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Design-Based Research as Professional Development: Outcomes of Teacher Participation in the Development of the Science Practices Innovation Notebook (SPIN)

Erin E. Peters-Burton [a], Hong H. Tran [b], and Brittany Miller [a]

[a]College of Education and Human Development, George Mason University, Fairfax, Virginia, USA; [b]Department of Mathematics, Science, and Social Studies Education, Mary Frances Early College of Education, University of Georgia, Athens, Georgia, USA

ABSTRACT

The use of data to explain natural phenomena has been a core feature of science education, and science educators continue to call for an increased emphasis on teaching data practices. This mixed methods design-based research study adds to the growing body of research on data practices in science by explaining the learning trends of science teachers involved in a three-year collaborative professional development (PD) using computational thinking (CT) and self-regulated learning (SRL) as a means to support teachers in implementing data practices. The PD resulted in long-term high-quality teacher learning outcomes for all three elements of the PD (data practices, CT, and SRL) despite the upheaval of teaching platforms due to the COVID-19 pandemic. Since the teachers were involved in design-based research, their professional learning focused on collaboratively creating an electronic, interactive notebook with lessons for use in science classrooms across the United States. Creating a common product as an outcome of the PD may have served as motivation for teachers to learn about and implement more data practices, CT, and SRL, which suggests that design-based research is another valuable design for teacher PD.

KEYWORDS

Computational thinking; data practices; design-based research; professional development; self-regulated learning

Research has indicated that effective professional development (PD) is participatory, long-term, and specific to and relevant for the teachers who are participating (Darling-Hammond et al., 2017; Loucks-Horsley et al., 2010; Luft & Hewson, 2014). Successful models of PD for science teachers include approaches such as learning cycles and research experiences (Enderle et al., 2014; Herrington et al., 2016). Collaboration stands out as a key feature in these PD models extending beyond teacher-to-teacher collaboration (Coenders & Terlouw, 2015; Herrington et al., 2016) providing opportunities to share expertise, learn from each other, and develop new teaching strategies (Vescio et al., 2008) and ultimately improving learning gains for students (Roth et al., 2011). Moreover, evidence is emerging that PD that involves broader collaborations can help teachers address equity issues in the classroom (Bancroft & Nyirenda, 2020).

The purpose of this paper is to present the learning trends of teachers involved in a type of long-term collaborative PD model through Design-Based Research (DBR). This DBR PD

CONTACT Erin E. Peters-Burton Epeter1@gmu.edu College of Education and Human Development, George Mason University, 4400 University Drive, MSN 4B3, Fairfax, VA 22030, USA

research involved collaboration among teachers, educational psychologists, school psychologists, science educators, technology educators, and software developers to design a web-based tool to support high school student engagement with data practices during science investigations. Teachers experienced developmental PD over three years to meet the goal of designing and testing the Science Practices Innovation Notebook (SPIN) for use not only in their own classrooms, but in high school science classrooms across the United States. SPIN is a web-based interactive notebook that supports self-regulated learning (SRL) of high school students engaged in data practices and computational thinking (CT) by guiding students through teacher-authored investigations in physics, chemistry, biology, and Earth science while collecting learning analytics for both teacher feedback and educational research.

Conceptual framework

Four integrated conceptual frameworks were used for this study: DBR (Bannan-Ritland, 2009), data practices (Weintrop et al., 2016), CT practices (Wing, 2006), and SRL (Zimmerman, 2000). The following section describes each framework and then explains how they were integrated to design the research, product development, and PD experiences with the teachers.

Design-based research

DBR, specifically the Integrated Learning Design Framework (ILDF, Bannan-Ritland, 2009), was adopted for this study as it provided guidance in the form of iterative phases for collaboratively designing an educational product. Previously, this framework has been leveraged for collaborative learning with teachers by Bannan (2013) and Bannan et al. (2010). The study by Bannan (2013) indicated that across ILDF phases, the research questions, design criteria, and corresponding evaluation cycles became progressively more sophisticated and complex. Bannan et al.'s study (2010) showed the incorporation of mobile devices into an overarching instructional intervention not only promoted enhanced geological observation and reasoning but also facilitated shifts of agency, social structures, and cultural practices. The ILDF supports multiple objectives (content knowledge, pedagogical content knowledge), multiple contexts (data practices, CT, and SRL), and multi-layered collaborations (researcher-teacher, researcher-software developer, teacher-

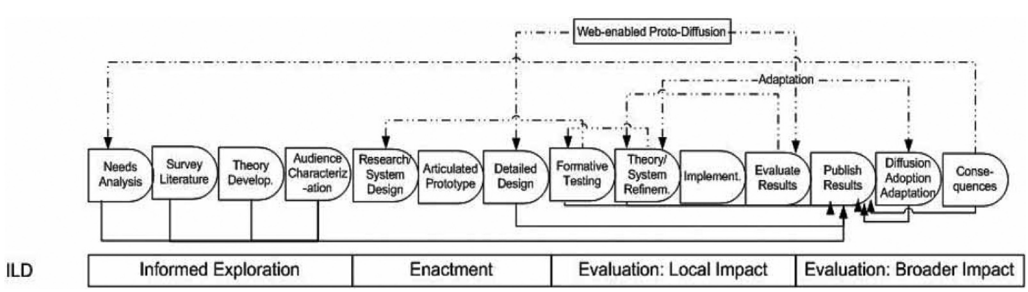

Figure 1. Integrated learning design framework (ILDF) used for the study.

student, student-student). The ILDF has four iterative phases, *Informed Exploration, Enactment, Local Impact*, and *Broader Impact* (see Figure 1). This study, a part of a larger research study, took place during the first three phases of the ILDF.

The intention of the *Informed Exploration phase* (IEP) is to identify the general problem, conduct research to better understand the problem, and define the problem so that the eventual product serves the needs of the users (Bannan-Ritland, 2003). Because DBR is intended to be collaborative, all of the stakeholders come to the context expecting to learn. The purpose of the *Enactment phase* (EP) is to take what was learned from the IEP, create a rough idea of an educational product, and continue to perform small, iterative tests to refine the product (Bannan-Ritland, 2003). There are two purposes of the *Local Impact phase* (LIP): to determine how well the product works for the students of the teachers who designed the product and to make initial determinations about how well the product will scale up for use in other teachers' classrooms (Bannan-Ritland, 2003). The purpose of the *Broader Impact phase* is to test the product in full classrooms of teachers who were not involved with the design. However, this paper will focus on the development of teacher knowledge and skills from the IEP, EP, and LIP of the project. A description of PD activities characterizing each phase can be found in the methods section.

Data practices framework

During IEP, teachers identified a need for students to engage in data practices more fully during science investigations. Weintrop et al. (2016) identified five data practices that scientists engage in which intersect with CT: (a) collecting data, (b) creating data, (c) manipulating data, (d) visualizing data, and (e) analyzing data. Weintrop et al. (2016) established these categories for better understanding ways people use CT and automation of data to study science. Collecting consists of using computational tools to make observations and record information. Creating consists of generating data through computational tools such as simulations. Manipulating consists of cleaning and organizing data for analysis or communication. Visualizing consists of the use of tools to create graphic summaries of data for analysis and communication. Analyzing consists of the use of descriptive and inferential statistics to explain outcomes. During the IEP, teachers and researchers reconfigured the five data practices to fit the way students do science investigations. The adaptation resulted in five categories: (a) creating, (b) collecting, (c) preparing, (d) visualizing, and (e) analyzing. Creating data was placed before collecting data as teachers indicated students needed to understand the phenomena and the variables before they collected data, thus changing the essence of the term "creating" for the science context. The term "manipulating" was replaced with "preparing" because teachers felt that the term manipulating could be misinterpreted by students to mean changing the numbers to fit a preconceived notion.

Despite the ubiquitous presence of data practices in science education, there are few studies that examine how teachers teach and how students learn data practices. Implications from those studies offer three primary insights into teaching and learning of data practices. These include the need for authentic learning scenarios that use real data sets and engage students with the entire cycle of data practices (Gold et al., 2015; Lesh et al., 2008; Masnick & Morris, 2002; Newton, 2000), the usefulness of technology tools such as data-logging and graphing technology for students learning about data practices (Barton, 1997; Newton, 2000; Rogers, 1997), and the importance of addressing students' often unsystematic approaches to working with data. Kanari and Millar (2004) examined students' practices when collecting data on an experimental investigation and found that most students did not repeat measurements to check on their validity while Masnick and Morris (2002) found that students' conceptions of error are not well integrated into measurement processes or explaining experimental error.

Computational thinking framework

During IEP, the team identified that one way to support student data practices is by developing their CT skills. Teachers found that CT practices including decomposition, pattern recognition, abstraction, and algorithm building are naturally linked with data analysis tactics to solve many types of problems (Shute et al., 2017; Wing, 2006). Decomposition involves breaking down a complex problem into less complex sub-problems. Pattern recognition is the identifying, clustering, and modularizing of steps that repeat in order to cluster related parts of the problem by their recurring features. Abstraction is a process of identifying and organizing relevant information and removing unnecessary information in order to clarify problems and identify generalizable solutions. Algorithm building is the creation of a series of precisely defined steps or rules that leads to predictable outcomes.

CT is quite a new concept in science education, so science teachers are in need of PD to systematically prepare them for understanding the concept, designing CT learning experiences, and assessing CT (Angeli & Giannakos, 2020). However, there is little information available about effective PD to support teachers in their efforts to integrate (Jocius et al., 2020). According to V. Barr and Stephenson (2011), PD in CT needs to provide a clear definition of what CT is and how it applies to students and the disciplinary content. Jocius et al. (2020) reported positive outcomes on teacher understanding of the role of CT and self-efficacy regarding CT integration when they offered teachers a clear CT model. A few other studies also show promising results regarding teachers' beliefs and knowledge around CT (e.g., Adler & Kim, 2018; Bower et al., 2017). Furthermore, Ketelhut et al. (2020) offered elementary teachers a yearlong PD on CT and found that over time the teachers got better at integrating CT, advocating for continuous long-term CT PD, which results in sustainable shifts in teachers' integration of CT.

Self-regulated learning framework

During the IEP, it was articulated that a systematic way to structure learning tasks was needed in SPIN. Researchers adopted Zimmerman's (2000) model for the SRL framework. SRL is a cyclical, fluid process through which students proactively and intentionally manage and control their thinking, actions, and environments to attain personal goals (Zimmerman, 2000). Self-regulated students can motivate themselves, set goals, monitor their learning, and reflect on the learning process. From a social-cognitive perspective, SRL includes a *forethought* phase, during which students set goals and strategize a plan for approaching a problem; a *performance* phase, during which students enact the strategic plans and gather information about their goal progress; and a *self-reflection* phase, during which students evaluate their level of success based on pre-established standards, reasons for their success or failure, and lessons learned in terms of strategy use for improved learning and performance in subsequent tasks.

Studies of SRL PD for science teachers have investigated the support of teacher learning and support of teaching which fosters SRL skills for K-12 students (Kramarski & Heaysman, 2021). The duration of the PDs ranged from a few hours (e.g., S. Barr & Askell-Williams, 2020; Tran et al., 2022) to around 100 hours (e.g., Lewis et al., 2011; Michalsky & Schechter, 2018). In general, the short PDs aimed to align teachers' perceptions regarding SRL with SRL theories, while the long-term PDs targeted teachers' ability to use SRL strategies in their teaching (Adler et al., 2019; Kramarski & Michalsky, 2009, 2015; Lewis et al., 2011). Some examined how teachers implemented lessons (S. Barr & Askell-Williams, 2020; Eilam, 2017; Kramarski & Kohen, 2017; Michalsky, 2012), and a few gave science teachers the opportunities to share their experiences regarding enacting the lessons (e.g., Peters-Burton & Botov, 2017; Peters-Burton et al., 2020). All the PDs achieved their learning objectives to some extent. For example, Eilam (2017) found that teachers' metacognitive considerations and reflections on their planning and teaching were promoted with the use of a metacognitive tool, but no substantial changes occurred in enacting the lessons. S. Barr and Askell-Williams (2020) engaged four secondary science teachers in a researcher-facilitated professional learning community for 12 weeks (8 hours). The findings indicated that SRL content knowledge, pedagogical content knowledge, and constructivist beliefs were improved consistently for three of the four teachers.

Integration of the conceptual frameworks

DBR was used as an overarching guide for framing the PD and moving forward the ideas that would result in the SPIN product. Within IEP, the team identified the need for conceptual frameworks of data practices, CT, and SRL. As the IEP progressed, the team continued to refine the articulation of data practices as the learning tasks to be accomplished, and CT practices as the tactics to support students in data practice engagement. For example, when asked to create data, students were to identify the phenomena and the relevant variables for data collection to answer the research question. Decomposition could help students break down the phenomena into parts to see each individual variable, while abstraction could help students find the relevant variables and to not engage with extraneous ideas. SRL was used to help students identify their plan for accomplishing each data practice, monitor their progress, and reflect on their successes and failures before progressing to the next. We viewed CT and SRL as problem-solving processes (Peters-Burton et al., 2018), which helped to integrate the ideas into the context of data practices. Keeping in mind that the ideas for the conceptual frameworks were discovered and refined while situated in the DBR framework, we asked the research question, "What patterns emerged regarding teacher learning of data practices, CT, and SRL across three phases of DBR while designing SPIN?"

Methods

The research design for this study was concurrent mixed methods research in the context of DBR. Three of the four phases of DBR (Bannan-Ritland, 2009) served as the foundation for the study and helped the teachers to work toward a common end goal of developing SPIN,

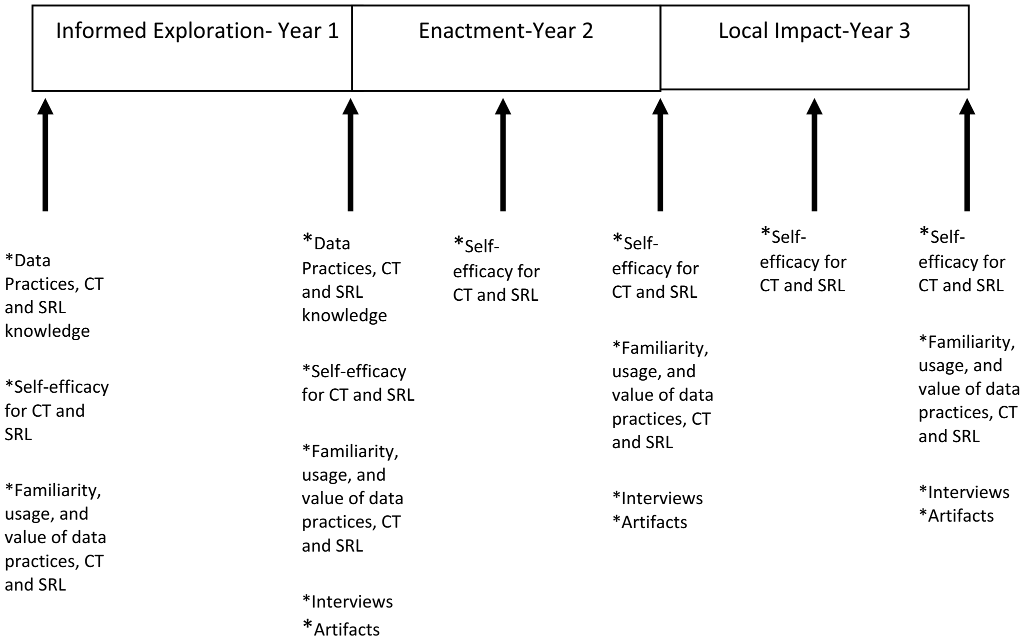

Figure 2. Timeline of data source collection across three years.

an online tool for students to support data practices in science by using CT and SRL as supports. Qualitative and quantitative data were collected across all three phases of the DBR. The mixed data sources were intentionally designed to complement and triangulate each other and were integrated throughout the study (Teddlie & Tashakkori, 2009). Figure 2 displays the timeline of the study. Attempts to minimize bias in this study were accomplished through the use of multiple data sources, data that represented multiple dimensions, interrater reliability, and member checks for correct representation of the results with the teachers in the PD (Maxwell, 2013).

Participants

Nineteen high school science teachers with an average of 15.5 years of experience, ranging 7–33 years, were involved in this project across the three years. Each teachers' pseudonym and demographic information can be found in Table 1.

Description of PD over three years

Year 1 (IEP) began in the summer with two weeks of intensive PD experiences on data practices, CT, and SRL. Teachers performed activities related to knowledge and application of data practices, CT, and SRL separately. They then integrated the ideas by designing opportunities for student engagement with data practices, CT, and SRL in lessons to be taught during the school year using lesson planning tools such as planning templates and task analysis tools (Peters-Burton et al., 2021). The intention was to use these lessons in SPIN. During the academic year in Year 1, teachers taught the lessons they designed and

Table 1. Participant pseudonyms and demographic.

Pseudonym	Total Years Teaching	Subject Taught	Grade Level	Type of Courses Taught
Zeke	11	Chemistry	9th	Research, AP
Kyle	10	Earth Science	9th	Individual Research, Research, Dual Enroll
Jace	8	Physics	9th-11th	Academic, AP
Jayla	12	Biology	9th and 10th	Academic, Research, Dual Enrollment
Miles	15	Chemistry	10th-12th	Academic, Research, AP
Carla	15	Biology	9th-10th	Academic, Research, AP
Ana	19	Biology	10th-11th	Research, AP
Kya	33	Chemistry	9th-12th	Research, AP
Chloe	29	Biology	9th and 10th	Academic, Research, AP
Jemma	11	Biology	9th-12th	Academic, Research, AP
Kylie	9	Biology	10th-12th	Academic, Research, AP
Sita	18	Biology	10th-12th	Research, AP
Hayley	7	Biology	9th, 10th, 12th	Individual Research, Academic, Research, Dual Enrollment
Sara	10	Chemistry	10th-12th	Academic, Research, AP
Eileen	23	Physics	11th-12th	Academic, AP
Lyla	20	Earth Science	9th, 11th, 12th	Research, Dual Enrollment
Elizabeth	19	Physics	10th-12th	AP
Lakshmi	18	Physics	12th	Academic, AP, Dual Enrollment
Eugene	8	Biology	9th-10th	Academic, Research

met in content area groups to discuss student outcomes, lesson revisions, and application of data practices, CT, and SRL in their classrooms. At the end of the year, the researchers conducted a needs analysis with teachers to determine their preference for the structure and content of the PD in Year 2.

In Year 2 (EP), teachers and researchers met again for a two-week intensive summer PD experience that focused on reflecting on the results of the implementation of the lessons, further lesson refinement, and pursuing an advanced understanding of CT and SRL. During the academic year, teachers and researchers met by content area groups to check the accuracy of integration of CT and SRL into data practices, reflect on the refined lessons taught, and to contribute design features for SPIN based on their reflection of the lessons.

Year 3 (LIP) was dedicated to converting lessons from business as usual to SPIN-appropriate lessons. During the year, teachers were given small components of SPIN to test. At the end of Year 3, lessons in SPIN were field tested by the teachers with small groups of students for the purposes of giving feedback for scaling up the following year.

Data sources

Data sources included (a) a test of knowledge and application about data practices, CT, and SRL; (b) a self-efficacy measure of data practices, CT, and SRL; (c) a survey of familiarity, value, and use of data practices, CT, and SRL, (d) interviews; and (e) lesson plan artifacts. Each data source was measured multiple times across the three years, as shown in Figure 2.

Test of knowledge and application for data practices, CT, and SRL

Each teacher took an open-ended test of knowledge and application about data practices, CT, and SRL that was assessed with a rubric at the beginning and end of the IEP. Two versions of the vignette were created for pre- and post-PD assessment to avoid threats to validity. Knowledge of CT, SRL, and data practices were assessed with one free-response question for each concept. The teachers were first prompted to define and describe their understanding of each concept. For example, "How would you define and describe CT? Provide as many details as you can using the space below." Next, application was evaluated with a vignette describing a struggling student in a science classroom. After reading the vignette, teachers were prompted to identify data practices, CT practices, and SRL by highlighting a section of the text and explaining their interpretation. In addition, teachers were asked to respond to open-ended questions about specific actions they might take to better promote CT practices and improve students' SRL. Teacher responses were assessed with concept-specific rubrics that endeavored to score the quantity and quality of teacher understanding of each concept as well as knowledge of specific vocabulary. Rubrics were completed independently by two or three researchers, who then met to discuss and resolve any discrepancies in scoring. Discrepancies found were minimal and typically demonstrated variance with mid-level scores.

Teacher familiarity, use, and value of data practices, CT, and SRL

Teacher familiarity, use, and value of each concept was measured with a 3-point Likert scale (1 = not often, 2 = somewhat often, 3 = very often) with question stems such as, "How often do you infuse CT concepts with your teaching?" The items assessed teachers' perceptions of use and value as well as how often they infused each concept into their teaching. There were 10-items for overall SRL and SRL components (i.e., goal setting, task analysis, motivation, time management, organization, help-seeking, anxiety control, self-monitoring, self-reflection, and adapting behaviors), five for CT and CT components (i.e., decomposition, pattern recognition, abstraction, algorithm building, and automation), and five for data practices and data practice components (i.e., creating, collecting, preparing, visualizing, and analyzing).

Self-efficacy of data practices, CT, and SRL

The self-efficacy scale, which had Likert scale ranging from 0 (certain cannot do at all) to 100 (highly certain can do), assessed teachers' efficacy beliefs to use each component of data practices, CT, and SRL. The scale was developed based on Bandura's (2006) guidelines. Items were developed by six experts, two experts in each of the domains (data practices, CT, and SRL). The initial version of the self-efficacy scale was developed and pilot-tested and refined with eight high school teachers. Following data collection, the experts examined the phrasing and sought to provide an even more specific context for the instrument. There were five items measuring data practices, five items measuring CT, and 10 items measuring SRL. A sample item was "To what extent can you develop lesson plans on data practices that enable students to successfully generate data from observations?" Teachers were asked to rate their efficacy for each item under two conditions: (a) when working with students whom teachers perceived as academically struggling (i.e., lower bound of efficacy), (b) when working with students whom teachers perceived as advanced or successful (i.e., upper bound of efficacy). Thus, for each item, the teachers reported their range of self-efficacy for teaching data practices, CT, and SRL.

Interviews

We conducted semi-structured, individual interviews with teachers at the end of each phase of the three phases of DBR. The interviews were approximately an hour each and focused on data practices, CT, and SRL learning in Year 1; on teaching data practices, CT, and supporting students with SRL in Year 2; and on small-scale implementation of SPIN for student learning of data practices, CT, and supports through SRL in Year 3. During the EP and LIP, COVID abruptly changed the format of participants' classrooms and teaching. Year 3 interviews, then, focused not only on teachers' knowledge and application of SRL, CT, and data practices, but also on the changes teachers experienced due to the pandemic and how these changes impacted perceptions and integration of these concepts.

Artifacts

We collected artifacts at the end of each year. In Year 1, we collected the offline lesson plans and documentation of CT integration using a task analysis tool (Peters-Burton et al., 2021). Teachers were asked to collaboratively develop five lesson plans per content area using a template that included standards, learning objectives, the components of a 5E lesson, and an assessment map. At least one teacher per content area committed to teaching the lessons. Student work samples were also collected and discussed during monthly content meetings. In Year 2, we collected 18 revised lesson plans and revised documentation of CT integration. The 18 revised lessons from the teachers were formatted and incorporated into SPIN. In Year 3, we collected the refined lessons embedded in SPIN, noting alignment with data practices, CT, and SRL supports.

Data analysis

We analyzed the data systematically as they were available over the three years. We integrated the qualitative and quantitative data by looking for connections between the themes in the scale responses and the codes and categories in the interviews and artifacts.

Qualitative analysis

We treated the interviews and artifacts for all teachers as a case study for each phase of the DBR (Yin, 2003). They were coded using an a priori codebook (Saldaña, 2012) created by defining the five data practices (create, collect, prepare [formerly manipulate], visualize, and analyze), the CT practices (decomposition, pattern recognition, abstraction, algorithmic thinking), and SRL processes (e.g., goal setting, metacognitive monitoring, self-evaluation). We sought out emergent codes, which resulted in two codes, "mistaking data practices for CT" and "Aha! Moment." All three researchers independently coded 30% of all interviews and artifacts and met to discuss accuracy of codes until consensus was reached. All three researchers then coded the remainder of the interviews and artifacts, spot checking each other's coding for accuracy by looking through a randomly selected 20% of all interviews and artifacts when a coder had completed the set. No major discrepancies in coding occurred in the second round of coding.

Quantitative analysis

Because our data did not meet conditions for normality, we used descriptive statistics and visualizations to make conjectures about teacher learning trends. Patterns in score changes were analyzed using visualizations.

Mixed methods analysis

Once qualitative and quantitative data were analyzed separately, the researchers organized all data sources sequentially in the DBR framework and examined trends and interactions sequentially. This allowed the researchers to qualify the quantitative data and quantify the qualitative data to look for coherence and divergence among the different types of data along the timeline of activities. For example, when we found a dip in self-efficacy scores for data practices, CT and SRL during Time 2, we returned to the interviews during that time to find why their self-efficacy was lowered. Conversely, when we read a unique passage in the interviews, we examined the scores to see if the quantitative data reflected that idea.

Findings

Data practices

As expected, high school science teachers were already familiar with the various data practices (Weintrop et al., 2016) although they did not initially use the vocabulary explicitly with their students. After Year 1 teachers began using the terms more explicitly with their students.

Informed Exploration phase (IEP)

According to the scores on the data practices knowledge and application assessment, teachers had knowledge of most data practices when they began the PD. Before the PD, teachers averaged 2.9 out of 4.0, with scores ranging from 1 to 4. After the PD, teachers averaged 3.8 out of 4.0 with scores ranging from 2 to 4. We believe that the average growth score of 0.93 out of 4.0 could be attributed to the teachers understanding the common terminology for data practices. Similarly, teacher interview results at the end of the IEP showed that teachers were familiar with create, collect, visualize, and analyze, but were less familiar with prepare, which was a trend found across the three years from the quantitative data. As stated by Eileen, “Collecting data takes time so sometimes we [teachers] give the students clean data.” Since teachers were giving students cleaned data, there was not a purpose for preparing the data. Figure 3 displays the teachers’ responses to the familiarity, use, and value of all data practices. Measures during times 1 and 2 occurred during the IEP.

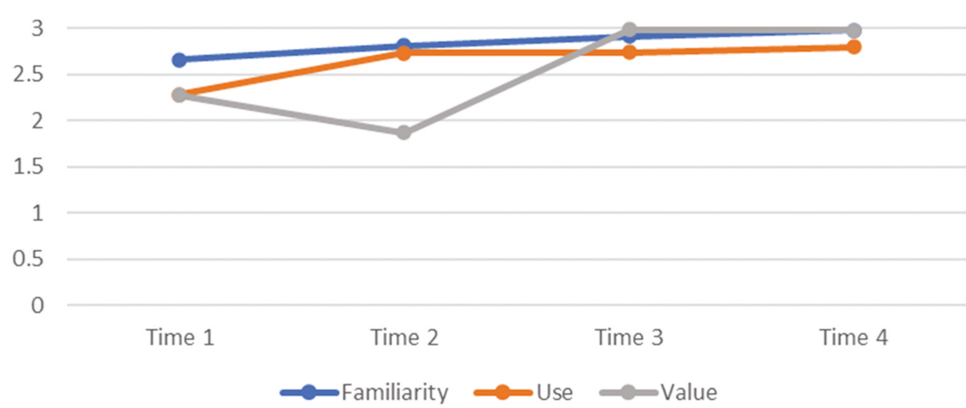

Figure 3. Average teacher familiarity, use, and value of data practices across the DBR phases.

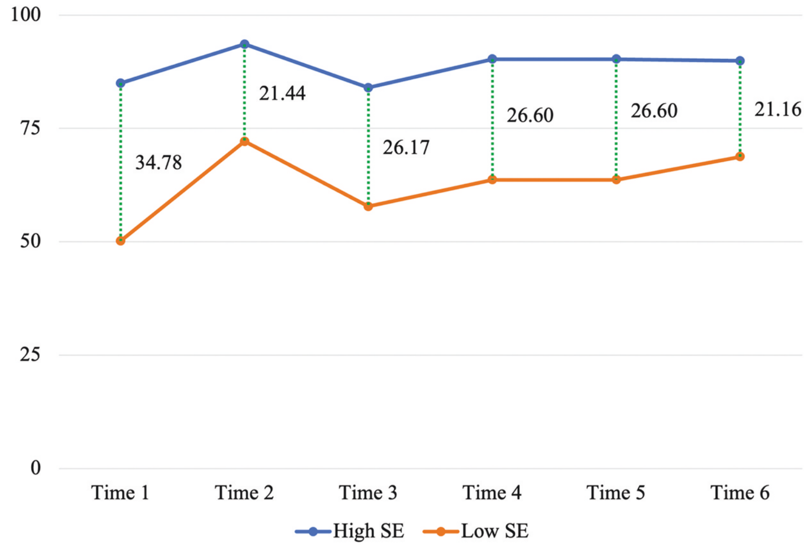

Figure 4. Average teacher upper and lower boundaries for self-efficacy of data practices across the DBR phases.

Notably, teachers' value of data practices dropped at the end of IEP, possibly because that simultaneously occurred with the beginning of COVID and the shift to teaching online.

During IEP, teachers noted in their interviews that they were not clear about the differences between create (designing the data collection) and collect (the act of collecting and monitoring data). This is exemplified in the self-efficacy scores reported by teachers during IEP (Times 1 and 2 in Figure 4). Teachers started with a lower self-efficacy score for their knowledge of data practices for both boundaries of their reported self-efficacy, which then increased at the end of IEP.

Enactment phase (EP)

By the end of the EP, teachers reported that not only were they using data practices in their classes more purposefully, they also were using the terms create, collect, visualize, and analyze. Kyle reported that the EP helped him to clarify what it is to create data,

> I think the biggest one that was new or kind of like a new thought about it was the creating the data aspect. I think that in a lot of my lessons, I have the students create the data, but I had never really thought about it in that way. The students are actually generating and creating their own data set that they are then going to use to analyze or visualize at the end.

Teachers' familiarity and use for data practices during EP maintained the same high levels that they had during IEP (Time 3 in Figure 3). Teachers' value for data practices increased during EP, and interviews indicated that when teachers shifted to online instruction, they had difficulty teaching students to do investigations with data. This instructional change demonstrated to teachers the importance of teaching with data in science. Sita noted,

> We need virtual labs where they can collect data [when we are teaching online]. And we can have these conversations [about data]. Because they're just analyzing a data set, or they're

> watching me collect, it's so hard. I think the big support we need is, if we're truly in this study with computational thinking and self-regulated learning focusing on data, we have to have support to know how it is we're going to get data for these students.

Elizabeth also noted "I think what was interesting was how the focus was different. Knowing that the data was perfect because it was virtual, . . . they were two different lenses."

During EP, the teachers' self-efficacy scores dipped slightly (Time 3 in Figure 4) but then raised to the IEP level (Time 4 in Figure 4), indicating that they initially had less self-efficacy for data practices during the implementation of the lessons than they did for planning the lessons.

Local Impact phase (LIP)

When lessons were converted to SPIN during LIP, teachers aligned their lessons explicitly to instruct students in all five data practices (a requirement in SPIN). A trend that was noted was that the data practice of prepare needed to be added or enhanced in the lessons for it to fit into the data practice tabs for SPIN. All of the other four data practices were well represented and consistent with the conceptual framework. This evidence indicates that although teachers knew about data preparation, they were not yet engaging students in the practice. As Miles stated, " . . . collecting and creating we tend to do a lot in terms of data practices; manipulating, we do sometimes, but more often we will visualize and analyze the data." Teachers' familiarity, use, and value for all of the data practices were maintained at the same high level (see Time 4 on Figure 3) and their self-efficacy boundaries for data practices also maintained at a high level (see Times 5 and 6 on Figure 4). The boundaries between high and low self-efficacy for data practices narrowed slightly as the DBR phases proceeded.

Computational thinking

CT was a newer content area for teachers and there were mixed perceptions related to its value and applicability throughout the project. Overall, teachers saw CT as important but challenging to integrate, especially during hybrid and online learning. Overall, they grew in their knowledge of and confidence of how CT might be integrated into high school science.

Informed Exploration phase (IEP)

Scores from the CT Knowledge and Application assessment before and after the IEP indicate that teachers improved their CT knowledge (1.9 out of 4 in the pretest, ranging from 1 to 3, and 3.1 out of 4 in the post test, ranging from 2 to 4). Similarly, teachers reported their familiarity with specific CT practices was minimal prior to the PD. Decomposition was the only practice that nearly half of the teachers felt familiar with at the beginning of the project.

ThatCT was new to the teachers was evident in their interviews, self-efficacy scores, and familiarity, use, and value scores. Teachers had the lowest scores for average familiarity, use, and value (1.95) compared with data practices (2.45) and SRL (2.25) and the lowest self-efficacy scores for CT (59.12 out of 100) compared with other content areas (66.30 for data practices and 62.09 for SRL). However, having experienced

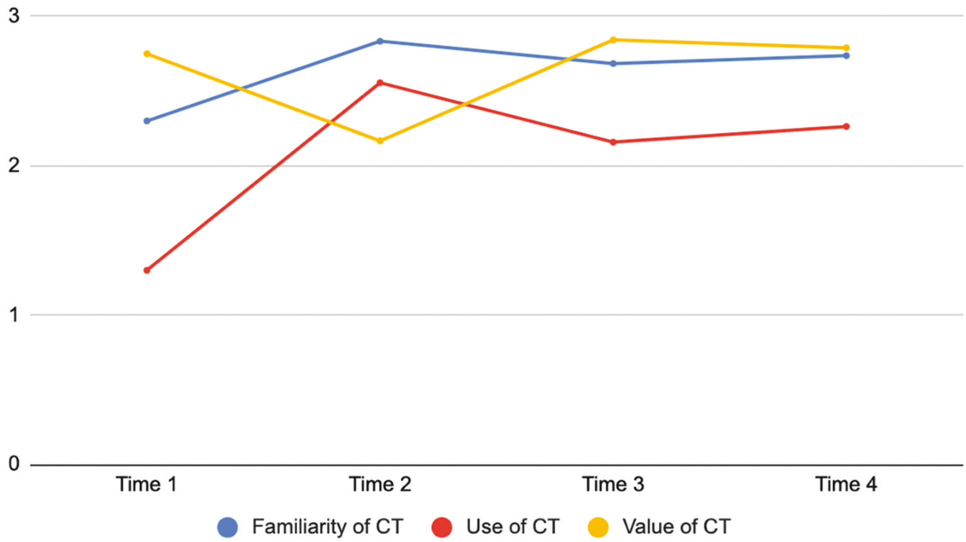

Figure 5. Average teacher familiarity, use, and value of CT across the DBR phases.

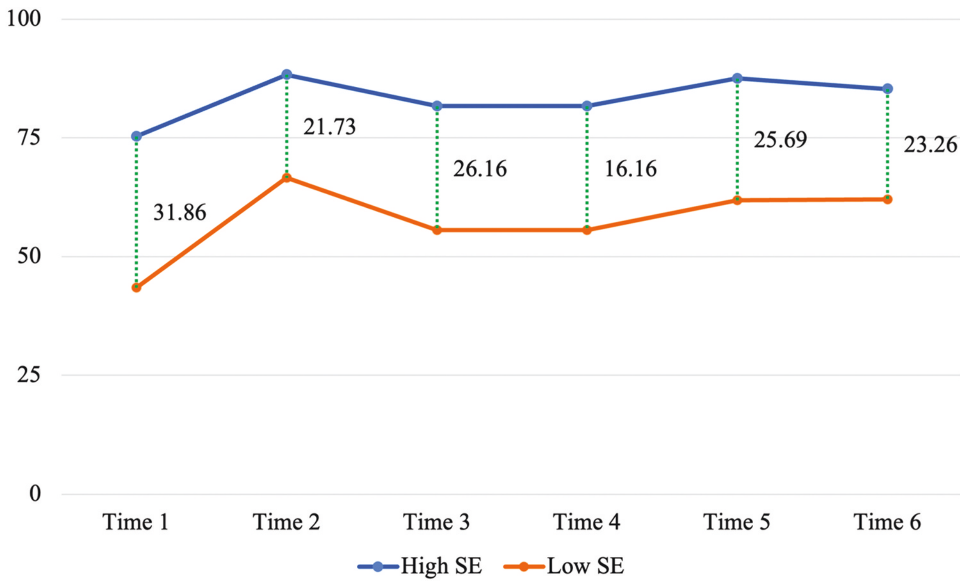

Figure 6. Average teacher upper and lower boundaries for self-efficacy of CT across the DBR phases.

the Year 1 PD opportunities, they quickly saw the importance of CT, as when Jace described, "the big takeaway for me from the computational thinking part was, this is, this is how, like, this is how smart people solve problems [. . .] how do we take this and turn it into the teaching of the, the practices." Their familiarity increased from a 2.3 to a 2.8, on a scale from 1 to 3 after IEP (see Times 1 and 2 in Figure 5). As familiarity with CT increased, so did self-efficacy for both upper and lower boundaries, as can be seen in Times 1 and 2 in Figure 6. Following the IEP, teachers felt comfortable with both decomposition and pattern-finding and were confident that they already promoted these practices in their lessons.

Enactment phase (EP)

The EP focused on continuing to build teacher knowledge while also working with teachers to design and implement lessons that incorporated CT into data practices. Self-efficacy for CT dipped slightly between Time 2 and Time 3 for both lower and upper reporting ranges, indicating slightly less self-efficacy for CT as they began to initially try out lessons and integrate CT within their classrooms (see Figure 6). As teachers shifted from planning lessons to actual implementation within their classrooms, they identified areas they wanted further support. For example, Carla, a biology teacher, reported,

> I think I've struggled to implement the algorithm and automation practices because I honestly don't really understand them very well myself. I hate to admit that this far along in the process. I don't really know what tools to use with students to implement the algorithm and automation practice.

This type of feedback was useful in providing further support to teachers throughout the EP.

During the EP, the COVID pandemic created an unprecedented shift in the teaching methods for all participants. While the teachers in this study continued to participate actively, their classrooms shifted to online or hybrid which impacted several perceptions related to CT. In the interviews, teachers discussed the challenges of trying to integrate CT with data practices and SRL in an online environment as well as the broader concerns about engaging their students. Jayla shared, "I've recognized [. . .] how challenging it [teaching CT] was to do this in a virtual environment and how important it is to get students to really engage with the data" and Zeke stated, "if you have them engage in the computational thinking if they're online, you're leading them up to a meltdown." In addition, teachers were less sure about their knowledge of abstraction and algorithmic thinking after EP.

Teachers keenly felt the importance of students thinking computationally but found it to be more challenging to incorporate outside of a traditional classroom learning environment. This was also evident in the data trends for familiarity, use, and value. As seen in Figure 5, teachers' value for CT increased while their frequency and utility for CT decreased. The main challenge discussed was lack of conversations and collaboration while online. Despite these struggles, teacher self-efficacy for CT remained consistent (Time 4 in Figure 6). By the end of the EP, students began to return to the classroom, and teachers' use of CT in their own lesson plans increased from 2.15 to 2.26 on a scale from 1 to 5.

Local Impact phase (LIP)

During LIP, teachers' lesson plans were transferred to SPIN and they had the opportunities to engage in these lessons as both teachers and students, exploring the potential issues and affordances of the software for supporting the instruction and integration of CT in small iterations. Overall, teachers' self-efficacy for CT continued to incrementally rise (see Figure 6, Times 4, 5, and 6) and familiarity, use, and value for CT practices were maintained at the same high level (see Time 4 on Figure 5) as they tested the tool. They began incorporating more abstraction and algorithmic thinking into the lessons, based on the lesson plan artifacts.

Self-regulated learning

Across the three phases of DBR, the teachers improved their understanding of the role of SRL in supporting data practices and CT during student investigations and indicated that they wanted more opportunities for students to self-regulate learning.

Informed Exploration phase (IEP)

The scores on the SRL knowledge and application assessment showed that the science teachers had some knowledge of SRL prior to the PD (1.8 out of 4.0, with scores ranging from 1 to 3). However, during the IEP, the teachers consistently reported that learning data practices and CT was a priority, as they could see the applicability in the classroom. SRL was not prioritized as a learning goal for the first year mainly because teachers were at capacity learning about data practices and CT and did not have any additional cognitive energy to take on another topic. For example, Elizabeth discussed her initial implementation of SRL in IEP,

> At this point, I don't think I've used it enough to have any kind of effect. Like it wasn't negative, it wasn't positive. And because I'm not sure if I had implemented it in the best way that it could have had an effect.

Even though the teachers did not prioritize SRL during IEP, their familiarity and use of SRL increased (as seen in Times 1 and 2 in Figure 7). Similar to teachers' value of data practices and CT, their value for SRL decreased in Time 2 when the classrooms started moving online. Regarding self-efficacy, teachers' scores markedly increased by the end of IEP in both lower and upper boundaries (Figure 8).

Enactment phase (EP)

The COVID pandemic changed teaching platforms in their school district from in-person to online or hybrid in the EP and the interviews at the end of the second year overwhelmingly indicated that teachers found SRL to be a higher priority than CT; however, they still held top priority for teaching data practices in their classrooms. Teachers reported

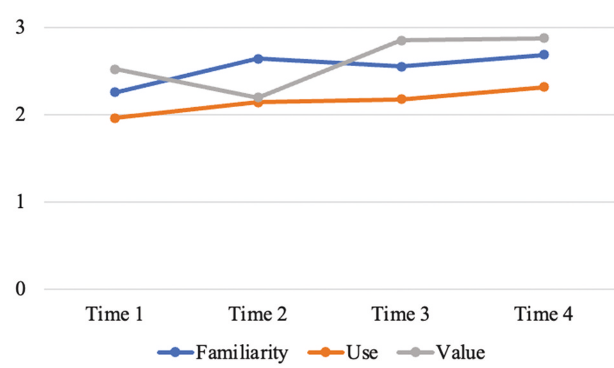

Figure 7. Average teacher familiarity, use, and value of SRL across the DBR phases.

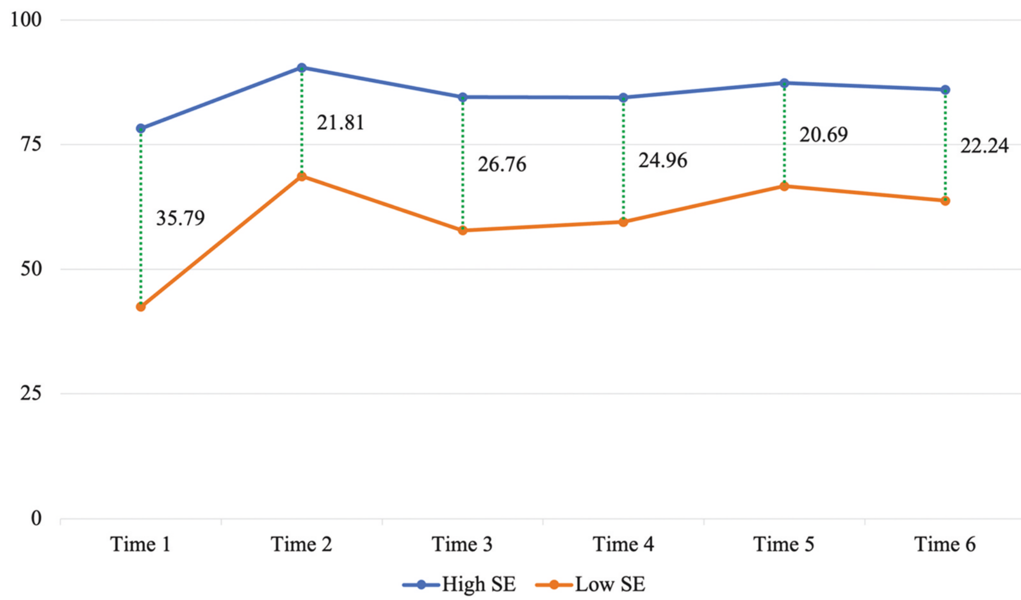

Figure 8. Average teacher upper and lower boundaries for self-efficacy of SRL across the DBR phases.

that they saw how important motivation and engagement were to learning when they were not with students in person. As Eileen stated, "I put more emphasis on [SRL] because that was something that I needed; I needed the kids to be better learners, better at managing their learning." Quantitative data also showed the increase in teachers' value of SRL, as seen in Time 3 in Figure 7.

When discussing how online and hybrid classes affected the implementation of SRL, teachers' responses showed a theme. For teachers who could foster their students' SRL skills to some extent before the pandemic, moving to online classes positively affected SRL implementation because online learning environments gave students more opportunities to practice what they have learned or opportunities to work more on their own. For teachers who did not foster SRL in their students before the pandemic or did not know the students in-person, the change negatively affected SRL implementation. Those teachers felt the need to foster SRL in students but said it was hard for them to do so in online classes. Interestingly, Lyla said that initially online learning positively affected the enactment of SRL due to the need for SRL, then negatively affected because students lost motivation for learning. She said that her students felt "it's Ok" not to try their best. Despite the divergence in teachers' perceptions of how online classes affected the implementation of SRL, overall, teachers' self-efficacy for SRL decreased and then roughly stayed the same in EP (Times 3 and 4, Figure 8) compared to the end of IEP (Time 2, Figure 8). Those changes might indicate that teachers faced some unexpected situations while implementing SRL in EP, which they were not aware of when planning the lessons in IEP.

Local Impact phase (LIP)

Teachers' familiarity, use, and value for SRL increased or maintained at the same high level (see Time 4 in Figure 7). Teachers' self-efficacy boundaries for SRL increased (Time 5 in Figure 8), then slightly decreased (Time 6 in Figure 8). The difference between upper and lower boundaries for self-efficacy of SRL narrowed across the DBR phases indicating teachers gained more confidence in supporting SRL for students whom teachers perceived as academically struggling students compared to the gain in supporting advanced or successful students. During the LIP, teachers noted they wanted more opportunities for students to reflect on their learning during the data practices in SPIN, indicating their value in seeking additional PD.

Integration of data practices, CT, and SRL

Examining how teachers integrated their learning about data practices, CT, and SRL gives insight into how teacher educators might go about designing PDs that have many different, yet integrated, components. We found three overarching findings across the DBR phases: (a) teachers felt that integrating three components was too much to take on initially, but using multiple examples of integration alleviated their concerns (b) contextual components such as type of learning platform can shift priorities of the teachers, and (c) collaboratively working toward a common educational product (SPIN) motivated teachers to continue the long-term PD.

Informed Exploration phase (IEP)

During the IEP, teachers noted that they could not integrate all three components and chose to learn how to integrate data practices and CT since these topics were most relevant to science. As Lyla stated,

> I think CT practices are not separate from data practices. CT uses student inquiry and investigations and apply their knowledge to solve problems and it also involves critical thinking, project-based learning, and it's basically identifies content related research question and then, which eventually needs to, it needs to do with data collection.

Enactment phase (EP)

During the EP interviews, 14 teachers reported that they understood how data practices, CT, and SRL were intertwined, but they needed extra support to integrate the three content areas. During this time, it was easier for the teachers to integrate CT with data practices than to integrate SRL with CT as evidenced in the lesson artifacts created during the EP. CT and data practices integrated: 2.43 out of 3 (range = 0.56); SRL and CT integrated: 1.92 out of 3 (range = 0.49).

Local Impact phase (LIP)

During LIP, teachers tested modular components of SPIN as they were being developed. The fragmentation of the development, while necessary, could have caused teachers to have difficulty understanding how the integration occurred in the online tool. However, when testing the completed beta version of SPIN, teachers were able to identify data practices, CT, and SRL as they were integrated in SPIN (see Figure 9). Teachers noted that when they

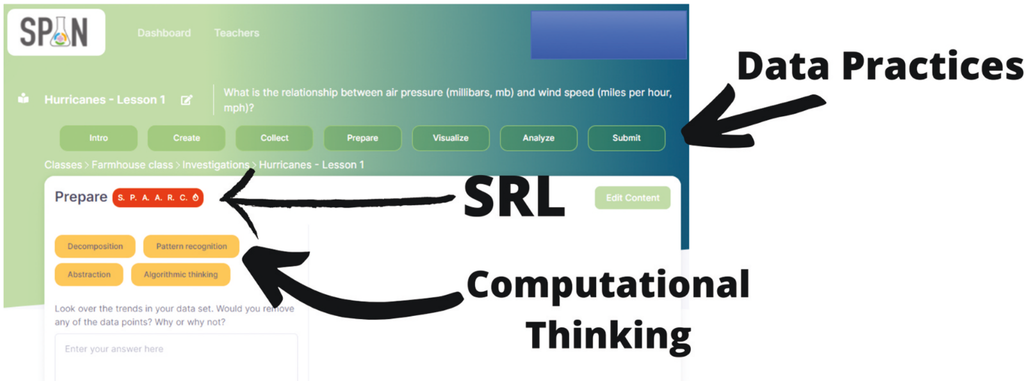

Figure 9. Screenshot of SPIN with data practices, CT, and SRL integration noted.

tested SPIN with students, the separation of each data practice with tabs in the notebook was helpful to teach students about data practices explicitly.

Discussion

The learning patterns of teachers demonstrated learning gains and maintenance in data practices, CT, and SRL over the three years of the DBR project, even when faced with challenges associated with the COVID pandemic. Similar to Bannan (2013), across ILDF phases, teacher learning became progressively more sophisticated, complex, and contextualized. DBR was used to design, implement, and broadly test an educational product, and the participating teachers persisted in the long-term PD because they were motivated to produce SPIN for use by other teachers. Evidence for their motivation lies in the features of SPIN that echo what has been documented in the literature related to data practices, which indicates that IEP is particularly effective in setting the stage for what teachers need in the PD. SPIN featured authentic learning scenarios, using real data sets, and engaged students with the entire cycle of data practices (Lesh et al., 2008; Newton, 2000). Additionally, it was found by Barton (1997) and Rogers (1997) that graphing technology helps students explore data easily and make meaning of data faster. Teachers incorporated features of CT and SRL that increased student support of visualizing data by helping students understand why they were creating graphs based on characteristics of the data set. Teachers also designed SPIN to help students use systematic approaches when they work with data, which was a need found by Kanari and Millar (2004) when they found that most students did not repeat measurements to check on their validity.

Engagement in DBR as PD also helped teachers incorporate more CT and SRL into their classroom cultures, as well as refining their already established data practices instruction, similar to the findings of Bannan et al. (2010). Because DBR used interactive cycles and multiple sources of feedback to track progress, the team was able to collaboratively converge on distinct definitions of CT used in the science classroom, as recommended by V. Barr and Stephenson (2011). The findings of this study confirmed the need for continuous CT PD in order to produce sustainable shifts in teachers' integration of CT (Ketelhut et al., 2020). Teachers had the lowest knowledge of CT at the beginning of the PD, but grew in knowledge and confidence for how to teach and integrate, as well as in their value of CT.

Teachers better understood how to foster SRL in students and value the roles of SRL in engaging with data practices across the three phases of DBR. By the end of LIP, teachers' familiarity, use, and value as well as self-efficacy of SRL increased. Even after three years of the PD, teachers wanted more opportunities for students to engage in SRL, showing their commitment to implementing SRL. As seen in multiple research studies, although short-term PDs can change teachers' perceptions, long-term PDs are needed for teachers to successfully implement SRL (Adler et al., 2019; S. Barr & Askell-Williams, 2020; Kramarski & Kohen, 2017; Kramarski & Michalsky, 2009, 2015; Lewis et al., 2011; Michalsky, 2012). This study corroborates those findings because teachers' perceptions about SRL increased from the IEP to the EP (short-term), their understanding of student support for SRL improved in the LIP (long-term), when teachers found SRL to be a higher priority than CT.

Implications, limitations, and future research

DBR as PD consists of several characteristics of effective PD for science teachers, given the findings of the learning patterns for the teachers. First, the PD was long term (Darling-Hammond et al., 2017; Loucks-Horsley et al., 2010; Luft & Hewson, 2014; Vescio et al., 2008). During the three years, teachers learned new concepts, enacted new instructional strategies, reflected on their practice, adjusted dynamic learning environments, and produced a web-based learning tool. Second, teachers had many opportunities to collaborate with other teachers, researchers, software developers, and students. A systematic literature review by Bancroft and Nyirenda (2020) showed most PD programs provide teachers with planned lessons instead of using teacher-authored lessons. The lack of teacher ownership might contribute to teachers not fully implementing intended learning experiences (Brown & Crippen, 2017). SPIN used teacher-authored lessons that gave teachers a sense of ownership but also facilitated the enactment of intended learning experiences. Because of the collaborative nature of DBR, the PD allowed for convergence on clear definitions of data practices, CT, and SRL for all stakeholders. By using CT and SRL as a means to support data practices, our PD proposed a systematic approach to implementing data practices that was co-created by educational researchers and teachers.

This study only examined the first three phases of DBR, and future work should take into account the entire process including whole class learning from the resulting instructional product. Additionally, future work could focus on DBR as PD in other contexts and with other stakeholders. Although this study provides initial information about how teacher high and low boundaries of self-efficacy for teaching diverse groups of students narrowed with continuous PD, more information about teacher ranges of self-efficacy for teaching different students is needed. This study also gives initial evidence that CT can be used as a means for learning other concepts. Future studies could examine how science teachers transfer what they have learned from using CT to support data practices to using CT to support student learning of other science practices.

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ORCID

Erin E. Peters-Burton http://orcid.org/0000-0003-1233-9119

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