Sky Network	0.63%	1
NISE Network	0.63%	1
PLANETS	3.80%	6
Smoky Mountains STEM Collaborative (SMSC)	5.06%	8
Solar System Ambassadors	4.43%	7
SciAct STEM Ecosystems	3.16%	5
I'm not sure	10.76%	17
	100	158

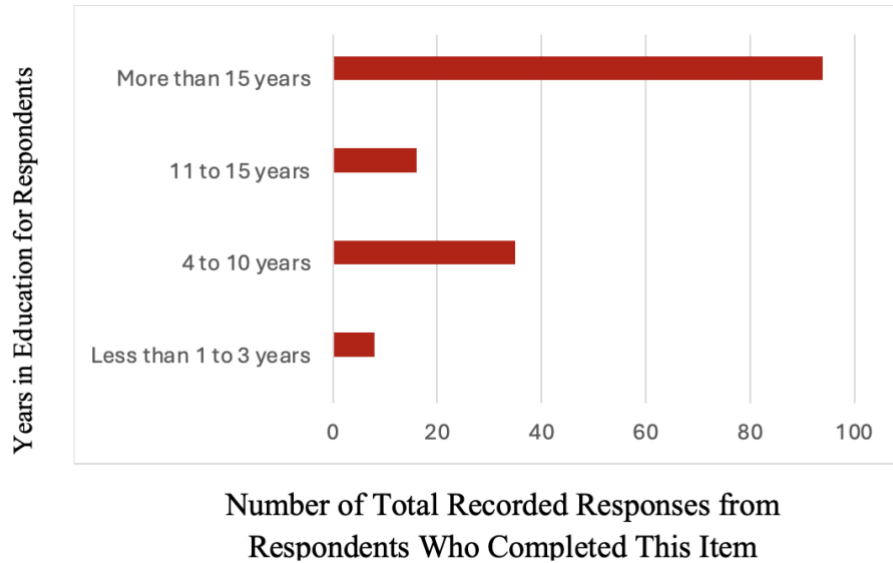
Section 3 of the survey presented the remaining educator and school demographic questions. Figure 2-2 shows a breakdown of the respondents' educational settings. While most respondents reported being in an urban setting, the data show a relatively even distribution across urban (41%), suburban (30%), and rural (29%) educational settings.

Figure 2-2: Educational Settings of Survey Respondents



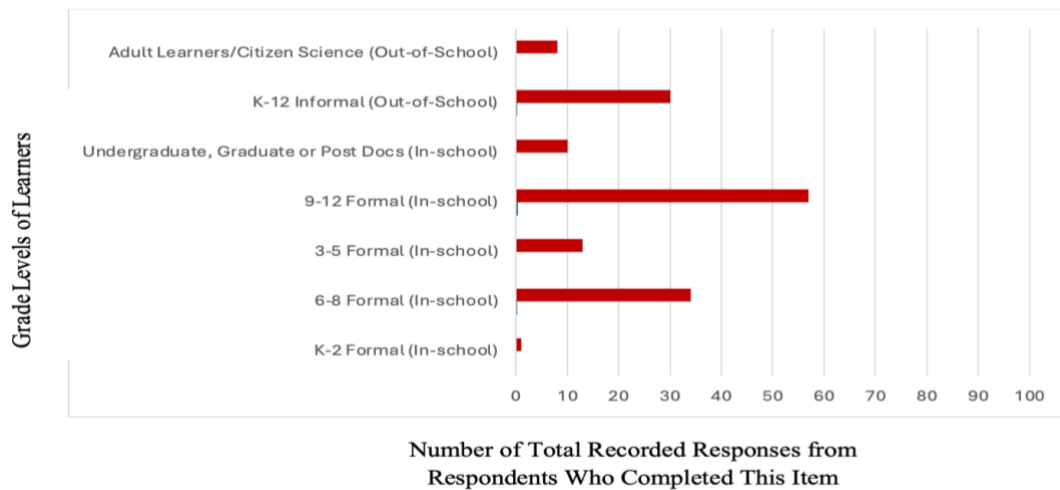
Most (61%) respondents reported having at least 15 years of educational experience. Other respondents reported experience levels from 1 to 10 years, as shown in Figure 2-3.

Figure 2-3 Distribution of Experience of Survey Respondents



Respondents were asked to report the grade level of the learners they serve. Approximately 24 percent of the respondents serve in informal educational settings as seen in Figure 2-4. The type of informal settings from which the respondents come is unknown, but several SciAct partners support museums, citizen science programs, and libraries.

Figure 2-4: Grade Level of Learners from Survey Respondents



Findings

The general statistics from Section 1 of the survey are presented in Table 2-3.

Table 2-3: IDEAS for Science Learning Survey Item Statistics

Domain & Question ID	Item#	Total (n)*	Mean	Standard Deviation (+/-)
D1-Q1	1	158	6.13	1.11
D1-Q2	2	158	5.68	1.20
D1-Q3	3	158	5.96	0.99
D1-Q4	4	158	5.91	1.10
D1-Q5	5	158	5.95	1.08
D1-Q6	6	158	5.87	1.18
D1-Q7	7	158	5.56	1.31
D2-Q1	8	158	6.05	1.02
D2-Q2	9	158	5.94	1.05
D2-Q3	10	158	6.13	1.00
D2-Q4	11	158	6.01	1.03
D2-Q5	12	158	5.99	1.16
D2-Q6	13	158	6.09	1.04
D2-Q7	14	158	6.09	1.10
D2-Q8	15	158	6.05	1.05
D2-Q9	16	158	5.65	1.26
D2-Q10	17	158	5.84	1.14
D3-Q1	18	158	5.76	1.18
D3-Q2	19	158	5.84	1.14
D3-Q3	20	158	5.82	1.14
D3-Q4	21	158	5.84	1.14
D3-Q5	22	158	5.80	1.12

* Represents the number of respondents who responded to all 22 items

The data showed that respondents had high confidence in their data fluency (mean score of 5.87; Domain 1) and in their data-rich instructional practices (mean score of 5.98; Domain 2). Domain 3, which measured the frequency of data-rich integration into the curriculum, scored the lowest, with a mean of 5.81. The standard deviation for each item was less than two, suggesting that the data are clustered closely around the mean and are less spread out.

Educator Data Fluency

More specific survey data on educators' data fluency by grade level are presented in Table 2-4, which shows increasing confidence levels in data fluency from grades 3-5 to 6-8 to 9-12, with a mean of 5.93 across these grade levels. K-2 data were not included in the analysis, since only one respondent identified as a K-2 educator. The standard deviation of their data could not be calculated. Although the undergraduate data are presented in Table 2-4, they were not included in further analysis because the researcher could not confirm with 100 percent certainty that this group was composed solely of pre-service educators. The mean data for data fluency in Table 4 are statistically significant ($p < .05$). A low p-value (typically less than .05) suggests the results are unlikely to have occurred simply by random chance.

Table 2-4: Domain 1 Responses from Formal Educators by Grade Level

Domain	Item Numbers	K-2 Mean (n= 1)	3-5 Mean (n=13)	6-8 Mean (n=34)	9-12 Mean (n=57)	Under-graduates Mean (n=10)
Domain 1 – Respondent Data Fluency	1-7	6.9	5.7	6.0	6.1	6.2

Note: Seven respondents did not identify their grade level. Data in grey columns were not considered in the analysis but are included for reference only.

The survey data fluency results correlate with the interview data. The interview responses regarding data fluency were consistent with educators' reports of a high level of data fluency.

Educators were asked to provide professional learning examples of how they have developed their data fluency. None of the educators cited specific professional training in data science, data literacy, or data-rich pedagogy that supports their confidence levels in data fluency. The majority of respondents reported attending at least one STEM-related training session. Table 2-5 summarizes their responses to professional learning experiences that shaped their data fluency. They indicated that these trainings partially supported their data fluency development, but they didn't attend them specifically for that purpose. One in three educators reported attending at least one NASA-centered training during their professional career. Seventy-eight percent (14/18 educators) reported attending at least one STEM-related professional development session organized by an external entity, such as a museum or educational center. Nearly all educators (16/18) identified that their primary professional learning experiences came from their educational institution or district, but these events were not necessarily focused on STEM pedagogical practices. Five of the eighteen educators reported drawing on their undergraduate and graduate experiences to develop their data fluency.

Table 2-5: Training That Shaped Educators' Data Fluency

Training that has Influenced Educators Data Fluency	Percent (%) of Interviewees Who Identified this Training in their Development of their Data Fluency¹	Total Number of Interviewees N=18
Attended NASA Professional Development	32	6
Attended STEM-related Professional Development Outside of School	78	14
Attended STEM-related Professional Development Organized by School or District	89	18
Drawn from Undergraduate or Graduate Work (including preservice experiences)	28	5

Six educators referred to a NASA professional development experience during the interview. Still, those who had the opportunity to participate in NASA training cited programs similar to those of Tim, a 10-year veteran educator. Tim attended NASA Space Grant training and received scholarships to attend the Johnson Space Center's summer "STEM camps" and the Space Science Conference.

Educators who received NASA training strongly felt that NASA's professional learning opportunities provided an understanding of how to utilize NASA data resources in the classroom, thereby enhancing their ability to interpret the data. When probed further about the NASA training or past experiences that contributed to educators' high confidence levels in data fluency, these educators specifically mentioned two resources from their trainings that were data-focused: (1) NASA images from satellites and Earth events such as the solar eclipse, and (2) satellite Earth system science data. Educators explained that associated lessons complemented their

¹ Some respondents identified more than one training experience.

training. They also referred to NASA's My NASA Data website as a source of satellite data used to understand scientific phenomena. Twelve educators referenced NASA websites at some point during the interview, although not all of these educators attended NASA training. In addition to the My NASA Data website, these twelve educators identified at least one of the following useful data-rich websites: NASA Worldview, NASA Next Gen STEM, NASA Explorer, NASA Discovery, Global Learning and Observation to Benefit the Environment (GLOBE), United States Geological Survey, and National Oceanic and Atmospheric Administration as sources for images and data that they used in their educational settings. When asked if NASA websites supported educators' data fluency, one educator, with eight years of experience, reported the following about the data resources from the websites: "[They] *are sometimes hard to understand, so it takes me a lot of time to figure it out and then figure out how to use it with my students. But when I do it, I learn a lot about how data works.*"

Other educators with less experience than Tim reported only in-house professional training in assessment and/or differentiated instruction for students with special needs. Richard and Dylan, with 6 and 5 years of teaching experience each, indicated that the training was required and provided by the district/school. Both educators stated that they also "*draw upon undergraduate work*" to make sense of data.

Two educators provided additional examples of how they enhanced their levels of data fluency. They used data visuals (graphs and maps) with their learners. For instance, Tina, a 19-year veteran of middle school science, stated:

"My level of data fluency is high because I give my students visuals with data in them. I needed to know what the visual is all about, so I could explain it to my students."

Connie, a 7-year high school integrated science educator, stated:

“I used [NASA] satellite images to engage my students throughout the year on most of my units. So I learned about data when I gave these images to my students.”

In both examples, the educators noted that building data skills with their learners enhanced their understanding of how to interpret data. They were careful to note that if they couldn’t understand the data asset, they didn’t use it with their learners. They also reported that using NASA data assets sparked engagement and interest with their learners, even if it wasn’t directly related to their science content.

Data-Rich Pedagogy

Survey data on data-rich pedagogy by grade level are presented in Table 2-6, which shows a high frequency of data-rich practices. These reported values continually increased from grades 3-5 to 6-8 to 9-12, with a mean of 6.06 for these grade levels. The mean data for data-rich pedagogy in Table 2-5 are statistically significant ($p < .05$).

Table 2-6: Domain 2 Responses from Formal Educators by Grade Level

Domain	Item Numbers	K-2 Mean (n= 1)	3-5 Mean (n=13)	6-8 Mean (n=34)	9-12 Mean (n=57)	Under-graduates Mean (n=10)
Domain 2 – Integration of Data-rich Pedagogy	8-17	6.7	5.9	6.0	6.3	6.1

Note: Seven respondents did not identify their grade level. Data in grey columns were not considered in the analysis but are included for reference only.

Educators were asked to identify which principles of data-rich pedagogy they employed. Table 2-7 lists these principles, along with the number of educators who referred to or gave examples related to each in their interviews.

Table 2-7: Summary of Data-Rich Pedagogy from 18 Interviews

Data-Rich Principles	Percent (%) of Interviewees Who Referred to This Principle
Data-rich learning is accessible to all learners.	6
Data-rich learning is learner-driven.	17
Data-rich learning uses complex data sets.	0
Data-rich learning encourages a healthy skepticism.	0
Data-rich learning strengthens content knowledge.	22
Data-rich learning utilizes the power of digital tools.	0
Data-rich learning draws on learners' personal, historical, and cultural contexts.	0

Interview data somewhat contradict the survey data. Interview responses indicate that educators explicitly referred to only three of the seven principles or incorporated them into their examples of data-rich practices. Most (78%) could not connect data-rich principles to pedagogical strategies that strengthen their learners' science content knowledge. While interview responses about data-rich pedagogical strategies confirmed that educators incorporate data into their curriculum and use various techniques, their variety of practices was limited to three. While most educators used pre-populated NASA maps and graphs, some required students to collect and organize data from field events. Others asked their learners to create visualizations from data tables or interpret provided graphs. These strategies were primarily used to enhance student engagement and maintain their interest in science content. Although educators couldn't comment on how the data-rich strategies or resources directly affected learning, they confirmed that using data in the classroom supported skills such as observation, inquiry, and analysis.

Frequency of Data Integration

Survey data for the frequency of data-rich pedagogy by grade level are presented in Table 2-6. The average frequency of data-rich practices across grades 3-5, 6-8, and 9-12 is 5.9. However, this average is not as high as those for data fluency (5.9) and pedagogy (6.1) for the same grade levels. These reported values continued to increase from grades 3-5 to 6-8 to 9-12. The mean frequency of data-rich pedagogy in Table 2-8 is statistically significant ($p < .05$).

Table 2-8: Domain 3 Responses from Formal Educators by Grade Level

Domain	Item Numbers	K-2 Mean (n= 1)	3-5 Mean (n=13)	6-8 Mean (n=34)	9-12 Mean (n=57)	Under-graduates Mean (n=10)
Domain 3 – Frequency of Data-rich Pedagogy	18-22	6.6	5.7	5.9	6.2	5.9

Note: Seven respondents did not identify their grade level. Data in grey columns were not considered in the analysis but are included for reference only.

Interviews included a question on how often educators use data in their classrooms. Instead of providing a concrete response on how often (weekly, monthly, etc.) they used data in their classrooms, educators focused on the challenges associated with implementing data-rich pedagogy. Two common responses emerged when asked about the difficulties of embedding data into their educational settings—the first focused on the lack of time. Ninety-five percent (95%) of interviewed educators cite time as a constraint to data integration. These educators also expressed frustration about covering too much science content in a school year. They indicated that adding more (data-rich pedagogy) “...is too much on top of too much,” as one educator said. Another educator commented, “*This is an example of depth vs. breadth. Our principal wants us to cover all of the content standards so students can do well on the state test, so spending time on things not in the curriculum like data [skills] doesn’t make sense.*” One high school educator said her biggest

challenge was navigating NASA websites for data imagery. This educator expressed frustration that NASA websites use different homepage formats, making it occasionally time-consuming to find up-to-date information. NASA frequently updates its portal/homepage, making it challenging to find the appropriate resources.

Data Analysis

Data from the survey and interview were analyzed to extract meaningful insights and actionable information. Analyzing data patterns and trends, or the lack thereof, can reveal relationships within the data, providing a deeper understanding of the level of data fluency and data-rich pedagogy among K-12 educators.

Educator Data Fluency

Both survey and interview analyses showed that formal and informal science educators were very confident in their data fluency. However, during the interviews, no educators mentioned specific professional training in data science, data literacy, or data-driven teaching methods. This suggests that educators may have had their own interpretation of data fluency when answering the survey, which differed from their responses during a more detailed discussion of data fluency in the interview. The interviews revealed they lacked support to develop their confidence in data fluency. Some educators said that previous STEM training helped somewhat in developing their confidence with data. Others mentioned that working on data skills with their learners improved their understanding of how to make sense of data. These results demonstrate the challenges of measuring educators' data fluency.

Data-Rich Pedagogy

The survey data analysis indicated that formal and informal science educators were also

highly confident in their data-rich practices; however, the interview data analysis did not correlate with these findings. From the survey data, educators in grades 3-12 reported agreement with data-pedagogy integration, ranging from 5.9 to 6.3, with 7 representing the highest level of agreement on integration strategies. However, interview responses from educators equated data-rich pedagogy with effective teaching practices. Three data-rich practices: data-rich learning is accessible to all learners; data-rich learning is learner-driven; and data-rich learning strengthens content knowledge, of the seven strategies listed in Table 2-7, were aligned between the survey and interview data results. While educators reported using multiple strategies with their learners, it is unclear why they only used these strategies. Again, educators are reporting the use of data-rich pedagogical strategies, but the variety of these strategies is limited. As a result, the qualitative and quantitative data are sufficient to answer our research question about the use of data-rich pedagogy; however, the question itself does not address the purpose or scope of the strategies employed.

Frequency of Data Integration

The survey and interview data were closely aligned regarding the frequency of data-rich pedagogy use. Study measures indicated that time constraints are the primary reason data integration rarely occurs in classrooms, a finding also supported by interview responses. Data show that educators are already overwhelmed by curriculum demands and struggle to incorporate data-rich pedagogy into their practice. They mentioned ongoing struggles to balance the breadth of teaching content versus its depth. It was clear from the interviews that educators agree that integrating data into their curriculum could make science content more relevant for learners. While the frequency of data integration appears to be a straightforward construct to assess, the data reveal that numerous factors must be considered when addressing this question.

These factors significantly influence educators' decisions to allocate time to incorporate data assets as a learning tool.

Discussion

In relation to the research questions, this study aimed to gain a deeper understanding of educators' data fluency levels and document their data-rich strategies, including the frequency with which they implemented data-rich pedagogy with their learners. Educators were recruited from NASA's Science Activation program and worked with NASA and/or their partner organizations. Participants taught in K-12 formal and informal education settings, with experience ranging from 1 to over 15 years. The mixed-methods approach enabled educators to share their perceptions of data fluency and discuss data-rich strategies.

The data revealed that educators have high perceptions of their data fluency; however, this may reflect varying personal understandings of what data fluency means in the context of science education. Educators reportedly developed their knowledge of data fluency primarily through their personal educational experiences rather than through formal professional learning. Educators also revealed that they often equated data fluency with specific data skills such as analysis or visualization. Data analysis and visualization are identified as two key data skills that, when applied, can help a learner make sense of data. These and other data skills require scaffolded development over time and do not define data fluency solely. Since none of the educators received formal training in data-rich pedagogies, they were unable to elaborate on how these missed opportunities might have impacted their data fluency. Professional learning opportunities for educators are necessary to provide instruction on data-rich practices and to outline the data skills required to support learners' understanding of science content. Ultimately, these professional learning opportunities can help them develop and advance their data fluency.

In terms of data-rich pedagogy, participating educators identified as having a high level of data-rich strategies for their learners. However, they reported using these strategies as opportunities to engage and connect with learners, not as skills-building tools. Educators cited limited data-rich strategies, indicating they are either unfamiliar with them or unsure how to implement them. Again, professional learning opportunities for educators can provide them with a variety of instructional methods, including data integration. As a result, educators can focus on teaching data skills to their learners while connecting them to science content.

Insights into the frequency of data integration suggest that formal educators are overwhelmed by the breadth and/or depth of science content they must cover in the school year; therefore, using data is more of a luxury than an iterative tool. Future practices of data-centric professional learning should incorporate methods that use data iteratively to integrate data skills into science content learning, much as educators believe a lab experiment reinforces a science concept.

In summary, the lack of professional learning opportunities for educators to transition from data skills to data fluency, and the resulting data-rich pedagogy, is apparent. Leaving the understanding and integration of data science to K-12 educators. This has led to inconsistencies in understanding, perceptions, and practices in this field.

Conclusion & Next Steps

This study's discussion emphasizes the importance of first exploring educators' data fluency and data-rich practices to support their learners. It is not enough to know what data fluency entails, or the strategies or frequency of data-rich practices. Without a clear understanding of how data integration can support learner outcomes, educators will likely continue to muddle along as best they can without the support of their schools, districts, or states.

Further research is necessary to understand how to effectively structure professional learning for educators, enabling them to enhance their data fluency and develop data-driven practices. This study also highlights the need for educational research to contribute to the ‘*how*’. Namely, *how* do educators learn to advance their data fluency? *How* do educators integrate data-rich practices with their science content, and *how* are data skills incorporated into these classroom strategies?

The next phase of this research involves collaborating with a small group of science teachers, each with varying levels of data expertise and experience, throughout the school year. This research will include group professional learning, one-on-one mentoring, and classroom observations at their school sites to evaluate how educators deliver data-rich pedagogy more effectively after receiving professional support. The research will also collaborate with educators to create classroom-ready materials suitable for their learners' age and data levels. As these educators understand and develop data content connections to support science learning and meet learner outcomes, the research will evaluate the effect this has had on their data fluency.

The following study is expected to make a significant contribution to educational research. Educators will use and evaluate professional learning strategies to assess their effectiveness in supporting the acquisition of various data integration strategies. Educators will determine their progress towards data fluency and discuss the factors that influence their growth in this area.

References Chapter 2

- Baker, E. A., Pearson, P. D., & Rozendal, M. S. (2010). Theoretical perspectives and literacy studies: An exploration of roles and insights. In E. A. Baker (Ed.), *The new literacies: Multiple perspectives on research and practices* (pp. 1–22). The Guilford Press.
- Banilower, E. R., Smith, P. S., Malzahn, K. A., Plumley, C. L., Gordon, E. M., & Hayes, M. L. (2018). Report of the 2018 national survey of science and mathematics education NSSME+. Chapel Hill, NC: Horizon Research, Inc.
- Bauder, J. (Ed.). (2021). *Data literacy in academic libraries: Teaching critical thinking with numbers*. American Library Association.
- Cliff, N. (1988). The eigenvalues-greater-than-one rule and the reliability components. *Psychological bulletin*, 103(2), 276.
- Cliff, N. (1988). The eigenvalues-greater-than-one rule and the reliability of components. *Psychological bulletin*, 103(2), 276.
- Collinson, V., Kozina, E., Kate Lin, Y., Ling, L., Matheson, I., Newcombe, L., & Zogla, I. (2009). Professional development for teachers: a world of change. *European Journal of Teacher Education*, 32(1), 3–19. <https://doi.org/10.1080/02619760802553022>
- Darling-Hammond, Burns, D., Campbell, C., Goodwin, A. L., Hammerness, K., Low, E. L., McIntyre, A., Sato, M., & Zeichner, K. (2017). *Empowered Educators: How High-Performing Systems Shape Teaching Quality Around the World*. John Wiley & Sons, Incorporated.
- de Ayala, R. J. (2022). *The Theory and Practice of Item Response Theory* (2nd Ed.). New York, NY: Guildford Press.
- DeBoer, G. (2019). *A history of ideas in science education*. Teachers College Press.
- Desjardins, C. D. & Bulut, O. (2018). *Handbook of Educational Measurement and Psychometrics Using R*. Boca Raton, FL: CRC Press.
- Finzer, W., Busey, A., & Kochevar, R. (2018). Data-driven inquiry in the PBL classroom: Linking maps, graphs, and tables in biology. *The Science Teacher*, 86(1), 28–34.
- Foote, K (2021). Dataversity.net. A Brief History of Data Literacy <https://www.dataversity.net/a-brief-history-of-data-literacy/>
- Fowler, F. J. (2009). *Applied Social Research Methods: Survey research methods* (4th ed.) Thousand Oaks, CA: SAGE Publications Ltd doi: 10.4135/9781452230184
- Gebre, E. (2022). Conceptions and perspectives of data literacy in secondary education. *British Journal of Educational Technology*, 53(5), 1080-1095.

- Glaser, B. (2008). The constant comparative method of qualitative analysis. *Grounded Theory Review*, 3(7).
- Glorfeld, L. W. (1995). An improvement on Horn's parallel analysis methodology for selecting the correct number of factors to retain. *Educational and psychological measurement*, 55(3), 377-393.
- Goldin, C. (1999). *A brief history of education in the United States*. Cambridge University Press.
- Gould, R., Machado, S., Ong, C., Johnson, T., Molyneux, J., Nolen, S., Tangmunarunkit, H., Trusela, L. & Zanontian, L. (2016). Teaching data science to secondary students: The mobilize introduction to data science curriculum. IASE 2016 Roundtable Paper
- Gulamhussein, A. (2013). Teaching the Teachers: Effective Professional Development in the Era of High Stakes Accountability. National School Board Association, Center for Public Education. <http://conference.ohioschoolboards.org/2017/wp-content/uploads/sites/17/2016/07/1pm111317A114Job-embedPD.pdf>
- Hardy, L., Dixon, C., & Hsi, S. (2020). From data collectors to data producers: Shifting students' relationship to data. *Journal of the Learning Sciences*, 29(1), 104–126.
- Hayes, K. N., Lee, C. S., DiStefano, R., O'Connor, D., & Seitz, J. C. (2016). Measuring science instructional practice: A survey tool for the age of NGSS. *Journal of Science Teacher Education*, 27(2), 137-164
- Hayes, K.N., Lee, C.S., DiStefano, R. *et al.* Measuring Science Instructional Practice: A Survey Tool for the Age of NGSS. *J Sci Teacher Educ* **27**, 137–164 (2016). <https://doi.org/10.1007/s10972-016-9448-5>
- Kastens, K. (2014). Pervasive and persistent understandings about data. *Boston, MA: EDC Oceans of Data Institute*. Available at <http://oceansofdata.org/sites/oceansofdata.org/files/pervasive-and-persistent-understandings-01-14.pdf>.
- Jain, S., 2025 What is Data vs. What is Information Blog <https://bloomfire.com/blog/data-vs-information/>
- Kirch, S. A., & Amoroso, M. (2016). *Being and Becoming Scientists Today: Reconstructing Assumptions about Science and Science Education to Reclaim a Learner–Scientist Perspective*. Springer.
- Lee, V. R. (2025). *Advancing Data Science Education in K-12: Foundations, Research, and Innovations*. Taylor & Francis.
- Kjelvik, M. K., and Schultheis, E. H. (2019). Getting messy with authentic data: Exploring the potential of using data from scientific research to support student data literacy. *CBE—Life Sciences Education*, 18(2), es2.
- Koretz, D. (2009). *Measuring up: What educational testing really tells us*. Cambridge, MA: Harvard University Press.

- Langreo, L. (2023). Education Week. With Data Science in Demand, This State Is Infusing Instruction With It <https://www.edweek.org/teaching-learning/with-data-science-in-demand-this-state-is-infusing-instruction-with-it/2023/09>
- Lee, V. R. (2025). *Advancing Data Science Education in K-12: Foundations, Research, and Innovations*. Taylor & Francis.
- Lee, V. R., & Wilkerson, M. (2018). Data use by middle and secondary students in the digital age: A status report and future prospects. Commissioned Paper for the National Academies of Sciences, Engineering, and Medicine, Board on Science Education, Committee on Science Investigations and Engineering Design for Grades 6-12. Washington, D.C.
- Louie, J. (2022). Critical data literacy: Creating a more just world with data. National Academy of Sciences workshop on Foundations of Data Science for Students in Grades K–12, September 13–14, 2022 Washington D.C.
- Margot, K. C., & Kettler, T. (2019). Teachers’ perception of STEM integration and education: A systematic literature review. *International Journal of STEM Education*, 6(2), 1–16.
- Maybee, C., and Zielinski, L. (2015). “Data Informed Learning: A Next Phase Data Literacy Framework for Higher Education.” *Proceedings of the Association for Information Science and Technology* 52 (1): 1–4. doi:10.1002/pa2.2015.1450520100108.
- McCoach, D. B., Gable, R. K., & Madura, J. P. (2013). *Instrument development in the affective domain: School and corporate applications* (3rd ed.). Springer: New York.
- National Academies of Science Engineering and Medicine (NASEM) (2022). Workshop on Foundations of Data Science for Students in Grades K–12, September 13–14, 2022 Washington D.C. <https://www.nationalacademies.org/our-work/foundations-of-data-science-for-students-in-grades-k-12-a-workshop>
- National Research Council, Division of Behavioral, Social Sciences, Board on Science Education, National Committee on Science Education Standards, & Assessment. (1995). *National science education standards*. National Academies Press.
- NGSS Lead States (2013). *Next Generation Science Standards: Appendix F - Science and Engineering Practices*. For States, By States.
- Oppenheimer, D., & Edwards, M. (2012). “Democracy despite itself: Why a system that shouldn't work at all works so well”. MIT Press.
- Penuel, W. R., & Means, B. (2004). Implementation variation and fidelity in an inquiry science program: Analysis of GLOBE data reporting patterns. *Journal of Research in Science Teaching*, 41(3), 294-315.
- Pratt, D.D. (2002). Good Teaching: One Size Fits All?. *New Directions for Adult and Continuing Education*, 2002: 5-16. <https://doi.org/10.1002/ace.45>

- Project 2061 (American Association for the Advancement of Science) (1993). *Benchmarks for science literacy*. Oxford University Press.
- Raffaghelli, J. E., & Stewart, B. (2020). Centering complexity in educators' data literacy to support future practices in faculty development: A systematic review of the literature. *Teaching in Higher Education*, 25(4), 435-455.
- Revelle, W. (2013). Find two estimates of reliability: Cronbach's alpha and Guttman's lambda 6. *Chicago, IL: Northwestern University*.
- Rowley, J. (2007). The wisdom hierarchy: representations of the DIKW hierarchy. *Journal of information science*, 33(2), 163-180.
- Rudolph, J. L. (2019). *How we teach science: What's changed, and why it matters*. Harvard University Press.
- Schultheis, E. H., & Kjervik, M. K. (2020). Using messy, authentic data to promote data literacy & reveal the nature of science. *The American Biology Teacher*, 82(7), 439-446.
- Street, B. V. (2003). What's "new" in new literacy studies? Critical approaches to literacy in theory and practice. *Current Issues in Comparative Education*, 5(2), 1-14.
- Street, B. V. (2005). At last: Recent applications of new literacy studies in educational contexts. *Research in the Teaching of English*, 39(4), 417-423.
- Street, B. V. (2017). New literacy studies in educational contexts. In J. Pihl, K. S. Van Der Kooij, & T. C. Carlsten (Eds.), *Teacher and librarian partnerships in literacy education in the 21st century* (pp. 23-32). Sense publishers.
- Tukey, J. W. (1962). The future of data analysis. In *Breakthroughs in Statistics: Methodology and Distribution* (pp. 408-452). New York, NY: Springer New York.
- University of California Los Angeles (UCLA) and the Los Angeles Unified School District (LAUSD). (2023) Introduction to Data Science (IDS) <https://www.introdatascience.org>
- Vahey, P., Finzer, W., Yarnall, L., & Schank, P. (2017). CIRCL Primer: Data Science Education. In *CIRCL Primer Series*. Retrieved from <http://circlcenter.org/data-science-education>
- WestEd (2025). *Boosting Data Science Teaching and Learning in STEM (Data Fluency)* project. (<https://mss.wested.org/resource/principles-of-data-rich-instruction/>).
- Whichello, S. (2025). Living and Teaching with Data: 2024 NC Data Science Education Summit Promotes Data Literacy in K-12 Schools
<https://datascienceacademy.ncsu.edu/2025/01/30/living-and-teaching-with-data-2024-nc-data-science-education-summit-promotes-data-literacy-in-k-12-schools/>

- Wilson Becho, L. (2019). Using Think-Alouds to Test the Validity of Survey Questions. Blog Post EvaluATE ATE Evaluation Resource Hub <https://evalu-ate.org/blog/becho-feb19/>
- Wise, A. F. (2020). Educating the next generation of data scientists for the next generation of data. *Journal of the Learning Sciences*, 29(1), 165–181
- Wolff, A., Gooch, D., Montaner, J. J. C., Rashid, U., & Kortuem, G. (2016). Creating an understanding of data literacy for a data-driven society. *The Journal of Community Informatics*, 12(3), 9–26.
- Wong, N., Elsayed, R., Perez, L. R., Daehler, K. R., & Chen, P. (2024). Toward a Theoretical Framework for Data Fluency Teaching and Learning in Middle School STEM. *Ninety-seventh annual international conference of the National Association for Research in Science Teaching (NARST)*. NARST
- Yong, A. G., & Pearce, S. (2013). A beginner’s guide to factor analysis: Focusing on exploratory factor analysis. *Tutorials in quantitative methods for psychology*, 9(2), 79-94.
- Yarnall, L., & Ranney, M. A. (2017). “Fostering scientific and numerate practices in journalism to support rapid public learning”. *Numeracy*, 10(1), 3.

Chapter 3 - Examining Data-Rich Pedagogy in Middle School Science Educators

Table of Contents Chapter 3

TABLE OF CONTENTS CHAPTER 3	45
ABSTRACT.....	45
INTRODUCTION.....	46
LITERATURE REVIEW.....	48
RESEARCH QUESTIONS.....	55
METHODOLOGY	55
PARTICIPANTS	61
RESEARCH FINDINGS.....	65
DISCUSSION AND IMPLICATIONS.....	80
REFERENCES CHAPTER 3	83

Tables and Figure Chapter 3

Table 3-1 – Classroom Observations.....	56
Table 3-2– Demographics of Educators and Schools in the Study.....	62
Table 3-3 – Data-Rich Practice (Observed/Reported) Alignment to NGSS.....	76
Figure 3-1 – Overview of Parallel Analysis: DRP, Data Skill Learner Groupings, and Data Resources	66

Abstract

As data science becomes more vital in the twenty-first century, educators continue to develop instructional strategies to incorporate data into their classrooms in meaningful ways. I recently collaborated with five middle school science educators on their data-driven strategies

through the Data Ecosystem Project (DEP). In this project, I focused on two key areas of K-12 science education: data-rich pedagogy in middle school science classrooms and how these data-driven strategies support science content learning. I asked educators to plan, implement, and reflect on data-infused lessons during the 2024-2025 school year. I provided these educators with group and individual professional learning support throughout the year. During the study, I conducted twenty-eight classroom observations and interviewed each educator.

While educators recognized the value of data-rich pedagogy in fostering critical thinking and real-world problem-solving, they faced challenges such as timing due to curriculum constraints and resource limitations, and some had confidence issues with their data skills when delivering their lessons. Educators' data-rich pedagogy included various learner groupings to support data literacy skills. They also utilized multiple data resources, primarily drawing on data from their work with Global Learning to Benefit the Environment (GLOBE) and the National Aeronautics and Space Administration (NASA). Educators reported that connecting data-driven instructional strategies to district- and state-level science content standards was achievable.

There are ongoing opportunities for educators to engage in professional learning to support the use of data in science education. Expanding this research to include educators from various grade levels and educational settings may yield a broader range of practices that link data concepts and skills to meaningful learning experiences in K-12 education.

Keywords: Data literacy, data-rich pedagogy

Introduction

One of the core principles of science education is the ability to work with, understand, and interpret data (Kind, 2009; English, 2016; Gebre, 2018; Kelley & Knowles, 2016; Kjervik & Schultheis, 2019). Addressing real-world questions and challenges requires collecting,

interpreting, and communicating with data. Data science education requires more than just the mere presence of data in science lessons; it requires data to be explored and interrogated as a tool to support learners' inquiry skills. Therefore, in addition to emphasizing data in science education, it is important to understand how, and to what extent, educators can implement data-centric pedagogical strategies. What approaches are educators using, and how do these strategies support their personal journey towards developing and delivering data-rich instruction in support of science learning and data literacy?

Data literacy for K-12 learners involves developing skills such as data collection, organization, visualization, interpretation, and communication (Ostrom, 2025). It is closely tied to the integration of science content because it combines technology and mathematics through data analysis and interpretation. Our interest in data literacy stems from our ability to read, understand, analyze, and communicate with data, which enables us to make informed decisions, drive innovative problem-solving, and achieve success. Additionally, data literacy provides a scientific context for understanding where data come from (Kjelvik & Schultheis, 2019).

Although science educators typically believe that data are a crucial part of science education, most interactions with data in science classrooms occur through labs or activities designed to teach established scientific relationships or concepts, rather than using data to engage with real-world problem solving in service of more deeply understanding those concepts (Ostrom Chapter 2, 2025; Finzer et al., 2018; Hardy, Dixon, & Hsi, 2020). Educators need support to enhance their knowledge and tools for integrating data into their classrooms, including subject-matter knowledge about data and how to work with and teach it (Kelley & Knowles, 2016; NRC, 2014). Broadly, this collection of knowledge and skills is often called “data-rich pedagogy” and includes instructional practices that engage learners in scientific content.

Although there is prior research and recent progress toward identifying data-rich pedagogy (DRP) in math education (Vahey et al., 2012), science education (Finzer et al., 2018), and computer education (e.g., Hassan & Liu, 2019), it remains unclear how this body of research applies to middle school science educators in ways that foster connections and patterns across science disciplines (Lee & Wilkerson, 2018). It is also unclear how educators' DRP is used to support science content learning and the development of learners' data literacy skills.

This study follows the DRP of five middle school science educators during the 2024-2025 school year to deepen understanding of how educators implement data-rich pedagogical practices. In some cases, in collaboration with the educator, I co-developed grade-specific, data-driven strategies to build learners' data literacy skills while supporting their understanding of science content. Helping learners develop data skills improves their ability to contribute effectively to society (Dorsey & Finzer, 2017; Lee & Wilkerson, 2018; Nadelson & Seifert, 2017). Educators determined how to implement data-integrated lessons, learner groupings, and appropriate resources. Another goal of the collaboration was to see if data-driven practices support science learning by aligning lessons with state-mandated science standards.

Literature Review

In improving data-rich pedagogy with science educators, it is important to consider the broader context, including understanding effective science teaching methods and how they align with science content standards. Only then can educators incorporate data into their instructional practices. In this literature review, I will discuss science education pedagogy more generally and explore how data-rich pedagogy aligns with science content standards. Then I will turn to a review of educational research that examines the intersection of science education and data-rich pedagogy. Along the way, I will note gaps in the research base that warrant my study.

Educator Data Practices & Learner Data Skills

Broadly defined, data literacy refers to the ability to collect, manage, evaluate, and apply data in a critical and informed manner (Ridsdale et al., 2015). Data skills in K-12 education encompass the collection, organization, visualization, analysis, interpretation, and sharing of data (Chapter 2). Effective data literacy education uses instructional methods that engage and motivate learners while encouraging them to make sense of data for problem-solving and solution development (Chapter 2). Best practices for teaching data literacy involve collaboration among educators, organizations, and institutions to ensure all stakeholders meet their goals; implementing diverse, creative teaching approaches and environments, including the effective use of technology; providing successive or iterative learning with integrated, complementary skills (e.g., project-based learning); emphasizing mechanics along with concepts (i.e., practical, hands-on learning); and increasing engagement with real-world data (Ridsdale et al., 2015).

In Chapter 2, I reported on science educators' examples of data-centric practices they use in the classroom. These practices were limited in scope and frequency and were primarily delivered to engage learners rather than to build their data skills. In Chapter 2, I also provided seven key principles of data-rich pedagogical strategies established by WestEd (WestEd, 2025):

1. Data-rich learning is accessible to all learners.
2. Data-rich learning is learner-driven.
3. Data-rich learning uses a variety of datasets.
4. Data-rich learning encourages a healthy skepticism.
5. Data-rich learning strengthens content knowledge.
6. Data-rich learning utilizes the power of digital tools.
7. Data-rich learning draws on learners' personal, historical, and cultural contexts.

The question remains: how are these practices carried out in a science classroom? In other words, what does learner-driven look like? Are they using their skills to collect and organize data? What data sets are appropriate for different grade levels? And how might digital tools help learners develop their skills in visualization and analysis of data?

The link between effective science teaching methods, alignment with science content standards, and the use of data integrations that support educators is emerging. Educational research has long focused on what educators *should do* in the classroom, but has overlooked *how* they can achieve strategic pedagogical goals. As research and data-driven practices continue to develop, we must explore and identify the support structures and/or credentials educators need for these data-rich practices. My project aims to address this gap in the published literature by examining not only *what* educators should do with data-driven practices, but also *how* science educators can implement them in their classrooms to support learners in developing their data literacy skills.

Educator Practices & Science Learning

I will use a report from the National Academies of Sciences, "A Framework for K-12 Science Education: Practices, Crosscutting Concepts, and Core Ideas" (National Academies, 2012), as the foundation for my conceptual framework connecting learners to science learning. The conceptual framework in the report was developed by a committee appointed by the National Research Council. I chose to focus on the practices of this framework because it builds on two earlier works on science standards: Benchmarks for Science Literacy, published by the American Association for the Advancement of Science (AAAS) (AAAS, 1993), and the NRC's National Science Education Standards (NSES) (NRC, 1996).

The National Academies committee set two primary goals for K-12 science education: (1) teaching all students science and engineering, and (2) laying the foundation for future scientists, engineers, technologists, and technicians (National Academies, 2012). They identified eight practices that are key to the scientific process and should be central to how learners participate in school science.

1. Asking questions and defining problems
2. Developing and using models
3. Planning and carrying out investigations
4. Analyzing and interpreting data
5. Using mathematics and computational thinking
6. Constructing explanations (for science) and designing solutions (for engineering)
7. Engaging in argument from evidence
8. Obtaining, evaluating, and communicating information

The committee established these eight practices to address a perception that previous standards documents had led some educators to focus too narrowly on scientific skills and procedures, such as identifying and controlling variables, classifying entities, and pinpointing sources of error. This kind of narrow focus overemphasizes the mechanics of experimental investigation at the expense of other important practices like modeling, explanation, and communication that contextualize the inquiry into a broader endeavor of sensemaking. Additionally, describing scientific practice in this way avoids the misconception that a single "scientific method" is standard to all science. Only by engaging in scientific practice can learners understand how scientific knowledge develops and why certain aspects of scientific theory are more firmly supported than others (National Academies, 2012).

Finally, the committee's report confirms that engaging in the science and engineering practices as they articulated them helps learners develop skills related to data literacy (National Academies, 2012). While the report emphasizes that practices such as modeling, developing explanations, and participating in argumentation are essential for acquiring new knowledge and learning science, it does not discuss how to implement these strategies effectively. What resources or experiences do educators need to provide learners with opportunities to engage in scientific practices and use data as a tool for scientific learning?

Hayes et al. attempted to bridge the gap between educator data-driven instructional practices and science learning by developing and testing a comprehensive survey to assess how science instructional practices align with NGSS science content standards (Hayes et al., 2016). Hayes' study aligns with the intent of my research as it presents a valid and reliable survey tool for measuring shifts in educator instructional practices based on NGSS science and engineering practices. Hayes' survey instrument is essential in understanding how instructional shifts occur in targeted professional development and implementation of broad science education policies. My study also includes an evaluation of how group and individual professional development influence an educator's instructional shift, using data. Hayes' survey includes an assessment of the following instructional practices:

1. Empirical Investigation: Focus on the investigation procedure: observing phenomena, asking questions, planning experiments, collecting data, analyzing, and interpreting data.
2. Evaluation and Explanation: Focus on modeling, evaluation, and argumentation: constructing explanations, evaluating appropriateness based on evidence (data), fitting models, and critiquing ideas

3. Science Discourse and Communication: Provide opportunities for participation in scientific discourse that enculturates learners into scientific language and practices
4. Engaging Prior Knowledge: Engage learners with their prior knowledge and real-world and home applications of science to bridge the gap between science epistemologies and learner experiences.
5. Traditional Instruction: Provide traditional educator-centered approaches, including direct instruction, demonstration, worksheet, or textbook work

Hayes et al. conclude that these practices align well with Next Generation Science Standards (NGSS), and NGSS's science and engineering practices, including ample connections to data analysis and interpretation. However, further research is needed to provide a nuanced understanding of educators' struggles in integrating data into their practices. I will consider these practices when collaborating with educators to provide professional learning and create data-rich lessons.

Learner Preparedness for Data Instruction

Educators strive to equip students with the skills and knowledge necessary to succeed in an increasingly data-driven world. These tools are foundational for practice in collecting, sorting, extracting, and analyzing data from different sources (Isreal-Fishelson et al., 2023). To maximize the potential of data science tools in K-12 education, it is crucial for educators to carefully select the right tools for their learners, as these tools themselves play a critical role in shaping learners' experiences (Pimentel, Horton, and Wilkerson, 2022).

Researchers have sought to establish a framework that connects science and data-driven pedagogical strategies. For instance, Maybee and Zilinski (2015) adopted a more holistic

approach to integrating data into science practices. They outlined seven teaching principles for learners to incorporate data into their science teaching.

1. Awareness: Teaching learners to understand data and its role in society;
2. Access: Providing all learners with the ability to identify, locate, and appropriately use datasets and databases;
3. Engagement: Connecting learners to evaluating, analyzing, organizing, and interpreting existing data for decision-making;
4. Management: Planning and managing data for learner exploration, including organization and analysis, as well as security protocols for data storage, sharing data, and data-driven documentation;
5. Communication: Providing learners with how to synthesize, visualize, and represent data;
6. Ethical Use: Identifying diverse data sources for learners, particularly those from human and social activities that connect to learner interests;
7. Preservation: Recognizing long-term practices for learners to store, use, and reuse data.

These practices are thoughtful, but the educators' approach to integrating these strategies remains unclear.

Synthesis

This literature review highlights how educators' data-driven practices can support learners in developing data skills and linking them to science content. The most inclusive study, conducted by WestEd in 2025, outlines seven data-focused teaching practices. These practices are supported by an analysis of NGSS, including the science and engineering practices, which help learners develop data literacy skills. These 2025 data-driven principles confirm earlier studies, such as the one conducted by Maybee and Zilinski in 2015, which also outlined seven

teaching principles for learners to incorporate data into their science teaching. But the question the literature review leaves unanswered is *how*. It's not enough to know what to do in the classroom to support learner acquisition of data skills. How do K-12 science educators embrace these practices to develop data skills in their learners? My study will address this gap by exploring how educators include data integration practices.

Research Questions

As part of this larger endeavor, the study was designed to understand how educators recognize and develop their knowledge of data-rich pedagogy in middle school science classrooms. It also sought to show how this knowledge could create data-rich strategies linked to science content knowledge. To accomplish this, the research addressed the following questions.

RQ1: What data-driven practices and data resources are middle school educators implementing in their classrooms?

RQ2: How do these educators group learners when using data-rich pedagogy to support science content standards?

RQ3: How do data-driven practices connect science content standards?

Methodology

In September 2024, I started a collaboration with five middle school educators that spanned the 2024-2025 school year. I collaborated with these educators as they developed and implemented DRP in their classrooms. I conducted classroom observations to document DRP and interviewed each educator at the end of the school year.

Classroom Observations

During the study, I conducted 28 classroom observations of the five participants who taught grades 6, 7, and 8. Table 3-1 shows a breakdown of these observations by educator and grade level. The observation template is included in Appendix C. Each observation lasted between 45 and 90 minutes, depending on the school, day of the week, and class section. Most observations were completed without interrupting the lesson, though I occasionally intervened to demonstrate a data-rich practice, which the educator repeated for the next class. Details of these moments are included in the research findings. Classroom dynamics, including class size and learner groupings, were recorded during observations. Data sources were also noted. Data-rich practices were recorded and aligned with the educators' expected learning outcomes related to data use.

Table 3-1: Classroom Observations

Educator	Grade Level			Total Observations
	6 th	7 th	8 th	
Liam		2	5	7
Jen		2	4	6
Nate			4	4
Carla	4			4
Barbara	1	3	3	7
Interview Totals	5	7	16	28

Note: shaded boxes refer to grades not taught by the educator or not included in the study.

Due to schedules, class timings, and the grade-level sections taught by each educator, the number of observations per educator ranged from 4 to 7 at each grade level. Observations were used to triangulate information and ideas discussed with each educator and at the end-of-year interview. Notes on individual learner responses to instruction were not recorded. Observation notes focused on educator practices and how educators responded to learner understanding and engagement. Educator handouts to their learners were also included in the observation notes. The

observation protocol included ten possible data-rich practices, supporting evidence, and a place to note the connection to science content for each practice. Unavoidable challenges were noted, such as a fire alarm, disruptive learners, or learners being pulled from the class by the administration. Each observation concluded with the researcher and the educator discussing the lesson's effectiveness and challenges.

End of Year Interviews

Each participating educator provided time for a one-hour interview at the end of the school year, using the interview template included in Appendix D. These interviews reviewed information and ideas discussed during group professional learning, classroom observations, and lesson development. The end-of-year interviews were divided into two sections. The first focused on the educators' data-rich practices and their alignment with science content standards. The second section addressed educators' self-assessment of their data-rich pedagogy and data fluency at the beginning and end of the year.

Interviews began with exploring how the educator used data practices throughout the year. They were provided with a list of entry points for data instruction: warm-ups, exit tickets, inquiry-based activities or labs, homework, science content instruction, or other entry points. Educators identified which entry point(s) they used and explained how their chosen entry point(s) supported data instruction and/or science content learning. The interview also included details about learner outcomes. Educators discussed how they achieved expected outcomes through their data-rich instruction and reflected on what they would keep or change to improve content and/or skill learning. They also identified the types of data tools (digital, equipment, or other) they used and their sources. Understanding the type and effectiveness of these tools helps

researchers determine if further evaluation or expansion is needed in teaching data science skills (Lee, 2025).

Data Collection and Analysis

Raw data were collected from both classroom observations and interviews. These data were manually analyzed and organized to address the research questions. First, personal details were de-identified. Second, the raw data were organized into three broad categories: application of data-rich practices, learner engagement structures, and the connection of these practices to support science content. Many of the raw data overlapped between these broad categories. Next, the data from each broad category were further separated into bins. Bins are similar to categories or codes that I used to further organize the data.

RQ1

To address the first research question, I separated the raw data from both observations and interviews by identifying the type of data-rich practice used or discussed by the educator. As a result, ten bins were created to accommodate the data-rich practices:

1. Data is integrated into the lesson,
2. At least one data literacy skill (in learners) is evident.
3. Data integration was used to support science content learning,
4. The educator demonstrated an accurate understanding of how to use data to support science content learning,
5. The instruction draws on learners' personal, historical, and/or cultural contexts,
6. Data-rich instruction was demonstrated by empowering learners to become "data detectives," to question and explore data stories for themselves, and to develop productive habits of mind such as perseverance and curiosity.

7. Meaningful data sets were used to foster learners' imagination and curiosity, encouraging them to find and explore questions that are meaningful to them.
8. Data-rich instruction demonstrated learner engagement with data science practices such as cleaning and transforming messy data for authentic purposes.
9. Web-based digital tools were used, and
10. Formative assessment(s) were used to ensure connections between data and science content.

Practices related to learner engagement (bins #2, 5, 7, and 8) and science content (bins #3 and 10) were put aside to address research questions 2 and 3, respectively. Therefore, bins 1, 4, 6, and 9 were primarily used to address research question 1, which pertains to actual data-driven teaching practices. Since some of the raw data overlapped with respect to the research questions, these data were placed in multiple bins.

RQ2

The second research question focused on learner groupings. Only classroom observations were used to document how learners were organized during the lesson. Learner grouping bins included: whole class, small groups of 3-4 learners, pairs, and individuals. In multiple observations, learners were organized and reorganized at least once or twice each time. This made categorization of the raw data challenging. Therefore, learner groupings were identified during each observation and were characterized by the tasks they performed. For example, an observation might have documented that a whole-class grouping was used during a read-aloud portion of the lesson, small groups were employed to address content-based critical thinking, and individuals were observed using a digital tool for independent reinforcement. Since learner group tasks were added as raw data, I further aligned (coded) the tasks performed within each

grouping. Tasks were categorized into two groups: one that used digital tools and one that did not. Coding these tasks under each group included reading, analyzing/interpreting data, creating visuals, performing data collection/organization, and sharing (project) results.

RQ3

To address the last research question, each data-rich practice observed in the classrooms or reported during the interviews was identified and coded as an NGSS middle school performance expectation, a science and engineering practice, a cross-cutting concept, and/or a disciplinary core idea. In some instances, data were identified with multiple codes, while other data aligned with just one code. Fifty-nine possible codes were considered when aligning a lesson to a middle school performance expectation. There are eight possible codes to align a task or lesson to a science and engineering practice as identified by NGSS in Appendix F (NGSS, 2013). There are seven possible codes for aligning a task or lesson to a cross-cutting concept, according to Appendix G, and/or forty-one possible disciplinary core ideas (NGSS, 2013). At first, the sheer complexity of this form of task/lesson coding seemed daunting; however, the process was fairly straightforward during the observation, as the educator provided a description of the lesson and learner tasks in advance. The observation allowed me to confirm and/or correct the coding as the tasks/lessons were observed. If an unscripted task was performed, it was coded after the observation.

Validating the Data for the Research

The data were validated to ensure consistency with the research questions. First, the data practices observed during the observation were discussed with the educator at the conclusion of the lesson, at the end of the school day, or within a week of the observation. At this time, educators had the opportunity to clarify the lesson or learner task's intent. They also identified

the data resource(s) used with their lesson. The identification of data resources was then added as an additional strategy within the educator's practice. The data resources were grouped (coded) as National Aeronautics and Space Administration (NASA), Global Learning and Observations to Benefit the Environment (GLOBE), National Oceanic and Atmospheric Administration (NOAA), United States Geological Survey (USGS), or other data sources, and other data resources. When multiple data sources were used, they were documented during the observation. The addition of this coding procedure was subsequently used to compare different data categories simultaneously, a practice known informally as parallel analysis. These data categories included data practice alignment to professional support and educator mastery of data (Chapter 4).

Further data validation was conducted to verify the observation and interview data on learner groups. At the end of the observation, the educator confirmed their learner groupings for various tasks within the lesson. During the interview, they discussed data-rich practices not observed and justified learner groups according to formative learner assessment during the lesson.

Validation of NGSS alignment was confirmed during the lesson observation and during discussions of unobserved lessons during the interview. Specifically, the performance expectation, science and engineering practice, and cross-cutting concept were validated with the educator. Disciplinary core idea alignment was not validated, as it was not matched to the performance expectation.

Participants

There were five educator participants in this study. Four educators were initially invited because of their prior connection to the researcher through a NASA-funded GLOBE Program. The fifth, a colleague of one of the other participants, volunteered and requested to join. The

selection criteria for the four initial educators primarily relied on convenience sampling, and they volunteered to participate. These educators were familiar with the researcher and had some prior exposure to data-rich practices.

All educators in this study had varied teaching experiences in schools with diverse demographics (Table 3-2).

Table 3-2: Demographics of Educators and Schools in the Study

Educator Demographics					School Demographics				
Educator	Years Exp.	Grade Taught	Gender	Ethnicity	School	Percent Minority	Free/Reduced Lunch	Pop.	School Type
Liam	6	8 th	M	White, non-Hispanic	A	67%	13%	601	Public Urban
Jen	10	7 th /8 th	F	Hispanic	B	98%	86%	492	Public Urban Charter
Nate	12	6 th /7 th /8 th	M	White, non-Hispanic	C	58%	26%	345	Public Urban
Carla	15	5 th /6 th	F	White, non-Hispanic					
Barbara	32	6 th /7 th /8 th	F	Hispanic, Native American	D	82%	100%	688	Public Rual
Average	15					76.3%	56.3%	532	

Note: Minority is defined as all races/ethnicities except white, non-Hispanic. U.S. federal standards define free/Reduced lunch.

Liam began teaching as a middle school math educator for two years before switching to teaching science four years ago. During the 2024-2025 school year, Liam taught six periods with no prep time in his schedule. He taught five 8th-grade science classes and a leadership class.

Liam's school, School A, implemented a modified block schedule for the academic year. Liam met with each science class for 80 minutes four days a week and 40 minutes on the fifth day. For the past four years, he has worked with the researcher.

Jen started her career as a marine biologist and worked for three years with the Department of Fish and Game. After finishing her work in the Marshall Islands, she moved to

California and began teaching middle school science. She began teaching ten years ago and has taught sixth, seventh, and eighth-grade science at the same school for a decade. In the 2024-2025 school year, she taught two eighth-grade science classes, one seventh-grade science class, and an advisory class.

School B followed a modified block schedule for the past year. Jen had each of her science classes for 85 minutes, three or four days a week. On the fourth and/or fifth day, she met with each class for 45 minutes. She has collaborated with the researcher for the past nine years. Since School B was mainly Spanish-speaking, she often incorporated Spanish translations in her instructional practices and handouts. Although Jen spoke Spanish to all of her learners, newcomer learners were paired with bilingual learners who translated as needed.

Nate: Nate taught middle school science in California for 12 years. During the school year, Nate also worked with climate change advocacy and climate justice non-profit organizations to support project-based opportunities for his learners.

School C included both an elementary and a middle school on its campus. Middle school learners (6th-8th) followed a modified block schedule. Nate had each science class for 75 minutes daily, four days a week. On Wednesday, a minimum day, he met with his classes for only 40 minutes. He taught one sixth-grade science class, two seventh-grade science classes, and two eighth-grade science classes. He has worked with the researcher on the GLOBE Program for the past two years. A select number of sixth graders follow the elementary school schedule to receive more support from educators.

Carla had 15 years of teaching experience at the elementary and middle school levels in California. She taught at the same school as Nate for the past four years. She taught a fifth-grade class, covering all subjects except physical education. She also taught fifth and sixth-grade

science for one hour each day, five days a week. The sixth-grade learners in her science class were the select few who followed the elementary school schedule. Nine of her 28 learners in the fifth and sixth-grade science class are sixth graders. She requested to participate in the study because she admitted she did not know how to integrate data in her classroom to support data literacy. She had no previous connection with the researcher.

Barbara was the most experienced educator in the study group and taught in New Mexico. The 2024-2025 school year marked her 32nd year in the classroom. Her science teaching experience had always been at the middle school level, and she had taught sixth-, seventh-, and eighth-grade science at School D for the past 25 years. For the past eight years, she has taught STEM-focused science classes. She had two seventh-grade STEM classes and two eighth-grade STEM classes. Additionally, she taught science to approximately 24 sixth graders for 10 weeks, with this block of learners rotating to another science educator and elective courses for the other 10-week blocks. The goal of the rotating block was to allow learners to experience different science class dynamics to decide whether to enroll in STEM science or traditional science for seventh and eighth grades.

Learners in her seventh and eighth-grade classrooms chose her STEM class over the traditional science classes for those grades. STEM science classes were learner-driven, emphasizing a project-based learning environment where learners controlled their learning and progress. The educator primarily acted as a facilitator, providing minimal daily instruction. Barbara also organized an after-school Lego robotics club and coached volleyball at her school, so she was very busy outside the classroom.

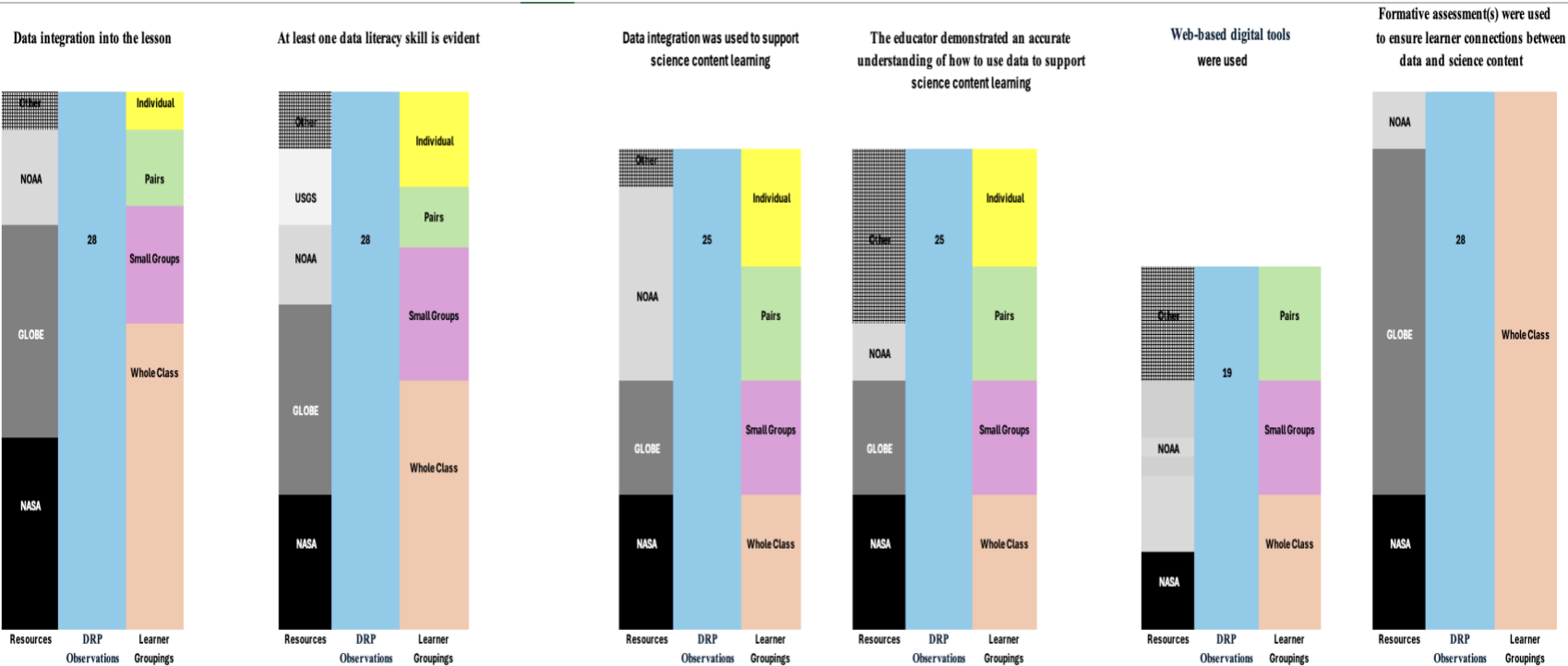
School D is a year-round school with 90-minute classes three days a week. On the other two days, classes are scheduled for 50 minutes. Barbara met with her learners four or five days a week, alternating each week. She worked with the researcher for five years.

All five educators shared a common trait: their motivation to use data-rich pedagogy as a tool to support learning in science. They were all eager to participate in professional learning sessions focused on data-rich pedagogy during the 2024-2025 school year. Additionally, although they worked in different school settings, they all followed state science standards and complied with their respective districts' rules, expectations, and regulations.

Research Findings

Educators were tasked with developing and implementing data-rich pedagogy in their classrooms. The first two research questions (RQ 1 and RQ 2) examine the types of data-driven practices, learner groupings, and data resources used by the middle school educators. Figure 3-1 provides an overview of a parallel analysis of three qualitative datasets. Only six data-rich strategies are presented in Figure 3-1. The other four strategies were omitted from the analysis as 50% or less of the classroom observations noted this practice.

Figure 3-1: Overview of Parallel Analysis: DRP, Learner Groupings, and Data Resources



While a variety of data-rich practices were observed across all 28 observations, Figure 3-1 shows that the learner groupings for these practices varied widely. The figure also shows that most practices occurred when learners were grouped into whole-class groups. However, educators reinforced whole-class instruction with small-group or pair work for exploration or practice. Since this study is not focused on surveying learner data outcomes before or after, it is unclear if one grouping strategy was more effective than another for a particular data-rich practice. A variety of data resources can also be noted from Figure 3-1. Clearly, working with NASA and GLOBE data dominated the data-rich instructional practices, but educators also used additional data resources from NOAA and USGS. Other data sources included state and local agencies, such as the California Air Resources Board and the UC Berkeley BECO2N Program. I selected the following cases based on specific challenges in implementing data-rich practices, learner grouping, and data resources. These cases begin by illustrating educators' challenges when executing their data-rich lesson plans. Suggested lesson execution strategies were provided to the educator to help mitigate the challenge.

Educator Challenges and Suggested Modifications

Challenge 1: Using Prior Knowledge to Support Data-rich Practices

One prominent theme that emerged from educators' data-rich practices was the need first to understand learners' prior knowledge. Educators found that their data practices needed to recognize learners' initial understanding of data skills before developing their teaching strategies for those learners. This led educators to modify their practice based on their learners' misunderstandings.

Liam's data-rich teaching focused heavily on incorporating math skills. With a strong background in middle school math, Liam incorporated mathematical concepts into his science

lessons. He mentioned at the start of the year that he includes mathematical problem-solving skills in his science class through:

- Making sense of problems,
- Reasoning abstractly and quantitatively,
- Constructing viable arguments,
- Looking for and expressing regularity in repeated reasoning,

During his first weeks of school, he assigned his learners to plot data points on an x-y coordinate graph from a physics experiment. Learners were in small groups. However, several groups did not understand x-y coordinate graphs, so they couldn't plot the data. As a result, he had to explain how to plot data on an x-y coordinate graph the next day and provided a blank graph for them to use. He continued this approach throughout the year, making fewer assumptions about learners' understanding of data visualizations by assessing their knowledge first, then adjusting his data-rich teaching strategies accordingly.

Another instance in which incorrect assumptions about learners' prior knowledge occurred during a different physics lab. Liam instructed his learners to identify various components of sounds and sound waves. Working in pairs, they moved from station to station, completing tasks and answering questions. One station featured two data visuals. One visual displayed different sound types, decibel levels, and atmospheric pressures in pounds per square inch (psi) and megapascals (mPa). The other visual showed the speed of sound in different physical media. Learners were instructed to write at least two *observations* about the visuals from this station. While analyzing data visualizations is important, Liam assumed students could understand the meaning of each component of the visuals. However, students couldn't interpret the units used for pressure (psi or mPa). Therefore, their observations, such as “rock concerts are

louder than cafeterias,” were correct, but they didn’t demonstrate a proper understanding of the data. This might also be a problem with the visuals themselves. For example, students can easily tell if a line on a graph is going up, down, or if one number is bigger than another, but they might not understand what the line or number represents. After class, I spoke with Liam and shared this observation about how students engaged with the visuals at the station. I recommended that he modify the station questions to better assess whether students could accurately read the graphs. For instance, educators can gauge understanding by asking students to explain the components (x-axis, y-axis, title, legends, colors) of the visuals. Instead of having learners write an observation, like one student’s comment, “*There are different colors in the graph,*” Liam could ask students to explain what the colors mean, describe the question the graph aims to answer, or identify trends related to colors. For more advanced students, he could explore deeper aspects of graphs, such as changes over time, cause-and-effect, or comparisons.

The second data station in the sound activity involved reading and analyzing data tables. Again, learners were asked to record their *observations* of the data tables rather than respond to questions about the data. Unfortunately, they were unsure of what the variables in the tables meant. I showed Liam my note where one learner commented, “*...sound ranges from 120 to 10.*” While valid, this observation does not target the intended learning outcome of comparing sound volumes. I discussed with Liam the importance of scaffolded instruction on interpreting data and data tables with his learners. During lunch, Liam modified the tasks at both data stations to focus more specifically on learner outcomes with data. Although learners still couldn’t identify psi or mPa in subsequent class periods, they could use the visuals to understand each graph’s components at the first station and how quickly sound travels through different physical media at the second station. In our afterschool debrief, I asked Liam how these revised tasks supported his

data-rich practices. He said the “[rewritten] *tasks required learners to show a deeper understanding of how sound travels through data comparison, and it taught learners the basic understanding of how to read a graph.*”

Challenge 2: Using Web-based Digital Tools

More and more districts have curricula that use web-based modeling and simulations. Another example of a struggle with data-rich practices occurred when educators were required to reteach or modify their practice while attempting to engage learners with digital tools. Jen asked her learners to use digital maps to analyze air pollution concentration and location data. Each learner had their own computer, so they worked independently of one another. The maps included topography lines and bar graphs of asthma rates across different areas of California. As I moved around the room during the observation, I asked learners what the ‘triangle’ on the map meant. When the first learner I asked said it represented a mountain, I realized there was a disconnect. In reality, the triangle indicated sample locations on the map, which was explained in the legend. I repeated the question to many in the class, and most responded with “*I don’t know.*” During lunch, I shared this observation with Jen. She was surprised they hadn’t taken the time to understand how to read the map, including legends, and agreed that she needed to include a prior step in her data-rich practice. This included a lesson on map reading. After reteaching how to read a map, I suggested that she ask learners to (re)create a map related to the lesson and to include a legend.

Using digital tools, such as the one Jen used, made assumptions about learners’ prior knowledge and required at least one instructional modification by the educator. Early in the school year, I observed Nate teaching a lesson using the Green Ninja digital curriculum on climate-related topics. The lesson included a whole-class read-aloud followed by an individual

gallery walk to different visuals around the room, where learners answered data-related questions about each visual. One visual focused on comparing precipitation and daily temperatures for a random city. It looked simple enough, with a line graph of annual temperatures on top and a bar graph of annual precipitation below. The x-axis was organized by month, using only the first letter of each month—J, F, M, A, etc. I stood next to this visual, and learners asked me what these letters meant.

Furthermore, the precipitation bar graph used the abbreviations "in." for inches of rain (y-axis) and "cm" for centimeters of rain (z-axis). Again, learners seemed confused about the abbreviations. The temperature graph included °F (y-axis) and °C (z-axis). Learners understood that F meant Fahrenheit, so they weren't concerned or maybe didn't notice the C values. After observing this in the first class, I talked to Nate during his prep period. He was unaware of the learners' misunderstandings about the visuals and asked how he could modify this lesson for his next class. I suggested some strategies for teaching how to read data visuals. We also revisited the whole-class reading he performed before the stand-up activity. He realized that if his learners didn't understand the data visuals in the gallery walk, they probably didn't understand the visuals in the reading either. For the next class, he paused during the reading to explain the components of the visuals, which closely matched those in the visuals around the room. He showed the visual from the text on his whiteboard, and together, learners identified the graph's parts, including how months were abbreviated by their first letter and what the x, y, and z axes represented. The gallery walk activity in the next class went smoothly, allowing learners to focus on analyzing the data instead of struggling with how it was presented.

Challenge 3: The Need for Scaffolding

In the cases described above for Liam, Jen, and Nate, data-rich practices were modified to provide learners with more context in a station setting or through digital tools. A case of data-rich modifications through scaffolding comes from an observation made in Carla's classroom. Although Carla is an experienced educator, she was unsure how to introduce data to her learners. She commented in her interview that she assumed her learners had never used or collected data before her class. She started by having her learners create a human histogram as a whole class using their Halloween candy collection data. Carla first asked the class to identify the types of Halloween candy they like to get during trick-or-treating. The class grouped the candy into gummies/chewies, chocolates, hard candy, lollipops, or mixed. The class attempted to answer the question: *What type of candy is given out the most during Halloween?* Knowing the learners had never collected data before, she scaffolded how to complete the homework assignment and data sheet that required trick-or-treaters to record the number and type of candy they received before eating it. They then brought their completed data sheets to school the next day.

Using their school's basketball court lines, Carla created an x-axis and a y-axis on the court, with the y-axis having no numbers and the x-axis with ranges: 0-5, 6-10, 11-15, and 15+. Without explaining the axes, she proceeded to the court activity. In the first round, learners were asked how many pieces of gummies/chewies they received. They moved horizontally along the x-axis and stopped at the amount they received. Carla instructed the learners to line up rather than bunch together as a group. One learner from each line counted the number of people in that line. Carla recorded the histogram data. Additional rounds of data collection were conducted across different candy categories.

She returned to the classroom and asked volunteers to create histograms of the data for each candy type on the whiteboard. However, only one learner could generate a data visual as he was the only one who knew what an x-axis and y-axis looked like. Even though they used the axes outside as a whole class, Carla soon realized that her learners missed the initial step of identifying the purpose of an axis. Carla stopped the lesson and took time to explain the purpose of axes in creating a data visualization. After learners created their data visuals, the class observed that five histograms represented their collective data on various candy types and amounts. It also allowed learners to answer their research question on the kind of Halloween candy given out in their neighborhood. We discussed showing this year's data visuals as a scaffolding introduction to data collection and visualization next year. I encouraged Carla to keep exploring data visualizations by showing learners different examples and asking them to identify the parts of each visualization. I also gave her a pre-made slow-reveal graph about snack foods to show her learners. Jen created this graph for her learners. Scaffolding of basic graph components was needed before asking them to create a histogram visual.

Another scaffolding case was observed in Barbara's classroom. She began the school year with an outdoor data-collection activity and paired her 6th graders. The activity required learners to measure the height of marked trees on their school's campus. The research question was, "*Which tree is the tallest?*" She handed each group a clinometer, written instructions, and a data sheet to record their measurements. Barbara quickly realized that her learners did not read the instructions on using a clinometer, so she spent time outside demonstrating how to take measurements to each team. This repeated data-rich practice took several minutes and slowed down data collection, causing learners to get off-task. After the class, Barbara immediately saw that she needed to scaffold how to read and follow instructions for her learners. In her next sixth-

grade class, she took the time in the beginning to explain the procedures using the instruction sheet as a guide. She did this by having one learner in the group read each step while the others acted out the procedure. This engaged all learners in the classroom, and she facilitated answering any questions or correcting their errors.

Outside, each team followed the procedures and calculated the height of a tree she had selected and previously measured. The teams compared their results, and she asked why the answers varied. The learners eagerly pointed out that the side of the tree they faced could influence their measurements. Others mentioned mistakes in using the equipment or in their calculations. Having learned how to measure tree height, they were asked to measure another tree.

I discussed the importance of scaffolding the activity with Barbara, mainly because none of the learners had used a clinometer before. She explained she intentionally gave minimal instructions because this approach mirrors her other STEM classes, where learners troubleshoot and learn independently, with the educator acting more as a facilitator than a direct instructor. I understood her reasoning, but the lack of scaffolding made learners feel disengaged. I encouraged her to add instructional scaffolding, since sixth graders often lack prior knowledge of how to manage their learning independently, especially in data skills.

The challenges of data-rich practices highlighted in this study's cases are familiar in education. Educators often face the choice between covering a wide range of topics or going in-depth. Do they spend time scaffolding or push forward, hoping most learners are keeping up? And how much effort do educators put into understanding the skill sets of their students? During their interviews, teachers in this study mentioned that they tend to learn as they go. Some also commented that they rely on other learners to support those who may need it.

Data Integration in Science Content

Educators involved in the study clearly reported that they are required to teach the state's adaptation of NGSS science content standards. Therefore, the second research question (RQ3) examined how data-driven practices support science content standards. I compared the data-rich practices I observed and/or the educator reported during our interview with the corresponding NGSS performance expectation (PE), Science and Engineering Practice (SEP), Cross-Cutting Concept (CCC), and Disciplinary Core Idea (DCI) listed in Table 3. This table was developed from chunking observations and end-of-year interviews with educators. To clarify, a PE describes what learners should be able to demonstrate they know and can do to show their understanding of a science concept (NGSS, 2013). A SEP is a skill scientists and engineers use to investigate the natural world and design solutions to problems (NGSS Appendix F, 2013). CCCs are broad concepts applicable across all science and engineering disciplines (NGSS, 2013). A DCI is a core idea or concept central to understanding a science or engineering discipline (NGSS, 2013).

Data from Table 3-3 show that all data-rich pedagogical strategies observed and reported by educators aligned with NGSS performance expectations and often included connections to SEPs, CCCs, and/or DCIs. Although these alignments were not explicitly communicated to learners or stated in lesson plans, it is clear that when various data practices were integrated into middle school science classrooms, they were designed to support science content. These practices also directly supported the development of at least one data literacy skill, such as collecting, organizing, visualizing, analyzing, interpreting, and communicating data. Educators also reported during the interviews that aligning data-driven instruction to science content standards was not difficult.

Table 3-3 – Data-Rich Practice (Observed/Reported) Alignment to NGSS

Data-Rich Instructional Practice	NGSS PE (Science Content)	Evidence of			Educator	Grade
		NGSS SEP	NGSS CCC	NGSS DCI		
Data collection surface and air temperatures	MS-ESS3-1&3 Climate factors – atmosphere	X		X	Liam	7 th
Data collection clouds, surface, air temperatures, humidity	MS-ESS3-1&3 Climate factors – atmosphere	X		X	Jen	8 th
Data collection tree height	MS-ESS3-3&4 Earth and Human Activity	X		X	Barbara	6 th
Data collection candy	MS-LS1-7 Healthy Foods	X			Carla	6 th
Slow-reveal snack foods	MS-LS1-7 Human Health	X			Carla/Jen	6 th /8 th
Nutrition label analysis	MS-LS1-7 Human Health	X			Barbara	8 th
Data collection water analysis	MS-ESS2-4 Climate factors – hydrosphere	X		X	Nate	8 th
Digital Tool – Gizmo	MS-LS4-1&4&6 Genetics and traits	X	X	X	Liam	8 th
Digital Tool – Green Nija	MS-ESS2-4&5&6 Climate factors – hydrosphere	X	X	X	Nate	8 th
Digital Tool – WISE	MS-ESS3-1&3 Climate factors – atmosphere	X	X	X	Jen	8 th
Digital Tool - Desert Data Jam	MS-ESS3-1&2&3&4&5; MS-LS4-1 Earth and Human Activity	X	X	X	Barbara	7 th
Data collection - heart rate	MS-LS1-2 Human Health	X		X	Liam	8 th
Data visualizations – air/surface temperatures	MS-ESS3-1&3 Climate factors – atmosphere	X		X	Jen	7 th & 8 th
Create data visualizations – candy quantities and type	MS-LS1-7 Healthy Foods	X	X		Carla	6 th
Create data map – water quality and location of faucet on campus	MS-ESS2-5 Climate factors – hydrosphere	X	X	X	Nate	8 th
Create data visualization - heart rate	MS-LS1-2 Physics – Structure and Processes	X	X	X	Liam	8 th
Create data visualization – ball distance/weight	MS-PS2-2 Physics – Motion and Forces	X	X	X	Liam	8 th
Create data visual– data jam: cow types/quantities, air quality	MS-ESS3-1&2&3&4&5; MS-LS4-1 Earth and Human Activity	X	X	X	Barbara	7 th

Specific cases on connecting data-rich pedagogy to science content emerged from observing educators. To engage learners, it is recommended that they be given a context or purpose for collecting or analyzing data or performing any data-related task (Jimerson et al., 2019). For example, Liam's station lab connected the data stations to his physics unit on sound. Carla's Halloween candy histogram activity was a good example of linking data to her instruction on her health unit. Other observations from Jen's and Barbara's field measurement activities connected to the climate.

In Jen's case, she designed a lesson on data literacy skills through data collection. She took her classes outside to the school's quad, where learners gathered data on land surface and air temperatures. Small groups chose their locations freely. Before going outside, Jen demonstrated how to operate the equipment and fill out the data sheet, since her learners had never used the equipment or collected any data outside before this activity. She also translated the datasheet to support Spanish-speaking learners, knowing they would struggle with an all-English data sheet. I observed the data collection activity and answered any technical questions learners asked while collecting their data. The small groups had about 20 minutes to complete the task. Keeping them on track was challenging, as they were often distracted and began collecting data on plant leaves and benches rather than the land surface. Unfortunately, before taking them outside, Jen did not connect the activity to the science content on weather and population. A simple presentation on urban heat islands and associated data might have prepared learners, or she could have shown them an aerial photo of the quad and asked learners to predict which surface areas would be hotter or cooler, then required them to explain their reasoning with their data after the activity. I discussed this engagement aspect with Jen when we reviewed the data sheets at the end of the day. She agreed that providing a purpose for the activity would have

increased engagement and possibly improved completion of the data sheets, as many groups left parts of the data sheets blank.

For instance, some learner data sheets failed to indicate whether data were collected in the shade or in the sun, and a few used the wrong unit for temperature (Fahrenheit instead of Celsius). Others lacked data or proper descriptors (e.g., blue top vs. playground). We decided to use the information on the data sheets to create a lesson on messy data. Jen developed a data table with field measurements organized by column and learner groups as rows. It was evident that much of the data was incomplete or confusing. This led to a new lesson focused on messy data, emphasizing the need for data organization. Using the data table, she asked her learners if they could compare air and surface temperatures at different locations in the quad. They quickly realized they couldn't confidently make those comparisons because much of the data was unusable. Jen realized that before making field measurements, she needed to provide scaffolding for her learners on collecting and organizing data, and a reason why taking these measurements supported their learning. This case again highlights that data-rich teaching not only requires scaffolding but also includes communicating the activity's context.

I also observed Barbara's eighth-grade STEM science classes early in the year. It was clear that the eighth-grade learners knew Barbara's teaching style, as they had also attended her seventh-grade STEM science class. With her eighth graders, Barbara used her understanding of her learners' prior knowledge in recognizing data trends to teach them how to analyze wildfire and prescribed burn data from Arizona and New Mexico. The science content on wildfires hit home with her learners. Over the past few years, New Mexico has experienced several destructive wildfires that have negatively impacted the school's community. Learners worked in small groups to analyze fire data, including location, affected area (acres), and fire duration.

After choosing at least one variable to plot, the groups created their visuals and exchanged them with another group. They were instructed to write down three “noticings” about what they observed from the other group’s visuals. They also listed questions they had about the visualization.

This lesson met many data skills outcomes for her learners. In addition to drawing on prior knowledge of her learners, she connected science content to their interests. She also gave them a choice of which data to plot. Offering choice connects science content to learners’ contexts (WestEd, 2025). However, I suggested to Barbara that next time she start class with some vocabulary review, such as prescribed burn versus wildfire, and a visualization of what an acre looks like using an aerial photo of the school campus. Even learners focused on STEM-centered curriculum could benefit from these support measures.

When I observed three of Barbara’s seventh-grade classes in a Data Jam project from the Asombro Institute, learners practiced their tri-fold presentations with me. The purpose of the extended unit was for learners to explore a particular science content related to air quality, health, or genetics. I gave feedback to each group on their data visualization and storytelling, and I also repeated this feedback to Barbara. Together, we realized that most groups needed more support connecting their data visualization to their selected science content. This one-on-one mentoring session, which included a project analysis with Barbara, proved valuable in her next steps in preparing her classes for the state fair.

These cases show the need to provide meaning and scientific context for the DRP and to use data to engage learners in supporting science content learning. Web-based tools with artificial intelligence may be the next step in engaging learners with data, but sense-making of the data must be included. Furthermore, educators reported that clear goals for data integration may be

necessary to foster learner engagement, so learners don't view the activity as just an opportunity to use computers or go outside.

Discussion and Implications

This study aimed to identify data-driven practices and their alignment with science content, learner groupings, and data resources used by middle school educators in their classrooms. To accomplish this, the research focused on three questions: *What data-driven practices and tools do middle school educators use in their classrooms? How do these educators engage learners with data to support science content? How do data-driven practices connect to science standards?* Five middle school educators with diverse backgrounds in data integration and years of teaching experience participated in the study. These educators invited the researcher to conduct classroom observations and participate in an end-of-year interview.

Findings revealed that educators used a variety of data-driven practices and tools with their learners. However, all educators experienced unexpected challenges when delivering their data-centric lessons. These challenges centered on scaffolding learners and understanding their prior knowledge and experiences. Educators made assumptions about learners' abilities, which often limited the effectiveness of the data practice. However, these limitations were short-lived, as one-on-one support helped educators become aware of the struggles so they could adjust their practice accordingly. Challenges such as these are not uncommon in the education sector. Planning (scaffolding) for learner understanding before and during a lesson using data is as important and common as in any lesson that does not use data. Scholars have documented that understanding learners' prior knowledge limitations is as vital as the educator's content knowledge (Rusznyak & Walton, 2011; Nilsson, 2009; Panasuk & Todd, 2005).

Educators structured their classrooms so that learners experienced data in a variety of formats or platforms. Learners were able to access and use the data tool independently and as a team. These learner groupings were strategic, and educators used their prior knowledge of learner behavior, along with the anticipated content delivery, when deciding how to group their learners.

Furthermore, educator data-centric lessons were aligned with NGSS performance expectations, science and engineering practices, and cross-cutting concepts. Some educators were more intentional in showing how the lesson related to science content for their learners, while others used data integration for specific projects. Educators reported that their data practices engaged learners in ways that other practices, such as reading and writing, could not.

What is the broader significance of the research findings? This study has shown that data-driven practices can support K-12 instruction by enhancing learner engagement while connecting to science content. Data-centric practices offer learners the opportunity to develop data skills, including making observations, collecting, analyzing, and interpreting data. Learners who have repeated interactions with data can personalize their learning as educators tailor lessons to meet their specific needs. Throughout this study, data were emphasized not as an “add-on” to instructional practice but as a tool for improvement, much as textbooks, videos, and digital simulations are used.

While the field of data science continues to grow in K-12 education, this study provides practical applications of data-rich practices, their challenges, and the connection between these practices and science content. Educators have found ways to support data literacy education by using instructional methods outlined by educational researchers, such as creating opportunities for learner-driven learning, using a variety of datasets, encouraging learners to ask questions, and

leveraging the power of digital tools. As a result, educators were able to connect science content to learner engagement and motivation.

This study not only highlights the different ways educators connected data in their classrooms but also how easily data integration aligned with state and district science content standards. While the contributions of this study support previous research findings on data integration practices, instructional challenges remain, and data sources and data manipulation can require additional support for educators. Data education researchers should address the addition of these complexities to data integration.

As we move forward with data science in the twenty-first century, science education should do the same. The potential implications of this study are based on the research findings from observations and interviews of participating educators.-If practitioners are expected to prepare their learners for post-secondary education, prioritizing data-rich practices in pre-service teaching programs is essential. In-service practitioners should be provided with meaningful professional learning in data science education, with an emphasis on not only the *what*, but also the *how*. This includes allowing them to observe and learn from one another during the school day.

This study has demonstrated the need for further research to assess how data-rich practices influence learner outcomes in critical thinking, problem-solving, and science content learning.-More research is also necessary to understand how supporting K-12 science educators in data-rich practices impacts learners across various curricula, such as math and engineering. This study serves as an initial guide to help educators develop their capacity and expertise, enabling them to modify their teaching methods to incorporate engaging data integration techniques that enhance science content.

References Chapter 3

- Deitrick, E., Wilkerson, M. H., & Simoneau, E. (2017). Understanding student collaboration in interdisciplinary computing activities. In Proceedings of the 2017 ACM Conference on International Computing Education Research (pp. 118–126).
- Dorsey, C. & Finzer, W. (2017). The data science education revolution. *@Concord*, 21(2), 4–6.
- English, L. D. (2016). STEM education K-12: perspectives on integration. *International Journal of STEM Education*, 3(1), 1–8. DOI:10.1186/s40594-016-0036-1
- Erickson, T., Wilkerson, M., & Finzer, W. (2019). Data Moves. *Technology Innovations in Statistics Education*, 12(1).
- Finzer, W., Busey, A., & Kochevar, R. (2018). Data-driven inquiry in the PBL classroom: Linking maps, graphs, and tables in biology. *The Science Teacher*, 86(1), 28–34.
- Gebre, E. H. (2018). Young adults' understanding and use of data: Insights for fostering secondary school students' data literacy. *Canadian Journal of Science, Mathematics and Technology Education*, 18(4), 330–341. DOI:10.1007/s42330018-0034-z
- Hardy, L., Dixon, C., & Hsi, S. (2020). From data collectors to data producers: Shifting students' relationship to data. *Journal of the Learning Sciences*, 29(1), 104–126.
- Hayes, K.N., Lee, C.S., DiStefano, R. *et al.* Measuring Science Instructional Practice: A Survey Tool for the Age of NGSS. *J Sci Teacher Educ* **27**, 137–164 (2016).
<https://doi.org/10.1007/s10972-016-9448-5>
- Isreal-Fishelson, R., Moon, P.F., Tubak, R., & Weintrop, D. (2023). Preparing students to meet their data: an evaluation of K-12 data science tools. *Behaviour & Information Technology*, 44(5), 934-953. <https://doi.org/10.1080/0144929X.2023.2295956>
- Jimerson, J. B., Cho, V., Scroggins, K. A., Balial, R., & Robinson, R. R. (2019). How and why teachers engage students with data. *Educational Studies*, 45(6), 667-691.
- Kelley, T. R., & Knowles, J. G. (2016). A conceptual framework for integrated STEM education. *International Journal of STEM Education*, 3(1). DOI:10.1186/s40594-016-0046-z
- Kelley, T. R., Knowles, J. G., Holland, J. D., & Han, J. (2020). Increasing high school teachers' self-efficacy for integrated STEM instruction through a collaborative community of practice. *International Journal of STEM Education*, 7(14), 1–13. DOI:10.1186/s40594-020-00211-w

- Kjelvik, M. K., & Schultheis, E. H. (2019). Getting messy with authentic data: Exploring the potential of using data from scientific research to support student data literacy. *CBE Life Sciences Education*, 18(2), 1–8. DOI:10.1187/cbe.18-02-0023
- Kind, V. (2009). Pedagogical content knowledge in science education: perspectives and potential for progress. *Studies in Science Education*, 45(2), 169–204.
<https://doi.org/10.1080/03057260903142285>
- Lee, V. R. (2025). *Advancing Data Science Education in K-12: Foundations, Research, and Innovations*. Taylor & Francis.
- Lee, V. R., & Wilkerson, M. (2018). Data use by middle and secondary students in the digital age: A status report and future prospects. Commissioned Paper for the National Academies of Sciences, Engineering, and Medicine, Board on Science Education, Committee on Science Investigations and Engineering Design for Grades 6-12. Washington, D.C.
- Maybee, C., and Zielinski, L. (2015). “Data Informed Learning: A Next Phase Data Literacy Framework for Higher Education.” *Proceedings of the Association for Information Science and Technology* 52 (1): 1–4. doi:10.1002/pr2.2015.1450520100108.
- Nadelson, L. S., & Seifert, A. L. (2017). Integrated STEM defined: Contexts, challenges, and the future. *Journal of Educational Research*, 110(3), 221–223.
DOI:10.1080/00220671.2017.1289775
- National Research Council. (2014). *STEM integration in K-12 education: Status, prospects, and an agenda for research*. National Academies Press.
- Nilsson, P. (2009). From lesson plan to new comprehension: Exploring student teachers’ pedagogical reasoning in learning about teaching. *European Journal of Teacher Education*, 32(3), 239-258.
- Ostrom, T. (2025). Dissertation Chapter 2 Data Science in K12 Education; A Study of Educator Proficiency in Data Fluency and Data-Rich Pedagogy, University of California Davis.
- Panasuk, R. M., & Todd, J. (2005). Effectiveness of lesson planning: Factor analysis. *Journal of Instructional Psychology*, 32(3), 215.
- Pimentel, D. R., Horton, N. J., & Wilkerson, M. H. (2022). Tools to Support Data Analysis and Data Science in K-12 Education. 22.
- Ravitch, S. M. & Carl, N. M. (2016). *Qualitative research: Bridging the conceptual, theoretical, and methodological*. Sage Publishing.
- Ridsdale, C., Rothwell, J., Smit, M., Ali-Hassan, H., Bliemel, M., Irvine, D., ... & Wuetherick, B. (2015). Strategies and best practices for data literacy education. *Knowledge synthesis report*.

- Rusznyak, L., & Walton, E. (2011). Lesson planning guidelines for student teachers: A scaffold for the development of pedagogical content knowledge. *Education as change*, 15(2), 271-285.
- Vahey, P., Rafanan, K., Patton, C., Swan, K., van't Hooft, M., Kratcoski, A., & Stanford, T. (2012). A cross-disciplinary approach to teaching data literacy and proportionality. *Educational Studies in Mathematics*, 81, 179–205.
- WestEd (2025). *Boosting Data Science Teaching and Learning in STEM (Data Fluency)* project. (<https://mss.wested.org/resource/principles-of-data-rich-instruction/>).
- Wilkerson, M. H., Lanouette, K., Shareff, R. L., Erickson, T., Bulalacao, N., Heller, J. I., St. Clair, N., Finzer, W., & Reichsman, F. (2018). Data transformations: Restructuring data for inquiry in a simulation and data analysis environment. In *Proceedings of the International Conference of the Learning Sciences*. London, UK.
- Wilkerson, M. H. & Polman, J. L. (2020). Situating data science: Exploring how relationships to data shape learning. *Journal of the Learning Sciences*, 29(1), 1–10.

Chapter 4 - The Effects of Professional Development and One-on-One Support in Developing Data-Rich Pedagogy and Data Fluency in Middle School Science Educators

Table of Contents Chapter 4

TABLE OF CONTENTS CHAPTER 4	86
ABSTRACT.....	87
INTRODUCTION.....	88
LITERATURE REVIEW.....	90
RESEARCH QUESTIONS.....	98
METHODOLOGY	98
RESEARCH FINDINGS.....	113
DISCUSSION	123
CONCLUSION	124
REFERENCES CHAPTER 4.....	128

Tables and Figures Chapter 4

Table 4-1 – Demographics of Educators and Schools	99
Table 4-2 – Classroom Observations	100
Table 4-3 – Group Professional Learning Webinars (Virtual).....	108
Table 4-4 – Summary of Individual Support Contact Topics for Each Educator.....	111
Figure 4-1 – Educator Data-Rich Pedagogy Educator Continuum	106
Figure 4-2 – Educator Data Fluency Continuum.....	107
Figure 4-3 – DRP Continuum with Educators’ Begin/End of Year Placements.....	114
Figure 4-4 – Data Fluency Continuum with Educators’ Begin/End of Year Placements... 	115

Figure 4-5 – Parallel Analysis of Data Practice and Alignment to Professional Support Measure and Science Content Connection.....	117
Figure 4-6 – Summary Correlation of Advancement on Continuums with Frequency of Data-centric Practices and Preferred Support Method.....	122
Figure 4-7 – Educator’s Roadmap to Data Integration.....	126

Abstract

Addressing real-world questions and challenges requires collecting, interpreting, and communicating with data. Data-rich pedagogy (DRP) is an approach where educators iteratively use various forms of data—such as visuals, tables, and maps—to connect to science content in a way that engages learners, develops their data literacy skills, and fosters their understanding of how and why we use data in science (Chapter 2). When educators can make sense of data sources through these interactions with data, they advance their development of data fluency (DF) (Wong, 2024). However, how do educators know what data-rich pedagogy looks like, and how skilled are they in delivering DRP and developing their DF?

My study explores the influence of professional learning events, in both group and individual settings, on educators' ability to integrate data into their science classrooms and improve their data fluency. Five middle school science educators with varying backgrounds in data integration and years of teaching joined the study. They attended five virtual professional learning webinars and received one-on-one mentoring throughout the 2024-2025 school year. The study used data-rich pedagogy and data fluency continuums, which required educators to evaluate their levels of each at the start and end of the school year.

Findings from this study show that educators successfully applied data-rich strategies they learned during professional learning events in their classrooms. They also reported that real-time feedback, or mentoring, on their data integration practices was an important practical form

of instructional support. Additionally, they indicated that professional learning was critical in understanding how to integrate various data sources, thus enhancing their data fluency. While they responded favorably to group professional learning, they emphasized that learning on a one-on-one basis was more meaningful in supporting their growth and use of data practices.

However, how feasible is it to scale up this professional support model? There are obstacles to giving teachers time to collaborate with colleagues at their school, district, or across districts during the school day. Removing these barriers and establishing educational environments that offer data-focused professional learning support and collaboration at both group and individual levels is vital.

Keywords: data-rich pedagogy, data fluency, professional learning

Introduction

There are numerous conceptual models of effective professional learning for educators. The models encompass a range of features that contribute to professional learning, thereby directly impacting educators' knowledge, classroom instruction, and learner achievement. There are even models that address one of the fundamental principles of science education: the ability to work with, understand, and interpret data from real-world contexts (English, 2016; Gebre, 2018; Kelley & Knowles, 2016; Kjervik & Schultheis, 2019). Professional models on data integration are also present in educational settings, such as those that offer educators support in understanding and recognizing that data literacy skills for learners can be used to reinforce scientific contexts (Kjervik & Schultheis, 2019; WestEd, 2025). However, educational research on the practice of these models with science educators is lacking. In fact, educators report that, despite advances in data science skills in the 21st Century and the need for learners to be data-

literate to succeed in post-secondary education, there is a lack of professional support for science educators in developing their data-rich practices and fostering data fluency (Chapter 2).

During the 2024-2025 school year, I provided group professional support and individual mentoring to five middle school science educators with diverse teaching experiences and backgrounds. The research study documents this support on data-rich pedagogical strategies and one-on-one support. Five group professional learning opportunities focused on data sources and practices were provided throughout the school year, advancing educators' awareness of how to connect teaching practices with data integration. Observations and real-time feedback of data-rich practices were also afforded to these educators throughout the school year. Educator challenges were documented and collectively discussed as they arose. One of the study's goals was to provide a researcher's perspective on the impact of small-group professional learning and one-on-one mentoring on the development of educators' data-rich pedagogy and data fluency; a perspective lacking in professional development literature.

Another goal of the professional learning sessions was to understand how data integration in the classroom can address real-world questions and challenges. Educators were provided with data-rich strategies to connect to science content in ways that engage learners, develop their data literacy skills, and foster their understanding of how and why data is used in science education (Chapters 2 and 3). This study will detail these professional learning strategies and one-on-one support topics used to help educators develop and improve their journey toward data fluency—the ability to make sense of data.

Two continuums were used to quantify data-rich pedagogy and data fluency, and to assess the impact of professional support on educators in these areas. The continuums required educators to self-assess the frequency and variety of data practices on one continuum and their

data fluency advancement on another continuum at the start and end of the school year. The continuums, response to professional support sessions, and end-of-year interviews helped me achieve my goal of determining how to enhance educators' ability to integrate data into middle school science classrooms, thereby supporting science content learning and advancing educators' data fluency.

Literature Review

It is left up to the educator to decide how to blend subject matter with data (Kelley & Knowles, 2016; NRC, 2014). Most traditional approaches to data interactions occur through labs or activities designed to teach relationships or concepts, rather than using data to engage in real-world problem-solving (Ostrom, Chapter 2, 2025; Finzer et al., 2018; Hardy, Dixon, & Hsi, 2020). Therefore, educators need targeted professional support that deemphasizes traditional practices and provides innovative data approaches to enhance their knowledge and tools for integrating data into their classrooms. Professional support for integrating data into science content must involve teaching practices that engage learners. This engagement with data is based on learners' prior understanding of what data are and why data drive scientific discoveries (Lee & Wilkerson, 2018; Wilkerson & Polman, 2020).

Traits of Quality Professional Learning

Conceptual models of effective educator professional learning illustrate a series of influences from features of the professional learning that lead to a direct impact on educator knowledge, an intermediate effect on classroom instruction, and a more distant influence on learner achievement (Cohen & Hill, 2000; Desimone, 2009; Heller, Daehler, & Shinohara, 2003; Scher & O'Reilly, 2009; Weiss & Miller, 2006). Professional learning also involves educators

both as learners and educators, allowing them to struggle with the uncertainties that accompany each role (Darling-Hammond & McLaughlin, 2011). Darling-Hammond et al. provide a short list of “must-haves” in professional learning (2017):

- It must engage educators in concrete teaching, assessment, observation, and reflection tasks that illuminate the processes of learning and development.
- It must be grounded in participant-driven inquiry, reflection, and experimentation.
- It must be collaborative, involving a sharing of knowledge among educators and a focus on teachers' communities of practice rather than on individual teachers.
- It must be connected to and derived from an educator’s work with their students.
- It must be sustained, ongoing, intensive, and supported by modeling, coaching, and the collective solving of specific practice problems.
- It must be connected to other aspects of school.

Professional learning programs differ widely in developing educators’ expertise and skills (Shulman, 2005; Wilson, Rozelle, & Mikeska, 2010). These variations make it difficult to identify the impact of specific features of professional learning interventions on particular aspects of educator outcomes (Scher & O’Reilly, 2009; Desimone & Garet, 2015). However, the literature broadly identifies that a critical aspect of professional learning is that it is targeted and delivered to relatively small numbers of educators (Heller et al., 2012). This can begin with preservice educators in the classroom and continue throughout an educator's career. Regardless of when and how professional learning is structured and delivered, its goal must deepen educators' understanding of the teaching and learning processes and the learners they teach (Darling-Hammond et al., 2017).

Professional Learning for Data-Rich Pedagogy

Little educational research has been published on professional learning traits focusing on developing data-rich pedagogy in K12 educators. However, Lee and Wilkerson (2018) connect professional learning for data literacy and technology integration in science education and offer four theoretical suggestions to support data-rich pedagogy for educators. Their suggestions include:

- Provide guides with the new technology educators can use through an entire inquiry cycle, enabling learners to experience different phases of working with data, including processing complex data sets.
- Use models or simulations that offer explicit connections between the data produced and science content topics;
- Encourage educators to go beyond noticing learner engagement, as technology for data collection and analysis can excite learners, and
- Evaluate how data tools help develop educators' comfort levels with large, complex datasets like public databases.

Lee and Wilkerson (2018) also emphasize the importance of helping educators see these tools and practices as sources of information rather than conveyors of objective truth. This is vital for developing data fluency and fostering a critical approach to data.

Alongside efforts to promote stronger data practices from professional learning, some organizations have focused on creating educator learning resources to help advance data fluency (e.g., Concord Consortium, Oceans of Data, Data Nuggets, Data Classroom). The team at the Concord Consortium, funded by a National Science Foundation grant, developed the Common Online Data Analysis Platform (CODAP), which offers free digital tools for educators and

learners to engage with complex data in interactive ways (codap.concord.org). Recently, they have started researching how learners acquire and build data literacy using CODAP with complex data sets (Deitrick et al., 2017; Erikson et al., 2019; Finzer et al., 2018; Wilkerson et al., 2018). Through their research, they have created a set of recommended data moves for educators to focus on when teaching their learners to work with data (Erikson et. al, 2019). The Erikson et. al study details six data moves worth mentioning for my study: filtering, grouping, summarizing, calculating, merging/joining, and making hierarchy. I carefully included these data moves during my small group professional learning sessions. Still, I used slightly different terminology: organizing (filtering), visualizing (grouping, summarizing, merging/joining), and interpreting (making hierarchy).

One-on-One Mentoring

The concept of mentoring has ancient roots. Over time, mentors have come to mean experienced, trusted advisors or counselors, and mentoring can take many forms. In business and industry, mentoring has generally taken the form of apprenticeships. For instance, white-collar professions such as politics, medicine, and law have formal mentoring programs for novices in roles such as pages, interns, or law clerks.

Mentoring has also occurred in public schools for many decades, as experienced educators voluntarily took novice educators under their wing. This form of mentoring sometimes serves as a shorthand of induction programs found in business and industry (Collinson et al., 2009). The education community has embraced formal mentoring as a necessary extension of learning about the complex role of educators and as a way to build learning habits. These mentoring programs are also designed to help increase novice educators' competence and confidence and link educator preparation programs with continuous professional development,

creating a seamless sequence of career-long learning (Collinson et al., 2009). Pairing mentor and novice teachers generally involves a one- to two-year program organized at the district or school level. However, not all districts and schools have a formal or informal mentoring program, leaving educators to fend for themselves, from navigating a bell schedule to integrating data into their unit plans.

Data-Rich Pedagogy (DRP) in Education

Over the past ten years, there has been an effort to recognize the need to blend science instructional practices with data-rich practices due to the increased reliance on data in the 21st Century. WestEd, a leading educational research organization, has led science education research efforts using programs such as Making Sense of Science, Boosting Data Science Teaching and Learning in STEM (Data Fluency) Project, and the PLACES Project (Broadening Data Fluency Through the Integration of NASA Assets and Place-based Learning to Advance Connections, Education and Stewardship). Through these opportunities, they have worked with science educators and education researchers to develop instruction practices related to meaningful data integration in the classroom. The WestEd researchers have identified the following seven principles of data-rich pedagogy, which were discussed in detail in Chapter 3 of this research (WestEd, 2025):

1. Data-rich learning is accessible to all learners.
2. Data-rich learning is learner-driven.
3. Data-rich learning uses a variety of datasets.
4. Data-rich learning encourages a healthy skepticism.
5. Data-rich learning strengthens content knowledge.
6. Data-rich learning utilizes the power of digital tools.

7. Data-rich learning draws on learners' personal, historical, and cultural contexts.

These practices are thoughtful, but the educators' choice of how to integrate one or more of these strategies is unclear. My study addressed this gap in data integration practices in Chapter 3 of this research.

Data Fluency in Education

The framework for data fluency acquisition and competency is not easily defined. Still, it is clear that for learners to master data and science skills and content knowledge, educators must *themselves* have a firm grasp of the discipline's essential ideas (Banilower et al., 2018; Darling-Hammond et al., 2017). In fact, preparing high-quality educators is one of the most important factors in enabling learner success. Without data-fluent educators, high-quality data science curricula and software are not enough to change learners' classroom experiences (Darling-Hammond et al., 2017). Without data-rich professional learning, educators use personal experiences that may or may not align with research and are rarely effective in preparing 21st-century citizens (Pratt, 2002; Gulamhussein, 2013; Banilower et al., 2018).

Most science educators entering classrooms over the past 5-10 years have taken coursework in content-specific sciences. However, few have completed multiple courses (or even one) in data science (Banilower et al., 2018). Since data science and its coursework are relatively new, few studies examine how educators can leverage their scientific backgrounds to incorporate data-rich practices into their teaching. If science educators lack experience in developing their data fluency, what do they rely on to introduce data practices into their classrooms?

Educators may be aware or may not possess the ability to nurture data skills in their learners. Their limited data science background and knowledge may limit their understanding of what data fluency involves. Additionally, the lack of high-quality professional learning in data

science integration hampers educators' ability to teach data literacy effectively. Data science instruction requires a comprehensive understanding of both disciplinary content and methods. It also requires dispositions that run counter to standard, efficiency-focused teaching practices, such as a willingness to tackle ill-defined problems, pursue unproductive paths, and develop new visual representations (Vahey et al., 2017).

A qualitative study titled *Towards a Theoretical Framework for Data Fluency Teaching and Learning in Middle School STEM*² conducted by WestEd, followed the development of data fluency skills in eleven experienced educators. These educators worked alongside a WestEd team to design and implement data-rich lessons in grades 6–9 mathematics and science classrooms (Wong et. al, 2024). The project's broader goal is to develop a Data Fluency Framework for Teaching and Learning, which describes the knowledge and skills educators need to support learners in their data fluency. The 2024 findings of the qualitative study acknowledge the need for professional learning targets for in-service K12 educators to equip them with data fluency skills:

- a broad exposure and understanding of a variety of data types and representations,
- emphasis on the roles humans play in all activities connected to data,
- an understanding of the tradeoffs between primary and secondary datasets,
- inclusion of data activities for learners that are both meaningful and feasible,
- acknowledgement of data to support science content goals,
- capacity to select technology supports specific to instructional purposes and learning goals, and

² STEM: Science, Technology Engineering and Mathematics

- knowledge of the habits of mind (skepticism, imagination, curiosity) that shape how learners approach data.

These professional learning targets allow educators to make sense of data and use it as a tool with their learners.

While structured professional learning and mentoring provide educators with some understanding of data science concepts, the field lacks clarity about how educators' knowledge and learning in these concepts affect their ability to deliver data-rich pedagogy and develop their data fluency. Further research is needed to understand how to support educators in integrating data tools into their classrooms and developing educator data fluency. The literature is clear that it is essential to provide structured professional learning events or opportunities for educators to collaborate and explore ways to help learners develop their data skills while connecting to science content. This study will do so and detail the professional learning strategies and one-on-one support topics used to provide this level of professional support. My study will also use a combination of structured professional development venues, one-on-one mentoring, and educator self-evaluations to determine whether these support structures resulted in more data-proficient and data-fluent educators.

My study will contribute to the research in professional learning and mentoring. It will provide a concrete approach for educational communities that combines small-group professional learning with continuous one-on-one mentoring to support educators' data-centric teaching strategies. This study will also reveal how educators use group professional learning sessions and individual mentoring to improve their instructional practices with data and data fluency.

Research Questions

This portion of my study aimed to improve understanding of how group professional development and individual mentoring can help educators recognize and develop their teaching knowledge with data, and improve educator data fluency. To accomplish this, I address the following:

RQ 1: What impacts do small-group professional learning and one-on-one mentoring have on developing educators' data-rich pedagogy and data fluency?

RQ 2: Can educators' iterative implementation and knowledge of data-rich practices expand their delivery of data-rich pedagogy and advance their data fluency?

Methodology

The overall research design for this study is based on collaborating with educators to develop, implement, and evaluate data-rich practices for their learners. This collaboration begins with professional learning sessions in which educators listen to and contribute to structured PL virtual events. Data were collected, organized, and analyzed from classroom observations and end-of-the-year interviews to answer the research questions:

RQ 1: What impacts do small-group professional learning and one-on-one mentoring have on developing educators' data-rich pedagogy and data fluency?

RQ 2: Can educators' iterative implementation and knowledge of data-rich practices expand their delivery of data-rich pedagogy and advance their data fluency?

Participants

There were five educator participants in this study. Four educators were initially invited because of their prior connection to the researcher through a NASA-funded GLOBE Program.

The fifth, a colleague of one of the other participants, volunteered and requested to join. The selection criteria for the four initial educators primarily relied on convenience sampling, and they volunteered to participate. Table 4-1 shows that all educators in this study had varied teaching experience across schools with different demographics.

Table 4-1: Demographics of Educators and Schools

Educator Demographics			School Demographics			
Educator	Years Exp.	Grade Taught	Percent Minority	Free/Reduced Lunch	Pop.	School Type
Liam	6	8 th	67%	13%	601	Public Urban
Jen	10	7 th /8 th	98%	86%	492	Public Urban Charter
Nate	12	6 th /7 th /8 th	58%	26%	345	Public Urban
Carla	15	5 th /6 th				
Barbara	32	6 th /7 th /8 th	82%	100%	688	Public Rual
Average	15		76.3%	56.3%		

Note: Minority is defined as all races/ethnicities except white, non-Hispanic. U.S. federal standards define free/Reduced lunch.

Note: More details about the educators participating in this study and their schools are provided in Chapter 3.

Data Collection and Analysis Procedures

Research Question 1 – Impacts of Professional Support

Classroom Observations. During the study, I conducted 28 classroom observations of the five participants who taught grades 6, 7, and 8. Table 4-2 provides a breakdown of these observations by educator and grade level. The observation template is included in Appendix C. Each observation lasted between 45 and 90 minutes, depending on the school, day of the week, and class section. Observations focused on three key aspects related to the research questions. First, I wanted to document the data-rich practices educators use with their learners. Second, I observed whether the educator had mastery of the data used. In other words, I assessed whether the educator was sufficiently familiar with the data to align it with the lesson and achieve the desired learner outcomes. Third, each observation noted whether the lesson was a direct or indirect result of a professional learning topic or one-on-one mentoring.

Table 4-2: Classroom Observations

Educator	Grade Level			Total Observations
	6 th	7 th	8 th	
Liam		2	5	7
Jen		2	4	6
Nate			4	4
Carla	4			4
Barbara	1	3	3	7
Interview Totals	5	7	16	28

Note: shaded boxes refer to grades not taught by the educator or not included in the study.

Due to scheduling, class times, and the grade-level sections taught by each educator, the number of observations per educator ranged from 4 to 7. Data from observations were coded manually and used to triangulate information and ideas discussed with each educator and at the end-of-year interview. Observation data coding closely followed the observation template. Notes on individual learner responses to instruction were not recorded. Observation notes also focused

on how educators responded to learner understanding and engagement. Educator handouts to their learners were also included in the observation notes. The observation protocol included 10 possible data-rich practices, each supported by evidence. Unavoidable challenges were noted, such as a fire alarm, disruptive learners, or learners being pulled from the class by the administration. Each observation concluded with the researcher and educator discussing the lesson, the data-rich practice, the origin or idea behind the lesson's development, and the educator's confidence in how the data were presented in the lesson.

Data Analysis for RQ1 from Classroom Observations. Classroom observations were manually coded according to the observation template. First, data practice(s) observed during the observation were placed into separate categories. Since there are 10 observable data practices, I limited the data analysis to the three most common. The categories were:

- Data integration into the lesson,
- At least one data literacy skill is evident, and
- Data integration was used to support the learning of science content.

After chunking (coding) these practices, I separated each practice into one of two bins. The first bin was called “supported content” and contained practices that originated from a group professional learning session or from a one-on-one mentoring session. This dataset was vital because it enabled the researcher to determine whether professional support for educators directly affected their teaching strategies. The second bin, labeled “original content,” contained data-rich practices created or used by the educator without the professional support provided by this study. Practices that required learners to use computer simulations and models were placed into this bin.

The second dataset related to educator competency in the data. The question was whether the educator understood how to use data to support learner science outcomes. Again, this dataset was important because it showed whether the educator could provide a data-rich learning experience by making sense of the data. I subjectively identified this dataset as either a yes or a no.

End of Year Interviews. Each participating educator provided time for a one-hour interview at the end of the school year, using the interview template included in Appendix D. These interviews reviewed information and ideas discussed during group professional learning, classroom observations, and lesson development. The end-of-year interviews were divided into two sections. The first focused on the educators' data-rich practices and the data they used. The second section addressed educators' self-assessment of their data-rich pedagogy and data fluency at the beginning and end of the year.

Interviews began with exploring how the educator used data practices throughout the year. They were provided with a list of entry points for data instruction: warm-ups, exit tickets, inquiry-based activities or labs, homework, science content instruction, or other entry points. Educators identified which entry point(s) they used and explained how their chosen entry point(s) supported data instruction and/or science content learning.

Data Analysis for RQ1 from Interviews. Educator responses were recorded. Educators' identification of the types of data tools (digital, field equipment, or other) they used and the sources of data placed into categories. Specific data tools were coded for evaluation in this study. They were grouped by whether the practice included a data tool. Data sources were recorded and categorized. Categories included NASA, GLOBE, NOAA, USGS, or other. This coding was necessary to determine whether educators used a wide range of data sources or relied

on a single source throughout the year. Understanding the type and effectiveness of these sources helps researchers determine if further evaluation or expansion is needed in teaching data science skills (Lee, 2025).

The interview also included a short discussion about learner outcomes. Educators discussed how they achieved expected learner outcomes through their data-rich instruction and reflected on what they would keep or change to improve content and/or skills learning. Learner outcomes were not part of this study, but understanding the rationale for selecting the data source and practice provided greater insight into how data integration was delivered.

Research Question 2 – Impacts of Iterative DRP Implementation

End-of-Year Interviews. The data to answer RQ2 came from a specific question during the end-of-year interview. This question concerned how often educators implemented data-rich practices in their classrooms throughout the school year. Educators were asked to respond freely, but given guidance on what constitutes a data-rich practice. For example, I gave educators examples of data-rich practices such as data collection and organization, working with or creating data visualization, analyzing data, interpreting data to solve a problem or answer a question, or sharing data from research. They were also given time guidance: daily, weekly, monthly, and once or twice per semester.

Data Analysis for RQ2 from Interviews. One interview question about data iteration was used to show how frequently educators incorporated data-focused lessons throughout the school year. These responses were paired with their advancement on the DRP and DF continuums. Additional data from two other interview questions focused on how the educators perceived their learning styles to determine if their progress on the continuums was related to how they learn or develop new skills. Specifically, I asked, “What influences you the most in your data-rich pedagogy acquisition?” and “What influences you the most in your data fluency acquisition?” Their responses were recorded and analyzed to see how they correlate with their self-assessments on the continuums.

Observation Data Validation

Observation data on data-rich practices were validated to ensure alignment with the research questions. Data practices observed during the observation were discussed with the educator at the end of the lesson, at the conclusion of the school day, or within a week of the observation. During this time, educators had the chance to clarify the lesson or explain how they had to adapt or modify their practice in response to informal learner feedback. They also confirmed the data resource(s) used with their lesson. If multiple data sources were identified during the observation, educators verified each source. Additionally, I confirmed with each educator the origin of their lesson. Did the lesson develop from a strategy provided in a professional support setting, or did the educator create or find the lesson elsewhere?

Interview Data Validation

Data sets from interviews were validated for accuracy based on educators’ responses to the before-and-after self-assessments on the DRP and data fluency continuums. For example, after educators evaluated their final position on the continuum, I asked them to provide a few

examples of their practice and the data sources they used. In their explanations, I asked them to specifically describe how the data source integrated into their data practice and how their experience with the data practice informed their progress toward data fluency. This validation process ensured that educators' self-assessments were thoughtful and that the datasets could be connected.

Lastly, interview data focused on how the educators perceived their learning. Specifically, I asked, "Can you elaborate on how either group or one-on-one professional learning has supported you to progress along the data-rich pedagogy continuum?" Educator responses did not need to be categorized, as they all consistently responded to this question.

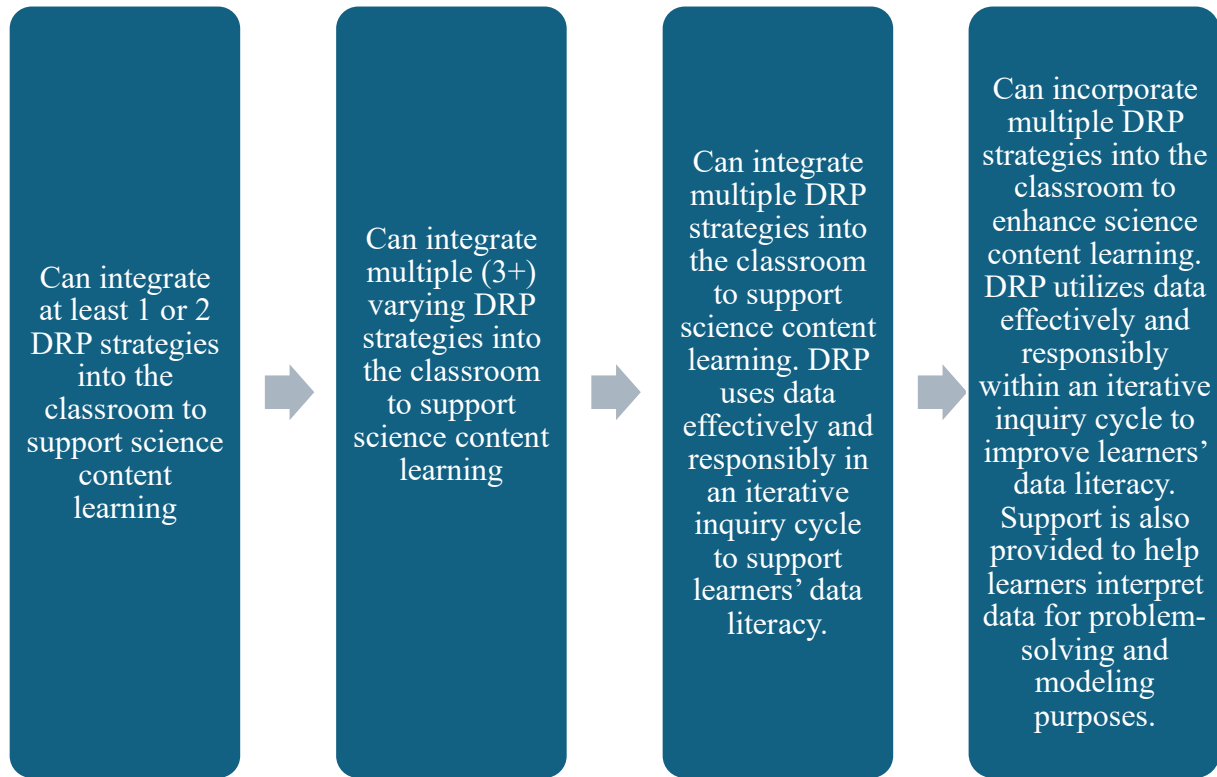
Continuums

To answer the research questions, each educator self-assessed their proficiency in data-rich practices and data fluency at the start and end of the school year using two separate continuums developed by the researcher.

Educator Self-Assessment on DRP Continuum

The purpose of the DRP self-assessment at the beginning of the year was to determine if PL and mentoring affected educators' DRP and if iterative implementation of data practices impacted their DRP. The DRP continuum is shown in Figure 4-1.

Figure 4-1: Data-Rich Pedagogy (DRP) Educator Continuum

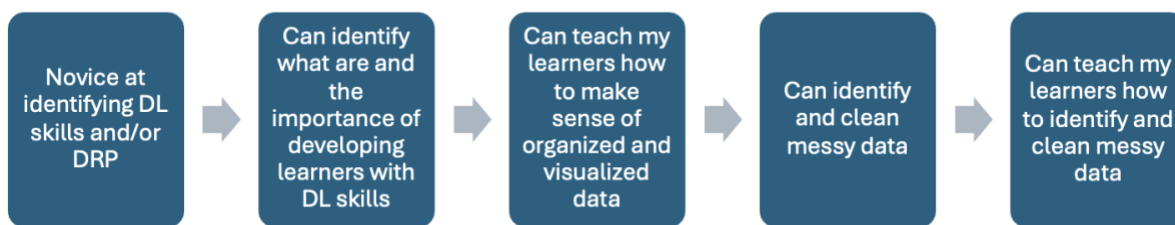


This continuum was designed to understand how educators gradually elevate their data-driven practices by implementing various data lessons in their educational setting. Furthermore, this research was designed to understand how group professional learning events and one-on-one support affected educators' DRP. The continuum was developed in response to an earlier study by the researcher (Chapter 2).

Educator Self-Assessment on DF Continuum

At the start and end of the school year, each educator also self-assessed their data fluency using a continuum I developed specifically for this research. Again, this continuum's purpose was to understand how educators advance their data fluency through iterative DRP implementation, PL, and one-on-one support. The DF continuum is shown in Figure 4-2.

Figure 4-2: Educator Data Fluency Continuum



This continuum was developed in response to an earlier study by the researcher (Chapter 2) that revealed educators' interpretations of data fluency varied. The DF and DRP continua were reviewed, and field experts provided feedback. These experts have over 50 years of combined experience designing and delivering professional learning incorporating K-12 data science education.

Professional Learning and Mentoring Contexts

The context of this research study relies on the delivery of its support structures. In other words, what circumstances and factors shaped educators' DRP and DF? This section describes the professional learning events and one-on-one mentoring structures used throughout the school year with the educators. Understanding this context will be crucial for interpreting results and explaining their significance.

Small-Group Professional Learning (PL)

The general outline of the group's PL during the school year included a 50-minute virtual webinar held every other month from September 2024 to May 2025. Specifically, the PLs focused on a) instructional strategies for teaching with data; b) data literacy skills for learners;

and c) how teaching with data supports science content learning. Table 4-3 displays the PL topics and schedule for each PL webinar, followed by independent practice suggestions.

Table 4-3: Group Professional Learning Webinars (Virtual)

Month	Topic	Independent Practice
September	What is Data Literacy, Data Rich Pedagogy and Professional content knowledge? Review individual continuums on educator data fluency and data-rich practices.	Identify where you fit into the DRP and DF continuums. Try a “slow-reveal” graph with learners .
November	Data Collection: Primary vs. Secondary. Resources on how to collect/find/use data to support science content learning.	Have learners perform one primary data collection activity with learners.
January	Data Visualizations: Data Matrix by grade level; tools for manipulating data	Engage learners in the data matrix activity; determine where learners are at in the ability to make data visualizations
March	Data Analysis vs. Data Interpretation; Data Storytelling	Break learners into groups and have them look at a data visual and analyze data and create a story about the data visual
May	End of year share out on favorite data moves during the school year and aspirations for next year.	Write a letter to yourself about your thoughts on 2025-2026 data integration aspirations. Researcher will not read but will mail letter back to educators at the beginning of the year.

A detailed look at each professional learning event is provided below:

September: This kick-off event introduced the study’s research questions to educators. In the first half of the webinar, after an icebreaker and brief introductions, I discussed the research process and defined key terms, including data literacy, data fluency, and DRP. The DRP and data fluency continuums were presented and reviewed during the event. Participants were asked to reflect on their previous teaching practices and identify where they felt they “fit in” on both continuums.

I provided educators with a data-rich practice to try with their learners. The practice was a slow-reveal graph (<https://slowrevealgraphs.com>). A slow-reveal graph begins with a graph that lacks context: its axes, numbers, legends, and title are removed. The goal was to spark discussion

about what learners notice and wonder about the visual they were examining. Parts of the data visualization (graph) were revealed gradually, allowing viewers to explore and analyze the different components of the visual. Ultimately, learners determined the context of the visualization and how its content connected to science content or other objectives. Learners were prompted to “tell the story” that the visual tried to convey. They were encouraged to complete a homework assignment where they tried the same or another slow-reveal graph with their learners. They were advised to focus on the “parts” of the visual (x-axis, y-axis, data points, title) with their learners before jumping into data analysis or interpretation.

November: We began with a brief share-out of slow-reveal graphs that the educators tried with their learners. I posed questions and asked for comments to help close the loop on key components of a graph. The focus of the November PL was on measuring data. Educators were asked to provide examples of primary and/or secondary data that their textbooks or other educational materials use to support science content learning. After discussing these data resources, educators were trained in field measurement protocols. They learned how to take their learners outdoors to collect air and surface temperature data. During the PL, I communicated that learners needed to know how to read an analog thermometer and operate an infrared thermometer safely. I provided educators with a sample datasheet so learners could record and organize their data by time and/or location. I explained that this activity practiced data literacy skills, specifically data collection and organization. DEP educators received a lesson plan they could adapt for their learners, along with the necessary equipment to perform the activity with them.

January: The January PL focused on data visuals and data tools. Educators were asked to bring a learner sample of the data activity from November. They were given a data matrix sorting

activity developed by Kristen Hunter-Thomson of Dataspire (<https://www.dataspire.org>). They were assigned the task of determining the complexity and appropriate types of graphs for middle school learners. There was a lengthy discussion and differing opinions about which data visualizations middle school learners should understand. A data tool (CODAP) was briefly introduced to educators to manipulate larger datasets (<https://codap.concord.org>). The presentation included a brief tutorial with instructional tools to teach data visualizations to middle school learners. As a homework assignment, educators were asked to have their learners create at least one data visual, based on the primary data they previously collected, using Google Sheets, Excel, or CODAP.

March: Educators combined their knowledge of data collection, organization, and visualizations with data analysis and interpretation. The PL began by showing DEP educators a picture of snack-food nutritional labels and asking them to analyze the data presented on them. Data analysis involved identifying the amounts of carbohydrates, calories, proteins, and fats. Data interpretation involved determining which snack was healthier based on their analysis. In other words, they needed to interpret the data to answer the research question. Educators were then asked to write a one- to two-sentence data story about the healthiness of the snack foods. After completing this activity, DEP educators divided into two breakout groups and analyzed and interpreted an additional data visual. Afterwards, each breakout team shared their visual, analysis, and interpretation. For homework, educators were instructed to replicate or create a similar activity with their learners to practice the difference between data analysis and data interpretation/data.

May: The final PL webinar was organized in response to educators' concerns about multiple days of district and/or state testing; therefore, this PL was a share-out session. Each

educator received a slide to complete beforehand. They were asked to share a data practice they used with their learners and summarize what they learned and what they plan to replicate or do differently next time with that activity. Data practices shared by educators included data collection events, visuals, and storytelling through a learner-driven research project.

One-on-One Mentoring

I also provided each educator with individual support contacts (mentors), which met regularly throughout the school year. Table 4-4 summarizes the topics discussed during these contacts.

Table 4-4: Summary of Individual Mentoring Topics for Each Educator

Educator	Prim. Data	Sec. Data	Excel/Google Sheets	Learner Strategies	Research Projects	On-Line Data Tools	Practices & Strategies	Messy Data	Other Data-Related Topics
Liam	X			X		X	X	X	X
Jen	X	X		X		X	X	X	X
Nate	X	X		X	X		X		X
Carla	X		X	X			X		X
Barbara	X	X		X	X	X	X	X	X

Individual support contacts for educators were provided through in-person site visits, virtual meetings, emails, and texts. Each contact topic is discussed below.

Primary Data Resources: Discussions centered on using the GLOBE Program for data collection. Protocols for measuring the hydrosphere and atmosphere were reviewed and practiced through hands-on training with GLOBE equipment.

Secondary Data Resources: Educators requested resources related to their content areas. The My NASA Data website, Earth System Data Explore, was provided as a resource for analyzing data visualizations to support learners engaged in research and the reinforcement of

science content topics on volcanoes, urban heat islands, and ocean currents

(<https://mydasdata.larc.nasa.gov>).

Excel, Google Sheets: One educator needed help understanding how to teach learners to create graphs from Google Sheets or Excel.

Learner Support Strategies: Throughout the school year, various learner support strategies were implemented. Educators inquired about learner groupings, collaboration, and the use of formative assessments such as exit tickets. By implementing these strategies, educators fostered a supportive and engaging environment that promoted learner success in mastering science content and developing data literacy skills.

Research Projects Using Data: Educators could have their learners participate in a student research symposium (SRS) in May. The SRS, organized by the GLOBE program, is a platform for young scholars to showcase their research and findings and receive feedback from STEM professionals. Nate was the only educator whose learners participated in the SRS. Still, Barbara's learners participated in a similar event at the STEM fair at New Mexico State University in Las Cruces, NM. Both educators needed support in guiding their learners through the research process, from asking questions to concluding.

Online Data Tools: Since CODAP was introduced during the January PL, some experienced educators needed extra support to help their learners upload and work with data using CODAP. This support was offered virtually by reviewing the CODAP tutorials with the educators.

Practices & Strategies Using Data: After conducting a classroom observation, all educators participated in discussions on pedagogical strategies for data use. These discussions were based on observations made during the classroom visit and ranged from learners not

understanding the purpose of using graphic legends to relating simulation models to data analysis and interpretation.

Messy Data: Two educators involved their learners in primary data collection, which resulted in several class sets of messy data. Working with one of the educators, a lesson was developed and tested on how to teach learners to identify inconsistent or incomplete data; therefore, it could not be used for analysis and interpretation. This collaboration resulted in a new lesson shared with other educators.

Other Data-Related Topics: A variety of additional data-related topics were discussed during one-on-one educator contacts. The main topics included: data accuracy and precision, identifying patterns and trends in data, datasets by grade level, data collection comparisons based on instrumentation (tools), research presentation templates, data sheets and organization, instrument calibration, connecting data measurements to a sense of place, adapting instruction to learner interests, and the iteration of data practices in the classroom.

Research Findings

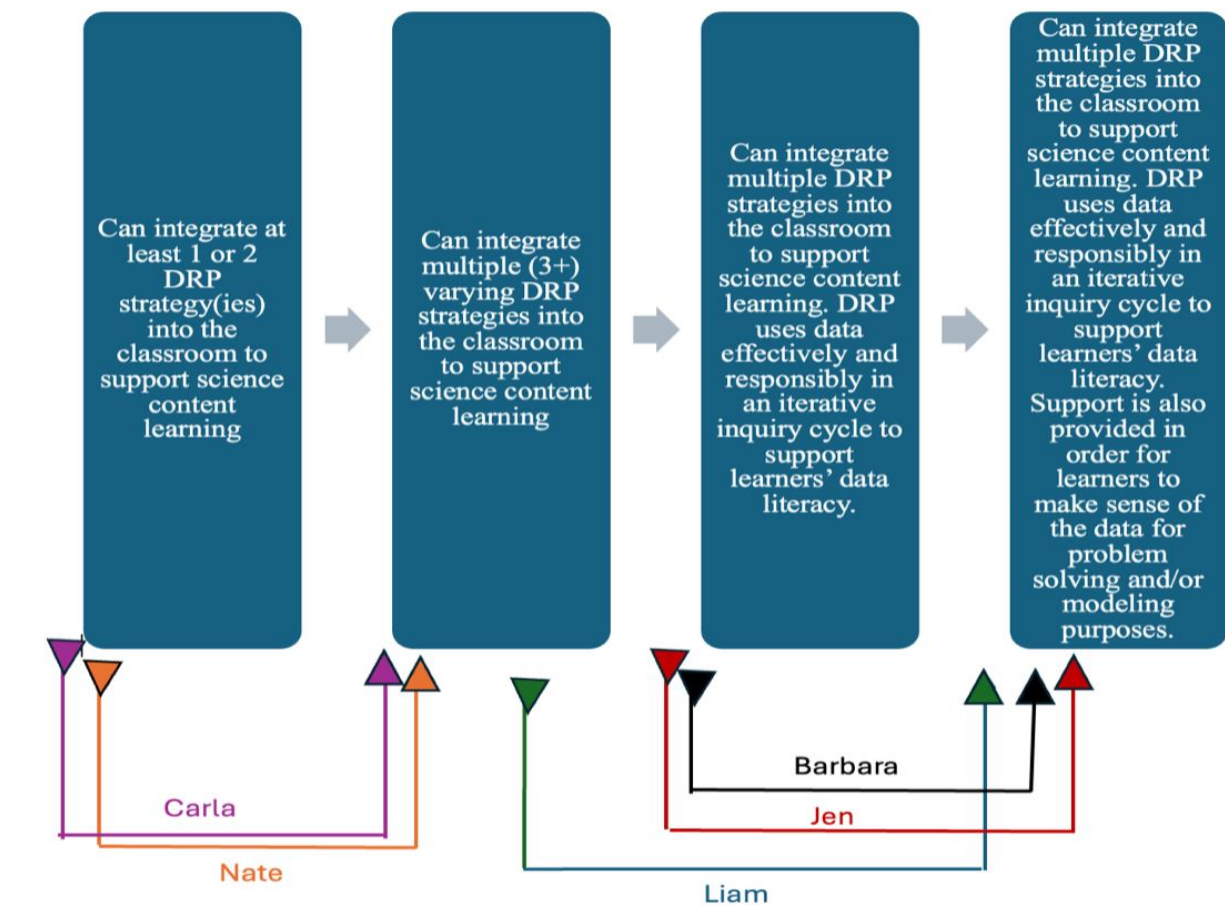
I collaborated with five middle school science educators in my study to uncover details about how professional learning events and one-on-one mentoring advance their data practices and data fluency. In RQ 1, I asked about the impacts small-group professional learning and one-on-one mentoring have on developing educators' data-rich pedagogy and data fluency. I present the findings to RQ1 as the results from a parallel analysis of data-rich practice, how the practice originated, and whether the educator mastered (correctly used) the data in the practice. In RQ 2, I was interested in whether educators' iterative implementation and knowledge of DRP supported their advancement on the DRP and DF continuums. I paired the analysis of their advancement on the continuums with their responses to interview questions. In this section, I present educators'

progress in self-assessments on both continuums before correlating these data with interview questions.

Advancement on the Continuums

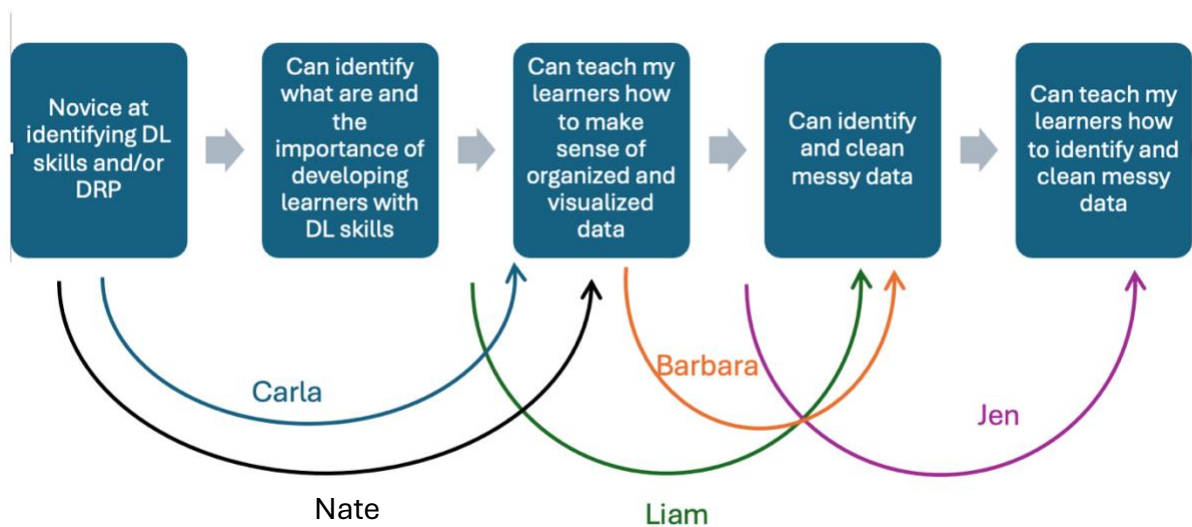
All educators reported progressing on the DRP continuum. Their beginning and ending placements on the continuum are shown in Figure 4-3. The continuum was designed to determine if educators participating in the study could advance their understanding and development of data-driven practices after an iterative process of delivering DRP throughout the school year.

Figure 4-3: DRP Continuum with Educators' Begin/End of Year Placements



I also asked the educators to look at the Data Fluency Continuum and place themselves on it at the beginning and end of the school year. The purpose of this continuum was to determine whether educators participating in the study had advanced their understanding and development of data fluency after receiving professional support and implementing several data-centric lessons. All educators in the study progressed along the continuum. Their beginning and ending placements on the DF continuum are shown in Figure 4-4.

Figure 4-4: Educator Data Fluency Continuum, Beginning/End of the Year



Educator Responses that Support Self-Assessments on the Continuums

As a novice in data integration, Carla reported her advancement on the DRP continuum was primarily attributed to her one-on-one support. She also indicated that learning about data skills and how to teach them during the professional learning sessions was the most significant factor in helping her advance along the data fluency continuum. Carla stated that her “*data fluency improved as I learned more about data-rich pedagogy and how I could apply it in my classroom.*” Nate also began with a limited understanding of data-rich pedagogy and had no idea what data fluency entailed; therefore, he assessed his data practices and data fluency towards the

novice side of the continuums. He stated that his self-assessment of his progress on the DRP continuum was based *“primarily on the work completed with my learners on their research projects.”* He said he had to know how to respond to questions on collecting and making sense of the data for his learners. His progress on the data fluency continuum was evident in his careful monitoring of learners' interpretations of the data in their projects. He said that he *“learned that students struggle with how to interpret the data, which is an important data literacy skill to have.”* He also stated that he quickly learned to scaffold and explain data outcomes for his learners.

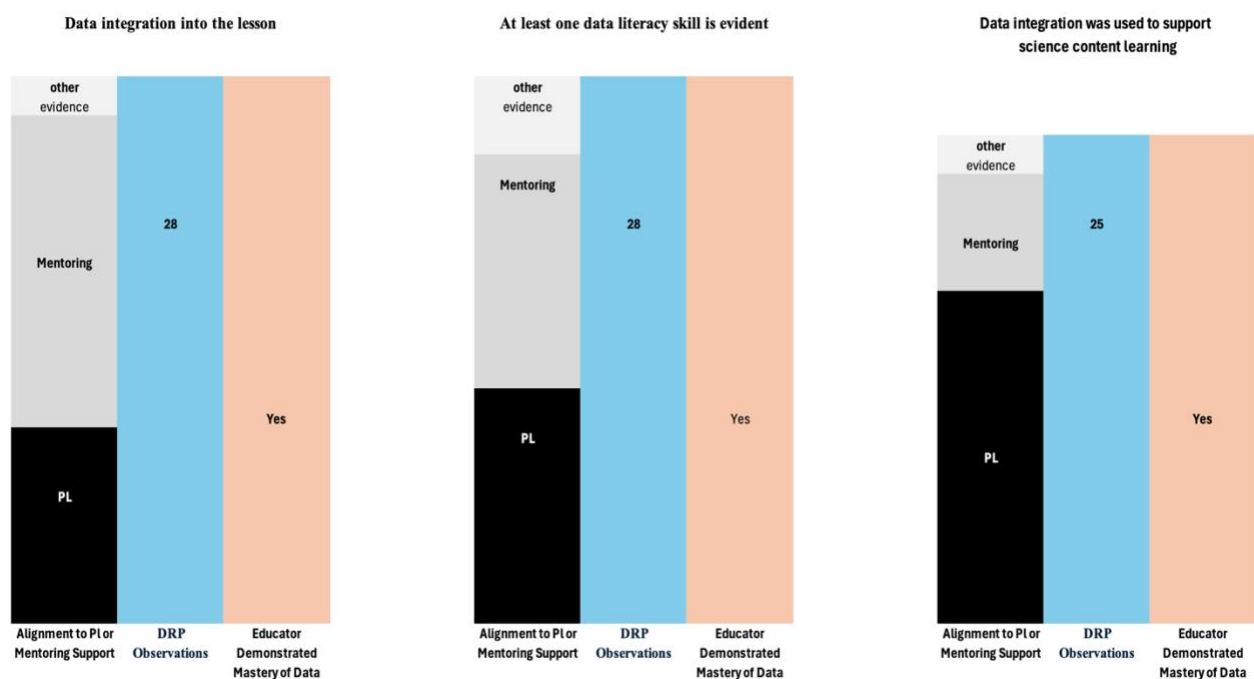
Liam positioned himself towards the second column of both continuums at the beginning of the year. During the interview with Liam, he said, *“Group professional learning sessions helped me get ideas on using data, but the classroom visits were more helpful.”* My observations of Liam at the end of the year revealed that he was focused on learner engagement and on specific data-collection, organization, and visualization literacy skills. This was a big jump from asking learners to write down their “observations” of data visuals.

Jen and Barbara entered the study with similar self-assessments of their ability to implement data-rich pedagogy and make sense of data. They both had aspirations to advance their learners' ability to manage messy data, placing themselves in the third column, demonstrating a strong understanding of how to manage data to fit their science content and improve learners' data literacy skills. However, only Jen could deliver the messy data content by the end of the year. Consequently, out of the two educators, only Jen placed herself at the end of both continuums. Barbara expressed interest in trying messy data with her eighth-grade students next year.

Research Question 1- Professional Support

Classroom observations and end-of-year interviews were used to answer RQ1. Parallel analysis shows a strong alignment between educators' mastery of data-rich practices and their use of data. Also, there was strong alignment between the data-rich practices and their sources in professional learning sessions or one-on-one mentoring. Figure 4-5 provides the results from the parallel analysis.

Figure 4-5: Parallel Analysis of Data Practice and Alignment to Professional Support Measures and Educator Mastery of Data



Educator Comments on Professional Support

During the end-of-year interviews, educators commented that their advancement in DRP and DF was attributed to their participation in professional development. This subsection highlights some of their statements.

Having had no exposure to data-rich pedagogy before the year, Carla shared, *“I really learned a lot from the virtual meetings. I liked how the [atmospheric] data we took helped my*

students develop arguments about weather trends. I also noticed that their writing improved by using data to justify their arguments.” Carla also mentioned that a support person was needed to guide her in starting her data-rich instruction. She added that although she relies heavily on the FOSS Curriculum (U.C. Berkeley Lawrence Hall of Science), she is glad “...to have new ways to use data with the curriculum.”

Nate gained significant experience working with data through his learners’ research projects. Nate explained that the suggestions I gave him between classes resulted in “...a clear improvement in their understanding of what to look for.” His approach included many opportunities for learners to collect, analyze, and interpret their data. He said that the professional learning sessions helped him because he learned what other educators at his grade level were doing with their learners. As a result, he set high expectations for his learners. For example, he expected them to make sense of the data, not just report it. He also required his classes to look for anomalies in the data. These data-driven, inquiry-based teaching strategies required Nate to understand and interpret where this practice might lead his learners. In other words, he had to anticipate possible outcomes of their data investigations and guide them through different scenarios of data interpretation, all while keeping them focused on answering their research questions about water quality. He also stated that his learning style is to work with and observe other educators. So, when I visited his classes and was able to identify and troubleshoot learner misunderstandings, he immediately understood and corrected his data practice. During the interview, Nate said, “*I really liked having students look at their data to tell a story about their project. I had never thought about that before. It helped them go through the analysis and interpretation process before data storytelling.*” He credits learner understanding on using data to “...complete research projects on lead and water quality of the school’s water

fountains and sinks. Students were interested in understanding the problem better and creating a project that addressed their concerns.... Ultimately, these projects were presented to one of our District's Board Members." Nate also admitted that if it weren't for the research projects, he would not be sure how to incorporate data-rich pedagogy into his science teaching effectively.

Liam was a former math educator who brought a strong understanding of the importance and use of data in the science classroom. During one visit, I observed his learners using Gizmo, an online data tool, which simulated genetic variation in phenotype and genotype. Gizmos allowed learners to manipulate variables and model simulations. I observed a Gizmo lesson on insect traits during one of my visits. Learner engagement was high, but it was hard to gauge their understanding of variable manipulations and the outcomes of these chromosomal changes. I saw Liam ask learners to close their computers to demonstrate a model of one of the genetic scenarios for the class. This was a necessary intervention, as it allowed Liam to give an informal assessment of the learners' work. At the end of the day, we discussed assessing learning understanding during the activity and the need to re-teach and re-focus learners during the lesson. Liam said, *"Feedback after an observation gives me the most support.* He also stated, *"The simulations they experience get students to immediately see the results from modifying the data, but it doesn't teach them ratios and proportions."* He felt this was a significant opportunity to bring data into the discussion of the number of insects that turned red/blue/or yellow. He stated that conversing with me about the lesson helped give him confidence that it was necessary to interrupt the lesson with his reinforcements. He expressed an interest in using Artificial Intelligence (AI)-generated simulations in the future. He indicated that AI simulations with built-in algorithms can be coded by learner input on various parameters. He also mentioned that he appreciated my suggestions about pre-assessing learners' abilities before engaging with data. He

learned that it is essential to include data talks with computer simulations so that learners can share and develop ideas about data and variables in small groups. He indicated that he plans to incorporate data talk scaffolding practices next year.

As stated earlier, Jen and Barbara brought strong data integration practices to the study. They both had previously created opportunities for their learners to use data and engage them in research investigations. Since they were more experienced when working with data, both felt the PL support was more for the other educators, even though it was not “*a waste of time*”, according to Jen. At the start of the 2024-2025 school year, both educators expressed curiosity about having their learners work with messy data. Therefore, my one-on-one interactions with these educators included discussions of messy data and how to use it as an instructional tool.

Jen and I also co-developed a data-rich activity that enhanced her eighth graders’ understanding of raw versus processed data. She delivered her initial lesson on messy data, but felt more time was needed for effective scaffolding. I observed Jen’s second lesson on messy data. After the lesson, we discussed our perceptions of the learner’s understanding. We both agreed that perhaps her learners need more experience collecting data and answering questions with it. She didn’t have time to develop these additional lessons or support tools because she started teaching messy data midway through the second semester. Jen also mentioned during the interview that although she “*...didn’t do a lot with messy data, I enjoyed creating a slow reveal graph on snack food and nutritional levels.*” She added that she “*...wants to do more with slow reveal but branch it out from just graphs to include maps.*”

Barbara admitted she didn’t have an opportunity to teach about messy data this year, but was hopeful to include a lesson with her eighth graders next year on raw vs. processed data. I shared Jen’s lesson on messy data with Barbara and discussed the need to scaffold data collection

variables. Barbara admitted that she learned most about DRP when I visited her sixth-grade classroom, where learners went outside to collect field data. She stated, *“The experience showed her that she made learner assumptions about data collection and organization.”* She also mentioned it was helpful for me to listen to her learners’ presentations on the Asombro project. It provided her with another educator’s perspective on what learners know and don’t know.

After completing the study, I reengaged with the educators to determine the type of professional support they received from others (district, school, outside organizations) during the 2024-2025 school year. Liam and Carla reported that their school provided monthly all-staff meetings, but did not include professional development components. Jen reported the same in her biweekly staff meetings. Nate received professional development opportunities from two partnering organizations, which enabled him to connect his science content to climate change and environmental justice. Neither organization provided data-rich teaching strategies, but provided data resources and support for research projects. Barbara also attended professional learning events. She attended and co-presented at the Data Science for Everyone (DSE) K12 conference in February 2025 and attended a robotics workshop for facilitators. Barbara reported that the DSE K12 conference was a “great opportunity” to discuss data-rich practices with other educators.

Research Question 2 – Impacts of Iterative DRP Implementation

Interviews were primarily used to answer RQ2. During the interview, I examined how educators self-assessed their progress on the data-rich pedagogy and data fluency continuums, and how this aligned with their reported iterative process for delivering DRP throughout the school year. I correlated educators’ responses to the following questions: “What influences you the most in your data-rich pedagogy acquisition?” and “What influences you the most in your

data fluency acquisition?” Figure 4-6 summarizes these correlations. I also included specific educator testimonials on how their iterative implementation of data-centric practices supported their advancement on the continuums.

Figure 4-6: Summary Correlation of Advancement on Continuums with Frequency of Data-centric Practices and Preferred Support Method

	DRP Level of Advancement		DF Level of Advancement		Frequency of Data-centric Practices	Preferred Support Method(s) that Influence DRP and DF Acquisition
Carla	Level 1 to 2		Level 1 to 2.5		every other month	• Watching/talking to educators • Professional Learning Sessions
Nate	Level 1 to 2.5		Level 1 to 3		monthly	• Watching/talking to educators • Professional Learning Sessions
Liam	Level 2 to 3.5		Level 2 to 3.5		weekly	• Watching/talking to educators
Jen	Level 3 to 4		Level 3.5 to 5		twice-weekly	• Watching/talking to educators • Repetitive Process/Feedback
Barbara	Level 3 to 4		Level 3 to 4		weekly	• Watching/talking to educators • Collaborating with others

Each educator shown in Figure 4-6 began at different DRP and DF levels along both continuums. Therefore, it isn’t easy to directly link progress on a continuum with iterative, data-focused practices. However, in this study, I examined the advancement of DRP and DF for two novice educators, Carla and Nate. While both advanced on the continuums, Nate used data-centric practices more frequently than Carla and rated his confidence in delivering DRP higher than hers. Liam showed the most progress on both continuums and reportedly implemented data-centric practices with his learners weekly. Educators Jen and Barbara, who started at a higher level on the DRP and DF continuums than the others, showed moderate progress (1 to 1.5 levels) on the continuums despite practicing data-rich methods weekly or twice weekly.

Regarding DRP and DF acquisition, educators reported that their preferred support method is working, watching, and collaborating with other educators. All five educators stated

that by working with other educators on DRP, they see connections with their own classrooms. They also reported valuing feedback from other educators they know and trust. So there is no direct correlation between a preferred support method and educator advancement on the continuums.

Discussion

This study sought to understand how group professional learning events and one-on-one support impact educators' data-rich pedagogy and data fluency (RQ1). It also aimed to examine whether educators' iterative implementation of DRP, their knowledge of DRP, and their preferred method of professional learning helped them advance their DRP and DF (RQ2).

Findings from observations showed that all five educators used a variety of data-rich practices, developed either by themselves or through professional support. Educators used professional support tools (group and/or one-on-one sessions) to guide their lesson planning and delivery using data. Therefore, this study confirms that professional support for educators is a practical tool in developing and delivering data-rich pedagogy. All educators highlighted that the most influential professional support tool was their collaboration with other educators. This collaboration was essential to their learning. Even experienced educators reported learning more from listening to, discussing, and observing their peers than from organized professional learning sessions. This form of collaboration also allowed educators to plan data integration in their classrooms, which includes an understanding of learners' prior knowledge. Their collaborative efforts also codified their scaffolding and use of data-centric resources, including digital tools.

These forms of professional support confirm the literature review that small-group professional learning in data literacy and data integration is essential for science educators. However, this study adds to the research by showing that providing educator support is needed

not only to understand DRP but also to develop and incorporate DRP with their learners.

Mentoring programs are critical for providing educator support; therefore, small communities of practice (COPs) where educators can meet and share DRPs are recommended as a result of this study. These COPs should be designed to help increase novice educators' competence and confidence in data integration. Educator preparation (pre-service) programs should also include data-rich pedagogy, which can have lasting positive effects when these educators are in the field.

Findings also revealed educators advanced at different levels along both continuums (DRP and DF). It was difficult to directly link progress on a particular continuum with iterative, data-focused practices. Still, novice educators in DRP reported that their confidence in delivering DRP advanced as they learned more about what learner data skills are and how to teach them. They also noted that seeing learner engagement with data collection and visualization encouraged them to incorporate these skills more frequently. This is an essential step to professional support not discussed in the literature, as professional development (PD) often ends at the conclusion of an event, with little to no follow-up with the attendees on how they adjusted their instructional practices based on the PD they attended. The continuums served as a tool to show the positive impact of professional support, iterative data-focused lessons, and delivery have on advancing educators' data-rich practices and developing their data fluency. This step in self-assessment is especially needed when providing professional support in an area unfamiliar to educators. This is evident in the marked advancement of DRP/DF for educators unfamiliar with data integration strategies.

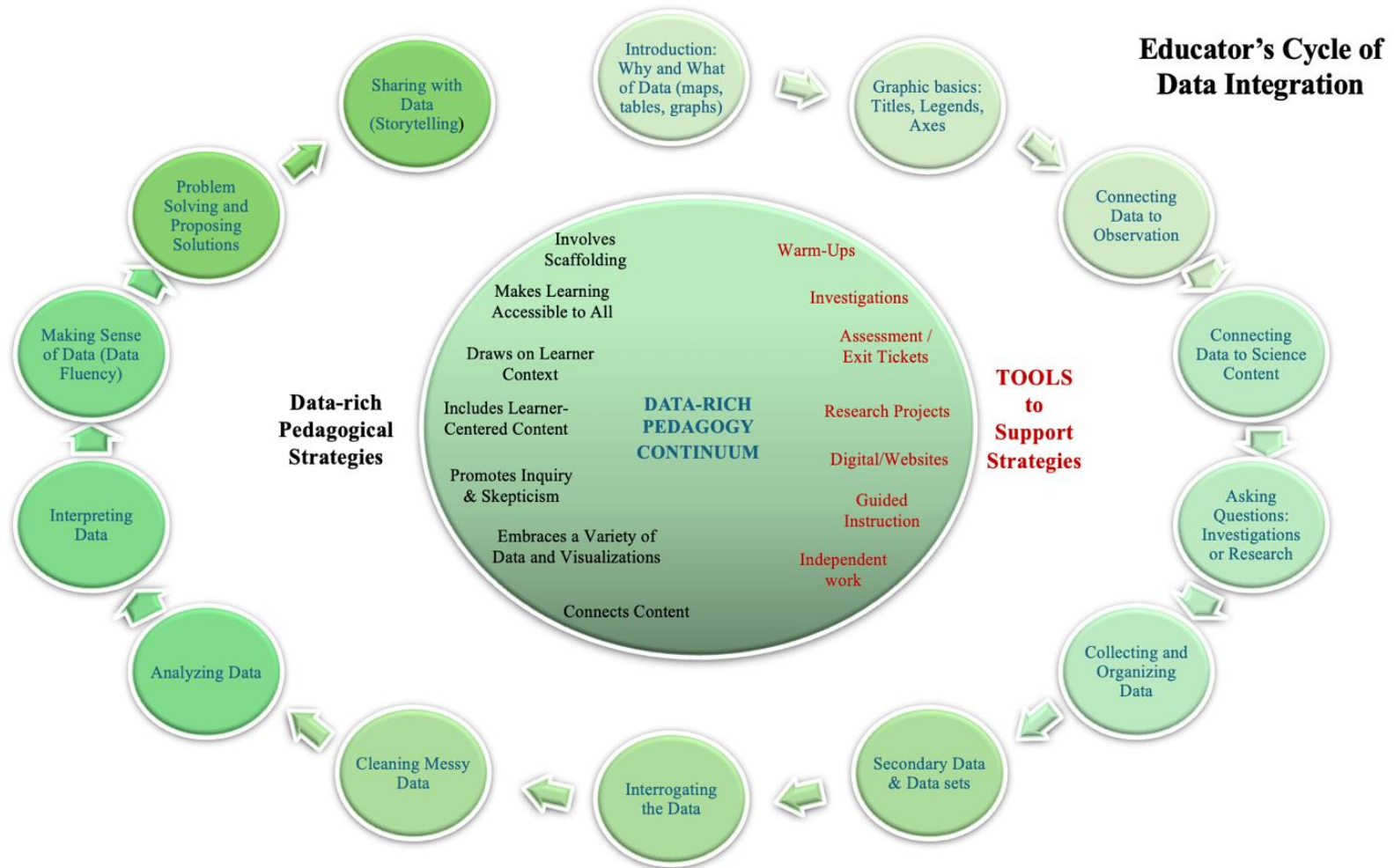
Conclusion

The overarching goal of this research study was to provide educators with an opportunity to assess and support their data-rich practices and to advance their data fluency. The overarching

contribution of this study is new knowledge on how to help science educators develop a variety of data-rich practices while advancing their data fluency. This contribution fills a gap in the literature by clarifying the connections between DRP, DF, and PD. Simply put, this study addresses the “how to” integrate data to support science content learning and data skills in learners. It discusses educator challenges and successes in integrating data into their curriculum.

Finally, this study provides educators with a roadmap for understanding the journey, techniques, and resources needed for their own path to data proficiency. This roadmap, presented in Figure 4-7, addresses educators’ personal interpretations of data-rich pedagogy and helps them understand the potential range and progression of data integration in their classrooms. This roadmap also allows educators to review and follow the map while personalizing their start and end goals throughout the year

Figure 4-7: Educator's Roadmap to Data Integration



Here's how the roadmap works. It starts with light green circles on the right side. These practices focus on the educator's process of acquiring background knowledge about learners' proficiency or prior understanding of data literacy skills. This study found that this was a recurring challenge for educators' ability to perform data integration. As educators progress along the map from right to left, the circles have darker shades of green. These circles incorporate more diverse strategies that link to learner data literacy skills and science content. The darkest circles on the far left reflect learners' data use in research projects and problem-solving activities as they (learners) advance their data skills and data fluency.

As educators move through the roadmap, they can use various data-centric strategies and tools identified in the inner circle to support their data integration practices. Not all educators can complete the roadmap from beginning to end with their learners, as those who teach lower grade levels (K5) cannot reach the darkest green circles, which are not appropriate for younger learners. But professional learning events and educators can refer to the Learning Data Science K12 progressions developed by Data Science 4 Everyone (DS4E) to assess where learners should be in their data skills development (<https://teachingdatak12.org>). Once educators understand where their learners' data roadmaps begin, they can concurrently follow this roadmap to data integration and making sense of data.

References Chapter 4

- Banilower, E. R., Smith, P. S., Malzahn, K. A., Plumley, C. L., Gordon, E. M., & Hayes, M. L. (2018). Report of the 2018 NSSME+. *Horizon Research, Inc.*
- Cohen, D. K., & Hill, H. C. (2000). Instructional policy and classroom performance: The mathematics reform in California. *Teachers college record*, 102(2), 294-343.
- Collinson, V., Kozina, E., Kate Lin, Y. H., Ling, L., Matheson, I., Newcombe, L., & Zogla, I. (2009). Professional development for teachers: A world of change. *European journal of teacher education*, 32(1), 3-19.
- Darling-Hammond, L., Hyler, M. E., & Gardner, M. (2017). Effective teacher professional development. *Learning Policy Institute*.
- Darling-Hammond, L., & McLaughlin, M. W. (2011). Policies that support professional development in an era of reform. *Phi Delta Kappa*, 92(6), 81-92.
- Deitrick, E., Wilkerson, M. H., & Simoneau, E. (2017). Understanding student collaboration in interdisciplinary computing activities. In Proceedings of the 2017 ACM Conference on International Computing Education Research (pp. 118–126).
- Desimone, L. M. (2009). Improving impact studies of teachers' professional development: Toward better conceptualizations and measures. *Educational Researcher*, 38(3), 181–199. DOI:10.3102/0013189X08331140
- Desimone, L. M., & Garet, M. S. (2015). Best practices in teacher's professional development in the United States.
- English, L. D. (2016). STEM education K-12: perspectives on integration. *International Journal of STEM Education*, 3(1), 1–8. DOI:10.1186/s40594-016-0036-1
- Erickson, T., Wilkerson, M., & Finzer, W. (2019). Data Moves. *Technology Innovations in Statistics Education*, 12(1).
- Finzer, W., Busey, A., & Kochevar, R. (2018). Data-driven inquiry in the PBL classroom: Linking maps, graphs, and tables in biology. *The Science Teacher*, 86(1), 28–34.
- Gebre, E. H. (2018). Young adults' understanding and use of data: Insights for fostering secondary school students' data literacy. *Canadian Journal of Science, Mathematics and Technology Education*, 18(4), 330–341. DOI:10.1007/s42330018-0034-z
- Gulamhussein, A. (2013). Teaching. *Center for Public Education page*, 1(3).
- Hardy, L., Dixon, C., & Hsi, S. (2020). From data collectors to data producers: Shifting students' relationship to data. *Journal of the Learning Sciences*, 29(1), 104–126.

- Heller, J. I., Daehler, K. R., & Shinohara, M. (2003). Connecting all the pieces. *The Learning Professional*, 24(4), 36.
- Heller, J. I., Daehler, K. R., Wong, N., Shinohara, M., & Miratrix, L. W. (2012). Differential effects of three professional development models on teacher knowledge and student achievement in elementary science. *Journal of research in science teaching*, 49(3), 333-362.
- Kelley, T. R., & Knowles, J. G. (2016). A conceptual framework for integrated STEM education. *International Journal of STEM Education*, 3(1). DOI:10.1186/s40594-016-0046-z
- Kjelvik, M. K., & Schultheis, E. H. (2019). Getting messy with authentic data: Exploring the potential of using data from scientific research to support student data literacy. *CBE Life Sciences Education*, 18(2), 1–8. DOI:10.1187/cbe.18-02-0023
- Lee, V. R., & Wilkerson, M. (2018). Data use by middle and secondary students in the digital age: A status report and future prospects. Commissioned Paper for the National Academies of Sciences, Engineering, and Medicine, Board on Science Education, Committee on Science Investigations and Engineering Design for Grades 6-12. Washington, D.C.
- National Research Council. (2014). STEM integration in K-12 education: Status, prospects, and an agenda for research. National Academies Press.
- Ostrom, T. (2025). Dissertation Chapter 2 Data Science in K12 Education; A Study of Educator Proficiency in Data Fluency and Data-Rich Pedagogy, University of California at Davis.
- Ostrom, T. (2025). Dissertation Chapter 3 Data-Rich Pedagogy in Middle School Educators, University of California at Davis.
- Pratt, D. D. (2002). Good teaching: One size fits all?. *New directions for adult and continuing education*, 2002(93), 5-16.
- Scher, L., & O'Reilly, F. (2009). Professional development for K–12 math and science teachers: What do we really know?. *Journal of research on educational effectiveness*, 2(3), 209-249.
- Shulman, L. S. (2005). Pedagogies. *Liberal education*, 91(2), 18-25.
- Vahey, P., Finzer, W., Yarnall, L., & Schank, P. (2017). CIRCL primer: Data science education. *CIRCL Primer Series*.
- Weiss, I. R., & Miller, B. (2006). Deepening teacher content knowledge for teaching: A review of the evidence. *Second MSP Evaluation Summit, Washington, DC*.
- Wilkerson, M. H., Lanouette, K., Shareff, R. L., Erickson, T., Bulalacao, N., Heller, J. I., St. Clair, N., Finzer, W., & Reichsman, F. (2018). Data transformations: Restructuring data for inquiry in a simulation and data analysis environment. In Proceedings of the International Conference of the Learning Sciences. London, UK.

- Wilkerson, M. H. & Polman, J. L. (2020). Situating data science: Exploring how relationships to data shape learning. *Journal of the Learning Sciences*, 29(1), 1–10.
- Wilson, S. M., Rozelle, J. J., & Mikeska, J. N. (2011). Cacophony or embarrassment of riches: Building a system of support for quality teaching. *Journal of teacher education*, 62(4), 383-394.
- Wong, N, Elsayed, R., Perez, L., Daehler, K., & Chen, P. *Toward a Theoretical Framework for Data Fluency Teaching and Learning in Middle School STEM. Ninety-seventh annual international conference of the National Association for Research in Science Teaching (NARST)*, (). Retrieved from <https://par.nsf.gov/biblio/10501737>.

Chapter 5 – Closing Remarks

Advocating for educator support has been a passion of mine since I began teaching in 1998. It was clear to me that the preservice program I attended was far from adequate in preparing me for the classroom challenges I faced. Early on, I was thankful I had a previous career in environmental management, where I learned how to problem-solve, think critically, and adapt to the changing environment. As data science becomes more prevalent, educators need support to develop their skills and understanding of how to use data with their learners. We already know that educators adjust their practice to teach learners from diverse backgrounds, cultures, and life experiences, and with varying levels of language proficiency, skills, and abilities. The need for educators to make sense of data and deliver data-rich pedagogy is yet another adjustment we are asking of our already-taxed educators. Understanding their support needs will be critical to ensuring our learners are data-literate in post-secondary education and as they contribute to their communities.

I want to clarify my positionality and the limitations of my research journey, as a researcher's subjectivity can influence the interpretation of qualitative research. I understand how my own twenty-nine years of experience in education as an educator and support provider may affect data collection and meaning-making processes (Ravitch & Carl, 2016). Limitations can affect research by restricting the study's validity, potentially introducing bias, and limiting the scope of conclusions. Acknowledging these shortcomings is crucial to research credibility, as it provides context for the findings, explains potential methodological flaws, and identifies areas for future research (Smith, 2025).

Positionality

In my first study, I served two roles. First and foremost, I was the researcher in charge of designing the study, which included a survey and a set of interview questions. I am also a member of the Science Activation community and a member of one of the partnering organizations, GLOBE Mission Earth. I have been a GLOBE Program Coordinator, supporting K-12 science educators through a NASA Science Activation grant, for the past 10 years. While my association with GLOBE Mission Earth was not a factor in the first study, I drew on that experience in my second study, when collaborating with middle school science educators. I used my experiences to offer insights during the professional learning events and through one-on-one support conversations. My role in the second study with middle school science educators was to design and lead a series of webinars on data-rich pedagogy and support educator practices through observation and mentoring. Since four of the five educators I previously worked with, my roles as a GLOBE program coordinator and a researcher coexisted.

Limitations of the Studies

My NASA study with educators from the Science Activation team had two apparent limitations. The first was the low response rate to the survey, including educators who did not complete all three sections and those who did not open or receive the survey. NASA and its partners requested that they disseminate the survey directly to protect educator anonymity. It is estimated that 15% of educators who participated in Science Activation completed the entire survey.

The second limitation of the first study stems from the survey title, “Investigating Data Expertise in All Stakeholders.” This title may have intimidated educators unfamiliar with how data is used in K-12 education, leading them to feel unqualified to participate. One respondent

highlighted this limitation during her interview. She began with an apology, stating that she is not familiar with data-rich practices and probably not qualified to share her thoughts. However, within minutes of the interview, it became clear that her teaching practices incorporated data. Perhaps the survey title could have been more exploratory, such as: “Exploring Data Experiences in K-12 Science Education.”

The limitations of the collaborative study with five middle school educators were also notable. Two key contextual factors limited this research: 1) four of the five educators were invited to participate based on their prior work with the researcher, and 2) the study was conducted over only one school year. Having previously built relationships with the four educators, they received comments and strategic suggestions during the one-on-one mentoring in a more familiar manner. Additionally, since these educators knew one another, they were more interactive during professional learning events.

Finally, I made a conscious effort throughout this study to be aware of the stressors and hardships that educators, especially those in urban public schools, face due to their administrative and testing schedules. This understanding helped me be forgiving when participants occasionally missed or left webinar sessions early. Since the group learning events were recorded, educators sometimes watched the recordings asynchronously. I also tried to review the webinar content with educators or reteach the key ideas they found beneficial. Even though they were financially compensated for their participation in the study, I recognized the value of their time and wanted them to feel it was worthwhile. A more diverse, larger group of educators could also provide greater opportunities for participants to support one another in advancing along the DRP and DF continuums.

Conclusions and Implications

The overarching goal of this research study was to examine how the educational community can support educators in acquiring data-rich practices and advancing their data fluency. It first required an initial understanding of where educators are with their interpretation of data-rich practices and their ability to make sense of data. Chapter 2, 'Data Science in K12 Education: A Study of Educator Proficiency in Data Fluency and Data-Rich Pedagogy Using NASA Assets' revealed that science educators have a personal understanding of data-rich pedagogy and data fluency primarily through their educational experiences rather than through formal professional learning. This confirmed the literature's findings that data science education and professional knowledge are underexplored and underdeveloped, and that educators need more support to define and improve their data integration and data fluency.

These findings prompted a deeper question on how educators respond to professional learning and individual support in understanding and improving their data integration and data fluency. Chapter 3, 'Examining Data-Rich Pedagogy in Middle School Science Educators,' presents the outcomes of educators' implementation of data-rich practices and their alignment with science content standards. This portion of the study focused on the “how” educators deepen their data-teaching practices to accommodate diverse learner abilities and learning styles through data integration. Understanding the “how” of teaching practices is an essential outcome for educational research, as it not only draws on the literature to identify data-rich practices but also explores the real-time mechanics and challenges of adapting these practices and developing data-centric lessons. Educators reported that their data practices effectively engaged learners in ways that other methods, such as reading and writing, did not.

Finally, this research focused on how the combination of group professional learning events and one-on-one mentoring supported the development of educators' DRP and DF in Chapter 4, 'The Effects of Professional Development and One-on-One Support in Developing Data-Rich Pedagogy and Data Fluency in Middle School Science Educators'. Findings revealed that when educators were given a choice of the most essential support structure for their learning, they all chose one-on-one mentoring and feedback as the most effective. However, they also stated that having the group professional learning sessions allowed them to talk to and learn from one another. Expecting improvement in data-rich practices and fluency using only one of these support measures may not have revealed the same positive results. It was clear that more time is needed to support educators with their desire to incorporate more data practices into their curriculum, provide engaging data skills to their learners, and improve their ability to make sense of data.

In conclusion, data literacy in K-12 learners is becoming increasingly vital for simply navigating daily life in a world awash in data. As data become more integrated, there is a need to align K-12 science education teaching with how learners experience data in the real world. And data literacy in learners, which includes the ability to work with and interpret data in authentic, complex contexts, requires educators to know how to implement data practices and tools.

I have learned through this research that educators, as learners, connect their personal learning about integrating data and making sense of it with the desired outcomes they had for their learners. Some experienced educators already know how to teach data skills with their learners. Still, only a few conceive of data as an integration tool to support a science concept. Novice educators are learning about data themselves because that knowledge has not been explicitly taught, or they lack the understanding of how data practices look in their classrooms.

More research is needed on how to turn data-rich practices into lessons that incorporate data, develop learner data skills, and lead the next generation of scientists toward more data-driven thinking and problem-solving.

Additionally, educator support for data science education is crucial. The various educator interpretations and instructional strategies on data practices need to be clarified and consolidated to make them tangible for K-12 science educators. Furthermore, educators need access to professional support for developing data-rich practices that may lie beyond their previous training and experience. The process for making this professional support accessible could include partnering with expert educators and researchers to surface instructional strategies for data literacy, build the field's knowledge in this area, and develop a framework. It could then include using that framework to support novice teachers in developing data-rich practices and address the need for data-fluent educators in K-12 classrooms. While this current study has attempted a preliminary exploration of professional support on data-rich strategies with a strong group of middle school teachers, there is still a long way to go to expand access to the vast world of data science education to ensure that future generations have the knowledge and tools to not only survive a data-rich world but to thrive and use that knowledge to enact positive change.

References Chapter 5

Ravitch, S. M. & Carl, N. M. (2016). Qualitative research: Bridging the conceptual, theoretical, and methodological. Sage Publishing.

Smith J, Noble H (2025) Understanding sources of bias in research *Evidence-Base Nursing* 2025;**28**:137-139.

Appendices

A – IDEAS Survey

Introduction

You are invited to take part in an educational research study: Investigating Data Expertise in All Shareholders for Science Learning (IDEAS for Science Learning) led by University of California Davis (UCD) School of Education's PhD student Tracy Ostrom. This study is funded by the National Aeronautics and Space Administration (NASA) through a fellowship grant. If you have any questions or need more information, please contact Tracy Ostrom at taostrom@ucdavis.edu or Dr. Cynthia Passmore, principal investigator, at cpassmore@ucdavis.edu.

Study Goal

The goal of this study is to determine educators' self-efficacy towards using data assets, from NASA and/or their Science Activation (SciAct) outreach partners, and providing data-rich instructional practices to support science content learning. Data Assets are: large and small data sets, curriculum, data tools including technology, data resources and materials such as maps, images, and tables, subject matter experts, or anything else that supports your work that you would not have otherwise. This survey is developed for:

- Formal science educators who work with youth in school-based settings;
- Informal science facilitators who work with youth outside of the school day;

Survey Components

This survey is divided into 3 parts. The first part asks you a few questions about your familiarity with data assets from NASA and/or its SciAct partners. The second section asks you the extent to which you believe an item related to data-rich instruction is true/not true based on your teaching practices and/or philosophies. The third part is about your educational setting. The entire survey is expected to be completed in about 20 minutes. At the end of the survey, I will ask you whether you wish to volunteer to participate in a follow-up virtual interview and/or offer your classroom setting for the researcher (Tracy Ostrom) to observe data-rich instruction with your students. I am offering a \$50 gift card to Amazon for all selected volunteers.

SECTION 2 Survey – Part 1 - Alignment to NASA and SciAct Partner Data Assets

1. Choose which NASA SciAct Partner do you receive data assets from. (**Data Assets are:** large and small data sets, curriculum, data tools including technology, data resources and materials such as maps, images, and tables, subject matter experts, or anything else that supports your work that you would not have otherwise.)

Mission Earth	AEROKATS and ROVER Education Network (AREN)	NASA Earth Science Education Collaborative (NESEC)	Challenger	Arctic SIGNS	STEM Enhancement in Earth Science (SEES)	Exploratorium: Navigating the Path of Totality	NASA SCoPE
	NASA Space and Earth Informal Science Education Network (SEISE-Net)	NASA Community College Network (NCCN)	NASA Universe of Learning	Solar System Ambassadors	Northwest Earth and Space Sciences Pipeline (NESSP)	NASA SMD Exploration Connection	NASA PLACES
GMRI	NASA Neurodiversity Network (N ³)	SciAct STEM Ecosystems	NASA Heat	ECLIPSE Soundscapes	Airborne Astronomy Ambassadors	NASA eClips	Native Earth/Native Sky (NENS)
Student Airborne Science Activation for MSI (SASA)	Planetary Resources and Content Heroes (ReaCH)	NASA Eyes	NISE Network (SEISE Project)	PLANETS	Cosmic Storytelling with NASA Data: Tools for Exploring Data Science	NASA's Universe of Learning	NASA@ My Library
Infiniscope	NASA Space Science Education Consortium	Earth to Sky	SciAct STEM Ecosystems	OpenSpace	NASA Heliophysics Education		Smokey Mountain STEM Collaborative

2. Indicate your familiarity and use of NASA data assets. **Data Assets are: large and small data sets, curriculum, data tools including technology, data resources and materials such as maps, images, and tables, subject matter experts, or anything else that supports your work that you would not have otherwise.**

- ☐ I am familiar with and use NASA data assets to support science learning weekly
- ☐ I am familiar with and use NASA data assets to support science learning occasionally
- ☐ I am familiar with NASA data assets, but not sure that I use them

- o I am familiar with NASA data assets, but don't use them
- o I am unfamiliar with and do not use NASA data assets

3. Please share what kinds of NASA assets you have used (if applicable)

4. Describe how you have used NASA data assets (if applicable)

5. Please identify your comfort level in using data assets in your science teaching

- o I am very comfortable using NASA data assets to support science learning
- o I am somewhat comfortable using NASA data assets to support science learning
- o I am somewhat uncomfortable using NASA data assets to support science learning
- o I am very uncomfortable using NASA data assets to support science learning

Survey

Please rate your confidence level in your ability to perform each task listed below

Item	Very True	True	Neutral	Untrue	Very Untrue
1. I encourage students to use data to address authentic/community problems.	1	2	3	4	5
2. It is important for students form questions about data	1	2	3	4	5
3. Students who think critically towards data-driven problems is a skill	1	2	3	4	5
4. Student understanding of data ethics to support claims is a STEM skill	1	2	3	4	5
5. Students should learn to use on-line tools to generate/manipulate data	1	2	3	4	5
6. Students engaging in data collection is essential in STEM skill	1	2	3	4	5
7. Data preparation skills (cleaning, organizing, filtering) are vital	1	2	3	4	5
8. Students' ability to evaluate the sources of data is fundamental in STEM	1	2	3	4	5
9. Students should be able to create multiple types of data visualizations	1	2	3	4	5
10. Use of technology tools is needed to create or interact with data	1	2	3	4	5
11. Using data descriptive statistics (e.g. mean, median, mode) is a skill	1	2	3	4	5
12. Student storytelling and the arts are ways to communicate data	1	2	3	4	5

Dimension 2 *Emphasis: Infusion of Data-rich Instructional Practices (D2)*

Item	Very True	True	Neutral	Untrue	Very Untrue
1. Daily data warm-ups reinforce science content	1	2	3	4	5
2. Using community-relevant data support continual science learning	1	2	3	4	5
3. Data use is a reoccurring process for students	1	2	3	4	5
4. Student data literacy is a marathon, not a sprint	1	2	3	4	5
5. Data analysis is a process that requires a lot of scaffolding	1	2	3	4	5
6. Persistent data integration reinforces student content learning	1	2	3	4	5
7. The development of student data literacy is a continuous process	1	2	3	4	5
8. Weekly data skills build student confidence with data use	1	2	3	4	5
9. Frequently connecting data within lessons or units is vital	1	2	3	4	5
10. Students need a variety of exposures to data	1	2	3	4	5
11. Scaffolding of student data skills takes time	1	2	3	4	5
12. Students have regular conversations involving data of some form	1	2	3	4	5

Dimension 3 *Recognition of Quality*: Data-rich Instructional Practices (D3)

Item	Very True	True	Neutral	Untrue	Very Untrue
1. My students use data to answer research questions	1	2	3	4	5

2. I required students to use data interpretation to answer questions	1	2	3	4	5
3. My students think and work with data through data inquiry	1	2	3	4	5
4. My students collect or assemble data to pose questions	1	2	3	4	5
5. It is important for my students to investigate how data are collected	1	2	3	4	5
6. I give opportunities for my students to collect data	1	2	3	4	5
7. I require my students to analyze data before drawing conclusions	1	2	3	4	5
8. It is important for my students to be able to communicate with data	1	2	3	4	5
9. My students develop data literacy skills through questioning	1	2	3	4	5
10. Data inquiry (knowing how data are measured) is important	1	2	3	4	5
11. I give opportunities for my students to analyze data quantitatively	1	2	3	4	5
12. Data-rich instruction requires me to have core levels of fluency	1	2	3	4	5

Dimension 4 Strategies: How to Use Data-rich Instructional Practices to Support Learners (D4)

Item	Very True	True	Neutral	Untrue	Very Untrue
1. Data visualizations support my student learning goals	1	2	3	4	5
2. Data use is a key factor in students' ability to problem-solve	1	2	3	4	5

3. Navigating through data sets improves student learning	1	2	3	4	5
4. Students' ability to use scripting tools (coding) is a needed STEM skill	1	2	3	4	5
5. Modeling with data is useful for student science learning	1	2	3	4	5
6. Data Science is connected to math and literacy	1	2	3	4	5
7. Argument from evidence helps solve complex problems	1	2	3	4	5
8. Data analysis reinforces student STEM skills	1	2	3	4	5
9. Searching for patterns in data guides students' critical thinking skills	1	2	3	4	5
10. Making observations supports students in STEM engagement	1	2	3	4	5
11. Data use supports learning important scientific concepts	1	2	3	4	5
12. Data use in an integrated setting enables students to think on their own	1	2	3	4	5

SECTION 2 Survey – Part 3 - Educational Setting

1. What best describes your science teaching setting?

☐ K-2 educator/science facilitator ☐ 3-5 educator/science facilitator ☐ 6-8 science educator/science facilitator ☐ 9-12 science educator/science facilitator	☐ In-school (formal) ☐ Out-of-school (informal) • Other Please specify _____ (afterschool program, library, museum, camp, etc...)
---	--

2. How long (total years) have you been involved with youth science education practices?

- ☐ Less than 4 years
- ☐ to 10 years
- ☐ More than 10 years

3. Please select the best answer that describes your educational setting

- ☐ Urban/City
- ☐ Suburban/town
- ☐ Rural
- ☐ Online (remote)

☐ Yes – I would like to participate in a short interview with the researcher and/or invite the researcher to observe a data-rich lesson. My name is _____

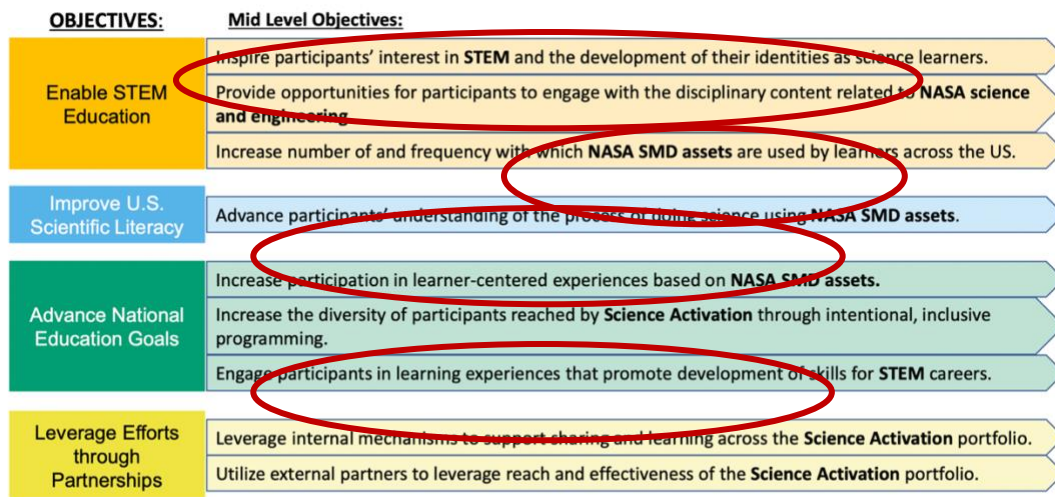
My email is _____ Repeat email _____

☐ No I cannot participate in an interview or observation. Thank you, good luck with your research

SECTION 3. Reflection

This survey is written for existing formal and informal educational professionals identified as working with NASA's Science Mission Director's (SMD) Science Activation (SciAct) Program. NASA's SciAct Program *is designed to help learners of all ages "do" science!* The program consists of a cooperative network of thirty-three teams from across the Nation that work with NASA infrastructure to connect NASA science experts, real content, and experiences with the community organizations and schools to do science in ways that activate minds and promote deeper understanding of our world and beyond. But is NASA's SciAct program meeting its objectives as shown in Figure 1?

Figure 1 – Science Activation Desired Outcomes³



NASA SMD assets = science content and data, space and airborne platforms, and scientific and technical personnel.

³ Kristin Erikson and Lin Chambers, Science Engagement and Partnerships Science Mission Directorate, NASA Headquarters October 19, 2020 https://smd-prod.s3.amazonaws.com/science-pink/s3fs-public/atoms/files/2020_SciAct_Primer_TAGGED.pdf

B – Interview Guide

Educator Interview Guide:

Section 1 - The school setting

- In order to gain a little perspective on your teaching setting right now, can you share with us a little about your years of experience in teaching science?
 - At that school, other school(s), grade levels, content areas
- And with that, can you describe your school setting?
 - Student population, demographics, school setting
- Any distinguishing features about the setting of your science classes, school or the community in which you teach that you can share?

Section 2 - Data Use

In this part of the interview I will be using the term *data assets*. For this research, I am defining data assets as a variety of tools-based learning which includes authentic data collection and data visualization such as charts, graphs, maps, tables, etc... I will also use the term *science learning*. For the purpose of this research, I am defining science learning as the ability of a student to acquire knowledge, ask questions, construct explanations of natural phenomena, test those explanations in many different ways, and communicate their ideas to others.

- What questions do you have about the idea of *data assets* and *science learning*?
 - Provide an example of how data assets help student learning science: colored map showing air temperature changes and sea ice melt over time. In this case the data asset was the maps of air temperature and sea ice and the science learning is the explanation of the natural phenomena of warming temperatures and ice melt.
- Can you please share how often you integrated data in your classroom?
daily weekly more than once per month monthly less than monthly
 - Probing questions:
 - Why did you choose this asset(s)?
 - Was this a new approach to science learning for you?
 - What challenges did you face, if any?
 - How did students respond to using a data asset to understand the content?
 - Do you have a favorite website or resource you use for data assets?
 - How do other science teachers at your school use similar data assets or approaches to science learning?
 - How would you modify this approach to content learning next time?
 - What worked well for you with this data asset/approach to science learning?
 - How would you interpret student learning based on the story you shared with me?
- Is there another story you would like to share with me on how you used data assets for science learning in your classroom?
 - Same probing questions
- If you don't have experience in using data assets in your classroom, can you share with me the challenges you are facing in being able to use data assets for science learning?

- Probing questions:
 - District rules?
 - Administration rules?
 - Resources/technology?
 - Team teaching?
 - Department obstructions?
 - Other challenges?

Section 3 - Educator Expectations

This section of the interview will focus on the science skills and outcomes (goals) science learning facilitators have for their students through the use of data assets.

- Please share with me your learning goals of your students. How did you come up with these?
 - District driven, personal, school administration?
- How do you evaluate if the students met these goals?
 - Formative, summative?
- Describe the ideal setting for using NASA data assets for student learning

Closing

Thank you for your time with this research. Input from educators is critical in education research and your thoughts and experiences on using data assets for science learning will be valuable to a variety of stakeholders in and outside of education. Creators of data assets can better understand the needs of the educational community so that their data is better geared for classroom use and appropriate training is designed and provided. District personnel and administrators need to understand the value of data assets for science learning and provide educators an opportunity to attend data training when it is offered. And finally, with the input from science learning facilitators from a variety of school settings and with a variety of teaching expertise, science learning can include an equitable opportunity for all students to do science and experience what it's like to be engaged in science learning.

- Would you like to share any final thoughts about using data assets for science learning?

I want to provide you with a gift card for your time, is there a specific on-line store that you prefer?

C – Observation Form

Data Ecosystems Project Classroom Observation Protocol

Updated 6/14/24

General Information

Date of observation:

Grade level:

Subject observed:

Location/Setting (e.g., classroom, park, etc.):

Number of students in the class during the observation:

List any data **resources** the educator used during the observation (e.g., primary data collection, secondary data type: graph, map, table, other; data origins – NASA, NOAA,; data tools - Data Literacy Cubes, digital [CoDAP], other):

Planned Instruction:

Select all data literacy skills used to engage learners:

- ☐ Making measurements (collecting data)
- ☐ Exploring data from secondary sources
- ☐ Organizing data
- ☐ Visualizing data
- ☐ Analyzing/Interrogating the data
- ☐ Using data to develop questions
- ☐ Using data to define problems
- ☐ Developing and/or using models with data
- ☐ Using web-based tools to manipulate the data
- ☐ Interpreting data and drawing conclusions based on the data
- ☐ Designing solutions based on the data
- ☐ Engaging in an argument from data evidence
- ☐ Obtaining, evaluating, and communicating (sharing) data/information

How is data-rich pedagogy carried out for the learners? (Check all that apply.)

- ☐ Listening to a lecture or presentation
- ☐ Video or other visualization(s)
- ☐ Reading
- ☐ Web-based
- ☐ Inquiry/Questioning
- ☐ Other (please specify)

How are activities structured for students? (Check all that apply.)

___ Whole Class ___ Small Groups ___ Pairs ___ Individual

Observation Form

1=Observed, 0=Not Observed

Data-Rich Practice	YES 1	NO 0	NGSS SEP CCC DCI	Supporting Evidence or Comments (NGSS PE)
Data integration into the lesson is evident.				
Lesson/Data were derived from PL event topic or one-on-one mentoring				
At least one data literacy skill was evident:				● Collection, ● organization, ● visualization, ● analysis, ● interpretation, ● sharing
Data integration was used to support science content.				What was the science content topic.
The educator displayed an accurate understanding of how to use data to support science content learning.				
The instruction draws on learners' personal, historical, and/or cultural contexts.				
Meaningful data sets were used to foster learner imagination and curiosity to find and explore questions that are meaningful to them,				
Data-rich instruction was demonstrated by empowering learners to become "data detectives," to question and explore data stories for themselves, and to develop productive habits of mind such as perseverance and curiosity.				
Data-rich instruction demonstrated learner engagement with data science practices such as cleaning and transforming messy data for authentic purposes.				
Web-based digital data tools were used as an instructional strategy.				Which ones/How?
Formative assessment(s) were used to ensure learner connection between data and science content.				Results? Next steps?

Lesson description (Completed at end of observation)
(Attach a copy of the lessons, materials, handouts, assessments, etc...) to this observation form.

Describe the lesson observed:

Is there evidence that aspects of the lesson observed included culturally and/or community-relevant pedagogy? If so, describe it below:

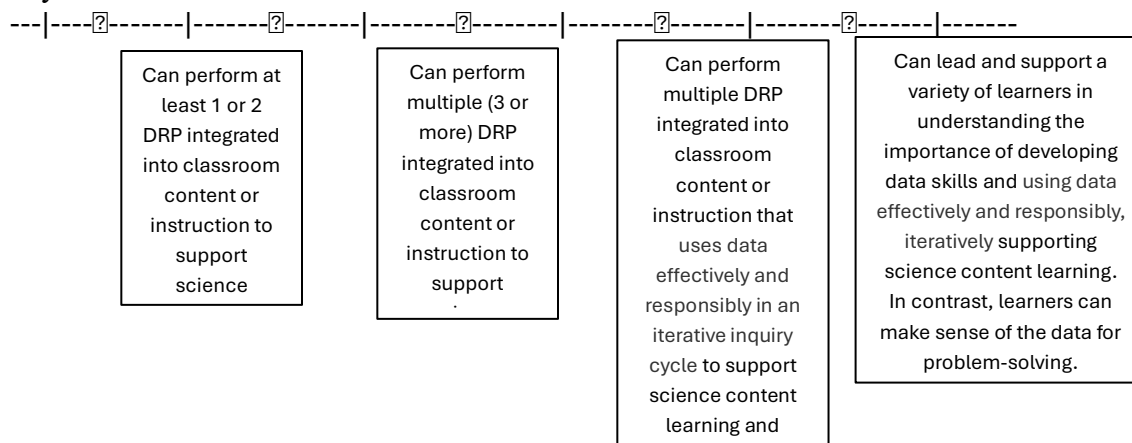
Summarize what worked and the challenges during the lesson:

D – Interview Form

1. Embedding Data into the Classroom

- What data pedagogy techniques do you use to support science content learning with your learners? (Check all)
 - Warm-ups
 - Exit tickets
 - Student Inquiry-based activities (labs)
 - Homework
 - Data-rich pedagogy on science content
 - Other – what?
- Would you say that the majority of the data that you use in your classroom comes from data collected by learners or from secondary data resources? Please explain...
- Can you tell me what your expected outcomes are for your learners when you integrate data into your classroom?
- Do you feel these outcomes are met when incorporating data/data-rich pedagogy?
- How often did you implement data into your classroom? (daily, weekly, monthly, a few times each semester, once each semester)
- What specific data resources are most helpful for your learners (websites, tools, etc.)?
 - Probe on the implementation of key strategies and resources

2. Data-rich Pedagogy - let's look at the data-rich pedagogy continuum. Can you identify where you were at the beginning of the year in your delivery of data-rich pedagogy and where you feel you are now?



3. Professional Learning and Pedagogy

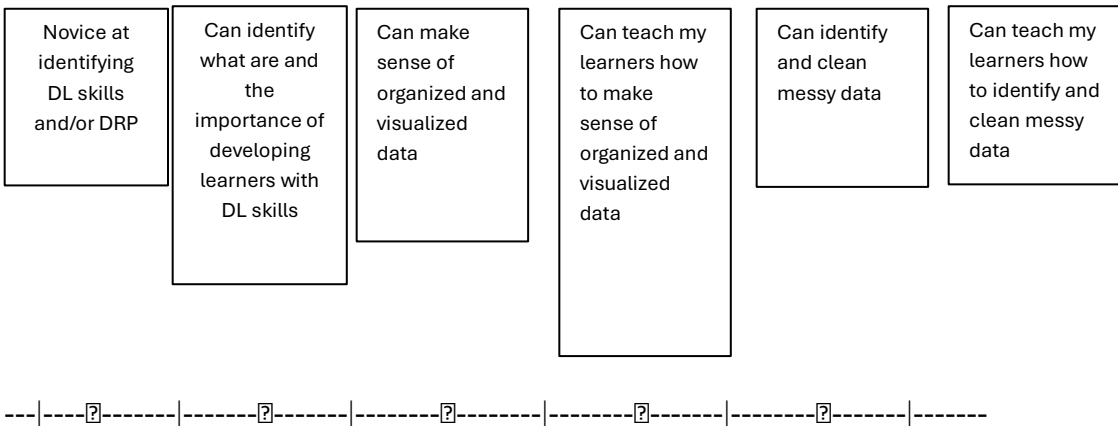
- Can you elaborate on how either group or one-on-one professional learning has supported you to progress along the data-rich pedagogy continuum?
- What works best for you as a learner to increase your data-rich pedagogy skills in your classroom?

4. Which of the following rings true for your learners?

- c Data-rich learning is accessible to all learners. Data-rich classrooms utilize the principles of universal design and culturally sustaining pedagogies to support all learners in growing and developing their data fluency.
- c Data-rich learning is learner-driven. Data-rich instruction promotes the use of data for purposes that matter to learners by empowering them to become “data detectives,” to question and explore data stories for themselves, and to develop productive habits of mind such as perseverance and curiosity.
- c Data-rich learning uses a variety of data sets. Data sets foster learner imagination and curiosity to find and explore questions that are meaningful to them and engage them in data science practices such as cleaning and transforming messy data for authentic purposes.
- c Data-rich learning encourages a healthy skepticism. Data-rich classrooms utilize scaffolds or routines for evaluating data sources, interpretations, and representations to prepare students to be critical consumers and ethical producers of data.
- c Data-rich learning strengthens content knowledge. Data-rich classrooms provide opportunities for learners to engage with data that are interesting, relevant, and potentially surprising in order to stimulate interest and support the content goals of the learning.
- c Data-rich learning utilizes the power of digital tools. Technology provides opportunities to find and access a wide range of datasets, generate displays, manipulate values and communicate insights about data that aren’t possible with paper and pencil.
- c Data-rich learning draws on learners’ personal, historical, and cultural contexts. Interacting with and using data that are contextualized, personal, historical, or culturally meaningful to learners, offers opportunities to explore socio-cultural impacts.

5. Educator Data Fluency – Let’s look at the educator data fluency continuum. Can you identify where you were in your own making sense of data, and where you feel you are at now?

The Educator Data Fluency Acquisition Continuum



- How does your expertise in using data as a teaching tool impact your ability to make sense of data? (Explain)
- What influences you the most in your data fluency acquisition? (Explain)
- How do your data resources and data-rich pedagogy connect to your personal data fluency?

6. Professional Learning and Data Fluency

- Can you elaborate on how either group or one-on-one professional learning has supported you to progress along the data fluency continuum?
- What works best for you as a learner to increase your data fluency?

7. Impact on students

- How do students’ attitudes towards data change over the year? (Explain)
- How does integrating data in your classroom affect your students’ attitudes towards science learning over the year? (Explain)

8. Educator background and support

- How many years of teaching experience do you have?
- What is it about your training or past experiences (ex., if teaching is a second career) that facilitates your willingness and ability to integrate data and/or deliver data-rich pedagogy?

9. Is there anything else you would like to share about your experience with the Data Ecosystems Project?