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# The Design and Effects of Educational Data Science Workshops for Early Career Researchers

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## Abstract

We report on the design, development, implementation, research, and iteration of two educational data science (EDS) workshops focused on using R and RStudio for 44 doctoral students with limited and varied EDS backgrounds. Through qualitative and quantitative analysis of pre- and post-workshop surveys, we found that participants in EDS workshops are concerned and even fearful, yet possess relevant assets that come from a wide range of background experiences. Pedagogical factors—including being patient amidst errors, coding collaboratively, and explaining technical concepts in an accessible and rigorous manner—were strengths of the workshops, while the need for more time was a key possible improvement. Furthermore, participants' self-reported confidence grew from before to after the workshop. Based on our initial design, revisions, and research findings, we describe five formative design guidelines for educational data science workshops that address doctoral students' goals and needs. In total, this work implies that well-designed workshops and short courses can offer opportunities for a wide range of educational researchers to extend their expertise with newer methods to carry out impactful work—in turn shaping the emerging EDS field.


**Keywords** Educational data science · Workshops · Short courses · Formative design guidelines · Situated learning · Self-directed learning

Today, there are more data than ever in the field of education. These data have emerged from a variety of sources, including the increased use of learning management systems across education (Krumm et al., 2018) and the proliferation of opportunities for distance and online education, both before and during the COVID-19 pandemic (Williamson et al., 2020). Furthermore, the amount of data in education is likely to keep increasing, at unprecedented rates, as artificial intelligence (AI) tools continue to be introduced to various learning environments (Selwyn et al., 2020). The vast amount of data in education has been reflected in the rapid rise of new fields of study in the past decade, including learning analytics and educational data mining (Krumm et al., 2018; Papamitsiou & Economides, 2014; Romero & Ventura, 2020).

Massive quantities of data are produced as educational technologies and technology-supported learning environments collect logged and stored records of learners' activity and interactions, called *digital traces*. These digital traces are data that can offer researchers opportunities to study social behavior at an unprecedented scale (Welser et al., 2008) by providing "comprehensive pictures of both individual and group behavior" (Lazer et al., 2009, p. 721) and "a moment-by-moment picture of interactions over extended periods of time" (p. 722).

Despite the ready availability of these data and the noted possibilities of what they could help educational researchers and practitioners understand, it is unclear who knows what to do with all these data. This remains true even as the emergent field of Educational Data Science (EDS) grows rapidly. Following McFarland and colleagues' (2021) conceptualization, here we define EDS as a broad set of applications to address educational issues using *novel* methods to make sense of *novel* data. Examples of *educational issues* include teaching, learning, and other processes in education. Examples of *novel methods* include computational (i.e., quantitative) approaches such as machine

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learning, natural language processing, learning analytics, and artificial intelligence. Examples of *novel data* include those captured by a learning management system or an online learning environment and are often collected in raw, unstructured formats.

Widespread and growing interest notwithstanding, there remain numerous barriers to accessing the skills and norms of EDS that educational researchers have not yet overcome. To start, fundamental ethical concerns must be navigated (Daniel, 2019; Greenhalgh et al., 2020). Numerous studies have raised concerns about consent in data mining research, starting with whether "participants" are even aware that their activity is being tracked and documented through the collection of digital traces (Fiesler & Proferes, 2018; Ifenthaler & Schumacher, 2016). These ethical questions are not easily addressed, and researchers must carefully weigh and seek a balance between oppositional values of open scientific inquiry and an individual's right to privacy (Rosenberg & Staudt Willet, 2021).

In addition to ethical concerns, access to educational data is far from fair and equitable, considering personal and cultural as well as political (i.e., how decisions are made and who they benefit) considerations (Daniel, 2019; Lee et al., 2021). First, educators and educational researchers likely experience varying availability of technologies such as computers with sufficient processing power, specialized software, internet access, and even webcams for online training. Second, access to educational data is often restricted for privacy reasons by educational agencies, such as data from the National Assessment of Educational Progress (National Center for Education Statistics, 2022). Third, educational researchers may have limited awareness of opportunities for training and learning experiences related to EDS—this may depend strongly on an individual's *social capital*, that is, what resources are available through their social connections.

Even when ethical issues are settled and access to data is obtained, the novel forms and vast quantities of data create additional barriers to entry into EDS. To start, large amounts of data can create challenges in conceptualizing the scale and scope (Daniel, 2019). Furthermore, new tools are required to handle the collection and analysis of data a large scale (Daniel, 2019; Mayer-Schönberger, 2015). The increased power of these tools has also increased the difficulty of learning how to use them well. For instance, Slater et al. (2017), in their software review of tools for educational data mining, noted the differences in *usability* between a ubiquitous tool like Microsoft Excel—excellent for smaller-scale projects—and more advanced, niche tools like Python and SQL that can aid work with larger scale datasets. Excel is relatively easy to learn to use but cannot work with large-scale data. In contrast, Python and SQL can handle massive datasets but are much more challenging for beginners to learn to use. In addition, Slater et al. (2017) reported numerous ways to analyze educational data, from foundational approaches to statistical modeling and visualization to more advanced learning analytics applications such as Bayesian knowledge tracing, text mining, probabilistic topic modeling, social network analysis, and process mining, to name a few. These novel forms of analysis can be remarkably sophisticated but are complex to understand and adopt.

EDS training and instruction are paramount with these many considerations in mind. Educational researchers—especially those lacking formal training in statistics, computer science, or data science—need a scaffolded approach to navigate the many, and growing number of, EDS tools and ethical questions. As McFarland et al. (2021) concluded in their historical retrospective of data science's intersection with education, the starting place for EDS research is to center on the well-being of learners and participants, following a Hippocratic Oath-like mandate to do no harm. Data are not abstract or neutral; they represent the activity and experiences of real people, no matter the scale at which they are collected. A humanistic approach, advanced by Lee et al. (2021) for K-12 learners, could be useful for the design and provision of learning opportunities for professionals. EDS training can serve as an entry point for educational researchers to acquire skills, knowledge, and practices common to data science and science, technology, engineering, and mathematics (STEM) fields. Then, in turn, learner-centered educational researchers may begin to influence the norms and practices of EDS.

The purpose of the present study was to explore the design and effects of data science workshops for educational researchers and establish guidelines for the formative design of future EDS workshops. Workshops are a useful setting in which to study EDS learning opportunities because they are a type of non-traditional or informal learning environment that may provide opportunities for educational researchers to overcome initial barriers and develop EDS skills (Feldon et al., 2017; Word, 2017). We designed and facilitated data science workshops for doctoral students (i.e., early career researchers) with limited and varied EDS backgrounds. We asked participants to self-report their experiences in the workshops as well as their perceptions of the effects of the workshops. In this process, we explored how participants' backgrounds and past experiences can help them to learn about (and to do) EDS, what specific barriers they encounter, what has helped them overcome those barriers, and what factors can make EDS workshops more or less effective for overcoming barriers and acquiring skills. We used this data from participants as grist to iterate on our initial workshop design and implementation in a second workshop. Last, we used this data to generate formative recommendations for the design of workshops that meet participants' needs and aims.

## Background

### Educational Data Mining, Learning Analytics, and Educational Data Science

For a range of educational stakeholders (e.g., administrators, educational leaders, educators, researchers, and analysts), data have long been a part of their work. What may be different now are the types and quantity of the data sources being generated by teachers and learners within educational systems (Fischer et al., 2020). For instance, learning management systems record what students submit as well as what they post in forums and even what web pages they access (and for how long) within the system. Furthermore, the range of methodological approaches available not only to researchers and analysts (Estrellado et al., 2020; Krumm et al., 2018) but also to educators (Estrellado, 2022) has motivated the development of new domains of practice and disciplines for research. Three of the most prominent currently are the educational data mining (Baker et al., 2016), learning analytics (Lang et al., 2022), and EDS (McFarland et al., 2021) communities. Within these communities, many methodological approaches are used, including machine learning, social network analysis, and natural language processing. These communities have differences—for instance, a greater focus on data from digital learning platforms (e.g., intelligent tutoring systems) in the educational data mining community relative to the learning analytics community. However, they share a focus on using *computational research methods*—that is, using computers and the powers of computation for research (Salganik, 2019).

Our focus in this paper is how the computational research methods of EDS can be taught to and learned by educational researchers. These researchers likely have a strong foundation in other methodologies, including advanced qualitative or quantitative methods, but may be newer to using newer computational methods, many of which involve or require users to code (i.e., do computer programming).

Other fields, such as statistics, have previously considered the role of computation in the curriculum. Statisticians and statistics educators have argued that *computers and computation* invite (or require) a rethinking of the traditional curriculum. In a key paper, Nolan and Temple Lang (2010) called for six topics—including advanced computing (e.g., using high-performance computing) and statistical computing (e.g., using R and R packages)—that historically had not been the emphasis of statistics education to be included in modern curricula. Scholars since have expanded on this call, increasingly emphasizing tools such as R and Python to teach specific skills like machine learning and reproducible research methods (Hardin et al., 2015; Horton & Hardin, 2021; Schwab-McCoy et al., 2021).

The role of computation has not been the focus of statistics educators alone, but also scholars within the purview of educational research. One locus of this research has been the educational activities of researchers who use computational and data science methods in their work. For instance, learning analytics researchers have developed educational programs to support others using learning analytics research methods (Kizilcec & Davis, 2022). Furthermore, the Society for Learning Analytics Research (SoLAR) often hosts workshops,[1] webinars,[2] and a summer institute[3] on learning analytics methods, from foundational approaches (e.g., processing data with R[4]) to advanced (Bayesian Knowledge Tracing[5]). Other conferences, including the American Educational Research Association (AERA), have hosted a range of workshops and webinars[6] related to research methods, many involving the use of the R programming language.

Despite these many educational initiatives, there is a notable gap in related research. This means there is limited information on the effectiveness or recommendations to guide the design of learning opportunities for professionals working in education—a gap we aim to address in this study. In sum, there have been abundant educational and training opportunities for educational researchers to learn about computational methods, but there is very limited related research. To start, we next review what is known about the effects of workshops in general.

### Effects of Workshops

We define *workshops* as one-off, relatively brief professional development and learning opportunities. We distinguish workshops from longer-term professional development programs, noting that duration has been consistently identified as a feature of effective professional development for educators (Desimone, 2009). However, despite the value of ongoing and long-term professional learning opportunities, it is not always feasible for teachers—or researchers—to engage in long-term offerings or participate in an open-ended learning community. We distinguish between workshops and longer-duration *coding boot camps*, programs that are sustained for a limited period but can span months, or at least

[1] https://www.solaresearch.org/events/lak/lak23/pre-conference-schedule/

[2] https://www.solaresearch.org/community/webinars/

[3] https://www.solaresearch.org/events/lasi/

[4] https://www.solaresearch.org/events/lak/lak22/pre-conference-schedule/

[5] https://www.solaresearch.org/events/lak/lak21/pre-conference-schedule/

[6] https://www.aera.net/Professional-Opportunities-Funding/AERA-Professional-Development-and-Training

several days to a few weeks (Feldon et al., 2017; Thayer & Ko, 2017). Far from denying the value of opportunities with sustained duration, we acknowledge that such programs are likely more beneficial to participants. Instead, here we aim to focus on the ubiquitous workshops offered to teachers, researchers, and other professionals that last between one-half of 1 day and 2 days in length. We focus on short workshops because these may be especially valuable when there are few instructors specialized in the domain, when learners do not have the time to commit to a longer-term offering, or when a rapidly growing domain (e.g., one that does not yet have widely available courses) begins to develop (Word, 2017). Thus, we aim to document the benefit and drawbacks of shorter offerings, especially in the nascent educational data mining, learning analytics, and EDS domains.

The best evidence of the effects of brief workshops comes from investigating whether or not they have any appreciable effect on participants. For instance, Feldon et al. (2017) conducted an experimental study of the effects of workshops and boot camps (specifically, pre-Ph.D. "bridge" programs) on students in the first year of a life sciences Ph.D. degree. The experiment compared Ph.D. students who participated in a workshop in the summer before the first year of their programs to those who participated the summer after. Collectively, the programs targeted scholarly development, including data analysis, writing, and understanding the discipline. Approximately 50 of 300 undergraduates had participated in one of several programs (workshops or boot camps), and no changes were identified across a range of survey and performance assessment (based on writing samples submitted by participants) outcomes. Feldon et al. (2017) concluded that these findings raise questions about the continued support (and funding) for such workshops or bootcamps—given the reported null findings.

This study (Feldon et al., 2017) provoked a response (Word, 2017) from The Carpentries, an organization that has provided many such workshops. The Carpentries is a non-profit that has provided over 1300 workshops focused on research computing (e.g., data processing, analysis, and modeling using statistical software and programming languages) to more than 37,000 learners (Sane & Becker, 2018). They draw on educational and psychological research findings to evaluate the effects of their workshops and design 2-day trainings for instructors (Sane & Becker, 2018). They have documented the positive impacts of their workshops (Jordan et al., 2017), including long-term, follow-up evaluations of outcomes amenable to valid and reliable self-reports, including programming usage and confidence using programming tools (Jordan et al., 2017). The Carpentries responded to the Feldon et al. (2017) study in a constructively critical manner, arguing that workshops can be effective when they target specific outcomes (e.g., a workshop on data analysis, rather than research skills broadly construed) that are assessed individually by specific programs (Word, 2017). Furthermore, workshop outcomes should be considered in terms of their type and timing—that is, when they might realistically be achieved by Ph.D. students. For instance, a workshop may not plausibly impact the quality of students' writing-for-publication, but it may bolster students' ability to confidently analyze the data used in a scholarly article. They concluded:

> For those of us who work within the short course mandate, then, the question becomes: how can we optimize that format to best meet learners' needs? When setting goals for impact, we tend to think in terms of how much and what type of impact we can have, and to focus our efforts accordingly (Word, 2017, p. 9).

## Conceptual Framework and Workshop Design

In our own practice of developing and refining 22 workshops led by one or both of the two authors, we have blended situated and self-directed perspectives in the evolving workshop design. A *situated* perspective views learning as an apprenticeship embedded in a community of practice, where knowledge and skills are developed while increasing participation and belonging in the community (Lave & Wenger, 1991). Adding situated learning to our workshop design has meant providing opportunities for participants to engage directly with the practices of the profession, with the goal of beginning to see themselves as members of the EDS community. Specifically, we have facilitated opportunities to learn the norms of EDS, observe demonstrations of writing code in R to analyze real educational data, and practice adapting the code to produce new outcomes.

A *self-directed* perspective is rooted in adult learning (Knowles, 1975) and emphasizes how learners take ownership of their learning goals, purposes, and processes (Louws et al., 2017). Self-directed learning is evident with learners seeking immediately applicable information to solve problems (Blaschke, 2012). Adding self-directed learning to our workshop design meant assigning pre- and post-workshop tasks such as figuring out how to download and access R on the participant's computer before arriving at the workshop and asking meaningful questions in the appropriate web forums after the workshop concluded. We provided opportunities for self-directed learning during the workshop time as our facilitation style has evolved to follow a pattern of introducing a new concept, demonstrating R code to achieve a result, and then having participants try to adapt the code to achieve a different result. By assigning intermittent, independent practice, participants have had to try different strategies for navigating recommended resources and asking for help. After each cycle through this pattern, we brought the whole group back together to discuss and reflect.

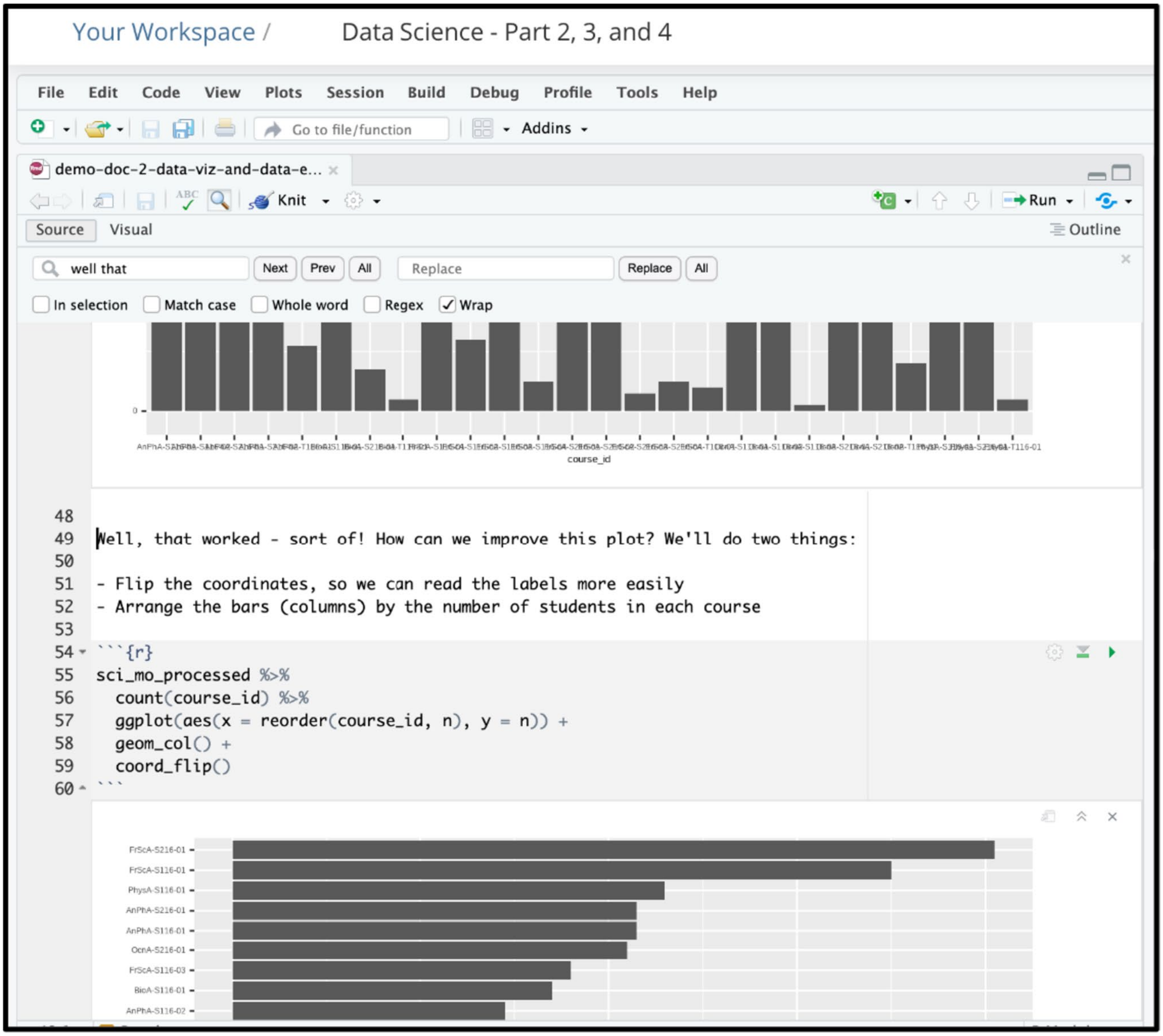


**Fig. 1** Participants' view of the R markdown document in RStudio Cloud

We used the platform RStudio Cloud, a web-based interface for the statistical software and programming language R. We set up the RStudio Cloud "workspace" in advance of facilitating a workshop, sharing a template with participants, who had only to create a username and password to log in. The benefit of this approach has been that no installation of software is required by participants, meaning they can start running code within seconds of logging in. In the RStudio Cloud workspace, an R Markdown document (Fig. 1) was the primary area where workshop participants worked, both independently and as a group.

The EDS workshops we designed, revised, and facilitated have included both situated and self-directed perspectives on learning, exemplified by the "Tech Support Cheat Sheet" illustration (Fig. 2; Munroe, n.d.) from the XKCD webcomic. Although this flowchart is light-hearted and humorous, we have referenced it often as we designed and revised the workshop agenda, and we typically share the comic with participants during the welcome and introduction to the workshop. The flowchart highlights both the situated and self-directed aspects of learning data science by emphasizing the project-based and problem-solving orientation of the workshop as well as the importance of knowing where, when, and how to seek help. However, handing this comic to someone new to EDS—without explanation—would likely be off-putting and, in the end, would not situate them in a community of practice or prepare them to self-direct their learning. Instead of an impersonal handoff, our evolving workshop design has afforded human connection by placing us in overlapping roles of facilitator, coach, mentor, friend, and cheerleader.

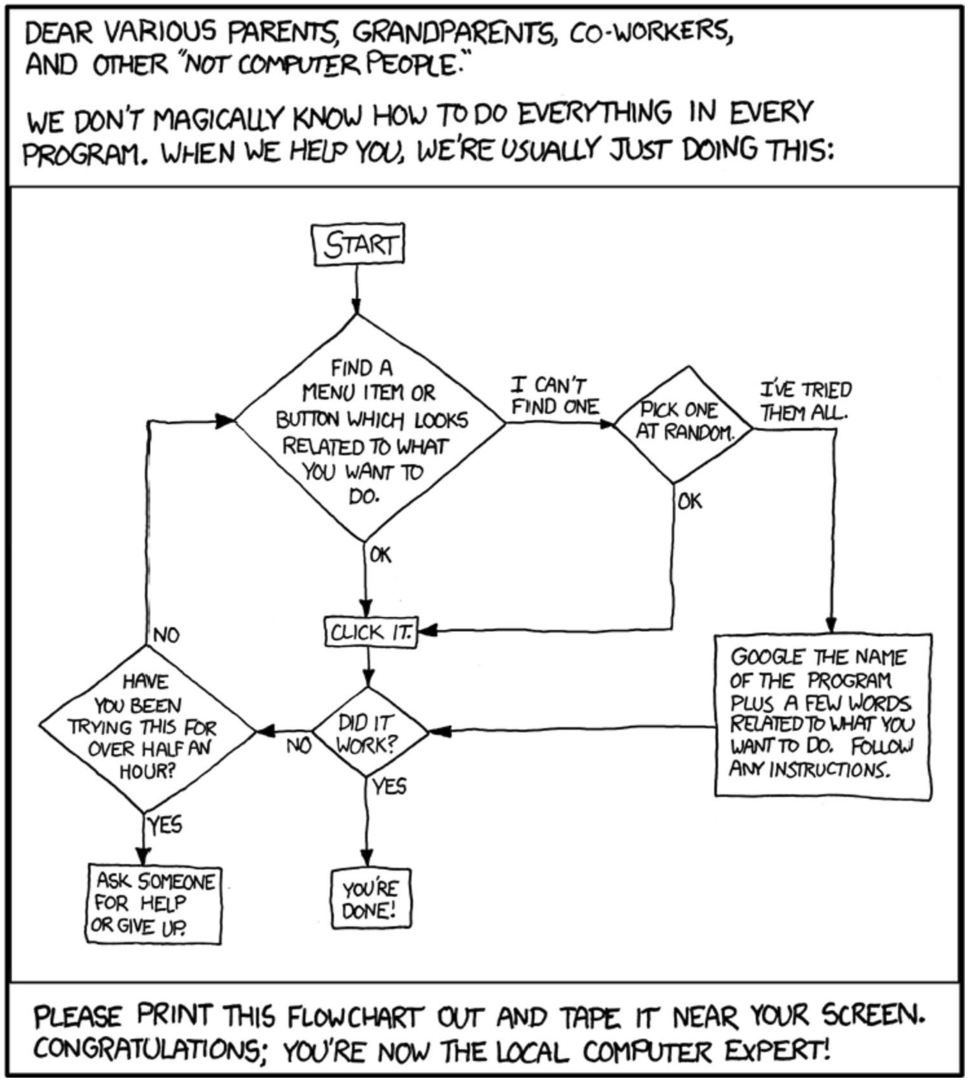


**Fig. 2** Tech support cheat sheet (Munroe, n.d.)

## Purpose and Research Questions

The purpose of this study was to explore the design and effects of data science workshops for educational researchers and establish guidelines for the formative design of future EDS workshops. We have been engaged in efforts over multiple years to support newcomers to develop the skills of computational research methods for EDS, and we have refined both workshop materials and the principles that guide them. Our goal in this manuscript is to describe concretely what we have done in the past (through 22 workshops involving one or both of the two authors) and what we have changed based on lessons learned. We seek to answer two questions through design-based research:

- *RQ #1:* How do educational researchers in a doctoral program situate themselves concerning data science?
- *RQ #2:* How did the design of the workshop help educational researchers overcome barriers to doing data science?

We explore the first research question in terms of software, professional experiences, intimidation, and reasons for participating. We explore the second research question in terms of strengths and areas for improvement for the workshop and the effects of the workshop on participants' confidence concerning working with data and computational research methods.

## Method

### Context

The context for the study was two 1-day workshops for doctoral students in education at a small-sized, regional University in the Southeastern USA. The doctoral program was hybrid (Bell et al., 2014), meaning that students participated in a residency during the Summer term and took online courses during the Spring and Fall semesters.

**Table 1** Study measures and associated survey questions

| | Measure | Question type | Pre- or Post-Workshop Survey |
|---|---|---|---|
| Measures for the 2020 workshop | Frequency of use of various tools | Fixed response | Pre |
| | Motivation for attending | Fixed response | Pre |
| | Perception of the workshop | Likert-type | Post |
| | Perspectives, skills, and confidence | Likert-type | Pre and Post |
| | How the instructor affected the experience | Open-ended | Post |
| Measures added for the 2021 workshop | Interest in specific skills and techniques | Likert-type | Pre |
| | Prior experience with data analysis | Open-ended | Pre |
| | Concerns about the workshop | Open-ended | Pre |
| | Strengths of the session | Open-ended | Post |
| | Ways the session could be improved | Open-ended | Post |
| | Demographic questions (field of study, professional role, gender, and self-identified race or ethnicity) | Fixed response | Pre |

The EDS workshops were embedded within a week-long summer residency for doctoral students. We characterize these learning experiences as workshops because they stood apart from the rest of the week's curriculum and activities—there were no explicit connections across the days of the workshop. The workshops took place during the Summer academic term, one in 2020 and one in 2021. Although the workshop was designed to be face-to-face, the COVID-19 pandemic caused the residency to shift to an online mode both summers. For both workshops, participants were assigned pre-work before the workshop.

The curriculum of both workshops had four primary components: getting set up and comfortable using R/RStudio, data visualization, regression modeling, and text analysis. Because the workshops were around 8 h long, introductions to (rather than in-depth treatments of) each of these topics were provided. At the end of the workshop time, resources for additional learning were shared and discussed.

## Participants

Participants were 44 doctoral students—27 in the 2020 workshop and 17 in 2021. All participants worked full-time in education in roles such as teachers (e.g., 8th-grade math teacher, associate professor of English; $n=33$), administrators (e.g., middle school principal, assistant principal for instruction; $n=6$), and instructional support staff (e.g., instructional coach, speech-language pathologist; $n=5$). Thirty-two identified as White, six as Black or African American, one as Asian, and five who indicated they preferred not to answer. Thirty-five were women, five were men, and four indicated they preferred not to answer.

## Measures and Data Sources

We adapted measures from existing, validated surveys for scientific computing (e.g., programming, analyzing data) workshops from The Carpentries project. Specifically, we adapted their Pre-Workshop (The Carpentries, 2022a) and Post-Workshop Surveys (The Carpentries, 2022b). For the initial workshop in 2020, we collected data on five measures (Table 1) through survey questionnaires. We selected these measures because of the crucial role of motivation and confidence for researchers new to using computing techniques and tools. We selected these measures considering the need for input on the design of the workshop and how participants' initial reasons for participating aligned with it. We were interested in disentangling design-related effects from those related to the specific instructor of the workshops. For the 2021 workshop, we adapted the previous survey questions in only minor ways (e.g., changing "instructor or helper" to "instructor"), retaining the meaning and nature of each question. To the existing questions, we added six additional measures and associated survey questions for the 2021 workshop (Table 1). The full surveys are included in the Supplementary Materials.

## Procedure

Approximately 1 week before each workshop, we sent participants a welcome email, which included a link to the Pre-Workshop Survey. The coordinator of the residency program sent a reminder to participants to encourage them to participate. Immediately following the workshop, the Post-Workshop Survey was administered. Each survey was estimated to take around five minutes to complete. We conducted the same research procedure in both years. After the first year, we made several changes to the design of the workshop based on the formative feedback that participants provided before and after the first offering. Specifically, based on feedback from year one's participants, we created a pre-workshop task that introduced participants to R, RStudio, and data science. At the start of the workshop in the second year (i.e., 2021), we reviewed the pre-workshop background learning materials, and this change allowed us to focus more of the time during the workshop on discussing applications and use cases for data science methods in education.

## Data Analysis

### Data Analysis for RQ #1

To analyze data for the first research question on how educational researchers in a doctoral program situate themselves concerning data science, we conducted several analyses.

To understand the reasons for participating in the workshop, we calculated the number of participants who selected each of the six reasons (and one option for other reasons) that were included in the survey from The Carpentries' Pre-Workshop Survey (The Carpentries, 2022a). An example reason is "To learn new skills." We report these numbers by year (i.e., Year 1, Year 2) and combined.

To understand participants' backgrounds, we carried out a thematic qualitative analysis (Saldaña, 2011) of participants' responses to the item, "Please describe what prior experience you have analyzing data." We entered the responses into a spreadsheet and both authors open-coded the responses for the key elements of participants' responses. We then discussed our open codes to create a set of codes and definitions that represented the nature and variation in our open codes about participants' backgrounds. Examples of these codes included "Degree related to data science" and "Work experience related to data science." We then coded all of the responses independently; an individual response could receive any number of codes depending on its contents. After independent coding, we met to discuss disagreements. We resolved our disagreements and updated the code definitions to better reflect the dataset. This process of refinement resulted in a smaller set of three codes that we then used to independently recode all of the responses. We then met again to discuss and resolve all discrepancies, resulting in one or more codes being assigned to each response.

We present our findings for this coding through the codes, descriptions, and their frequencies by the year of the workshop and overall and through illustrating each code with example responses.

In addition to the qualitative item related to participants' backgrounds, we coded another item on participants' sources of intimidation. Specifically, we coded the responses to the question, "What concerns do you have (or what challenges do you anticipate that you will have) about analyzing data?". We conducted a similar coding process to the one used for participants' backgrounds: open coding the responses, developing an initial set of codes and independently using them to code all of the responses, meeting to discuss disagreements and revise the coding frame, independently coding the responses with the smaller set of (for this item, two) codes, resolving disagreements, and presenting the findings through counts and examples.

### Data Analysis for RQ #2

To analyze the data for the second research question on how the design of the workshop helped educational researchers overcome barriers to doing data science, we carried out descriptive quantitative and qualitative analyses.

To understand the effects of the workshop, we examined changes between pre-workshop and post-workshop in participants' self-reports about two capabilities: being able to troubleshoot and their confidence in analyzing data. Specifically, we analyzed the responses to identical items administered in both the pre- and post-survey. Then, to facilitate the understanding of pre-post changes, we created visualizations with error bars of the mean pre- and post-workshop levels of these constructs.

We conducted thematic qualitative analysis (Saldaña, 2011) of responses, following the same procedure detailed in the previous section, "Data Analysis for RQ #1," to two additional open-ended questions related to the strengths of the workshop and areas for improvement. Toohe prompt regarding strengths was, "Please list the major strengths of this session." The prompt regarding areas for improvement was, "Please list the ways the session could be improved." We again analyzed these responses using a similar thematic coding process to the one used to code participants' backgrounds and sources of intimidation (see the third paragraph of the Data Analysis for RQ #1 section for details).

## Positionality

Our analyses (quantitative and qualitative) can be interpreted in light of our positionality as researchers. First, we recognize our experience leading workshops such as those we studied. The two authors have facilitated many workshops, a total of 22 between the two of us over the past 5 years. In addition, both authors have taught courses on learning analytics and EDS, and the first author has taught at a federally funded research institute on data science methods. These experiences build our credibility in terms of our

**Table 2** Reasons for participating

| Reason | Year 1 *n* (%) | Year 2 *n* (%) | Combined *n* (%) |
|---|---|---|---|
| As a requirement for my degree program or current position | 23 (85.2) | 14 (82.4) | 37 (84.1) |
| To learn new skills | 24 (88.9) | 10 (58.8) | 34 (77.3) |
| To learn skills that I can apply to my current work | 22 (81.5) | 11 (64.7) | 33 (75.0) |
| To learn skills that I can apply to my work in the future | 20 (74.1) | 12 (70.6) | 32 (72.7) |
| To refresh or review my skills | 8 (29.6) | 4 (23.5) | 12 (27.3) |
| To learn skills that will help me get a job or a promotion | 8 (29.6) | 1 (5.9) | 9 (20.5) |

ability to understand the experiences of participants in workshops across many contexts (and at many points over time). This has a bearing on our interpretation of these findings, which we consider on their own empirically, as well as in the broader context of our and others' experiences leading workshops. Lastly, we note that both authors have conducted many qualitative and quantitative analyses, seeing value in both thematic coding for qualitative analysis and advanced quantitative methods. This informs how we make sense of both qualitative and quantitative findings, balancing both in the present study. We leverage our experience with coding qualitative data together on past projects, leveraging our familiarity with each other and our ability to communicate and share norms to facilitate the coding.

## Findings

### RQ #1: How Do Educational Researchers in a Doctoral Program Situate Themselves with Respect to Data Science?

First, we present the reasons participants indicated for participating in the workshop (Table 2) as the number of percentages of responses coded with different qualitative codes (reasons). We observe that most participants indicated that this was a requirement for their degree program (84.1%) and an opportunity to learn new skills (77.3%) that can be applied in one's current work (75.0%) and in the future (72.7%). These findings were generally comparable across years, although we note that more participants in Year 1 indicated participation reasons related to learning new skills (88.9% compared to 58.8%) and learning skills that will help them get a job or a promotion (29.6% versus 5.9%).

**Table 3** Background of participants

| Code | Year 1 *n* (%) | Year 2 *n* (%) | Overall *n* (%) |
|---|---|---|---|
| Prior degree | 17 (63.0) | 9 (52.9) | 26 (59.1) |
| Work experience | 19 (70.4) | 6 (35.3) | 25 (56.8) |
| Data analytics and data science teaching experience | 4 (14.8) | 1 (5.9) | 5 (11.4) |

Through our qualitative analysis of participants' backgrounds (Table 3), we found that 59.1% of participants indicated that their prior degree was relevant to doing data science. These prior degrees ranged from those highly relevant to EDS (e.g., "Mathematical Sciences, with an emphasis in Statistics" and "computer science") to those less directly relevant (e.g., "general science"). Many participants noted that they had exposure to data analysis through their present (doctoral) degree programs, and more than half (56.8%) indicated that their work experience, including their analysis of data as teachers or administrators, was relevant. Many participants mentioned teaching as a way their experience relates to EDS. For instance, one participant who noted that most of their experience with data analysis was through their doctoral program commented, "I do small bits of analysis all the time to inform my teaching." Another participant noted, "I regularly analyze test data to guide my instruction, group students, and fill gaps for my students." A smaller number (11.4%) indicated that they taught data analytics or data science at the K-12 or undergraduate level. For instance, one teacher reported, "I currently teach 8th-grade math and the data analysis standards only include up to linear regression."

As the findings in Table 3 suggest, these prior experiences with and connections to EDS were commonplace, but not universal. For instance, one teacher noted their lack of prior experience, explaining "I have very little experience analyzing data." They continued, "Most times others will analyze the data and then tell me what needs to be done as a result of the data."

Regarding sources of intimidation (Table 4), most participants (84.1%) indicated that technical factors were the most concerning. One participant stated this poignantly: "I really do not understand the statistical stuff. I might as well be reading Russian." Another participant noted, "It really freaks me out. I am not strong at math or with numbers. I do not feel confident talking about data or statistics." Even when

**Table 4** Sources of intimidation for participants

| Code | Year 1 *n* (%) | Year 2 *n* (%) | Overall *n* (%) |
|---|---|---|---|
| Technical factors | 22 (81.5) | 15 (88.2) | 37 (84.1) |
| Social factors | 1 (3.7) | 2 (11.8) | 3 (6.8) |

**Table 5** Changes in key outcomes

| Item | Year 1 M (*SD*) | | Year 2 M (*SD*) | | Overall *M* (*SD*) | |
|---|---|---|---|---|---|---|
| | Pre- | Post- | Pre- | Post- | Pre- | Post- |
| Confidently work with data | 3.58 (0.35) | 4.76 (0.25) | 2.67 (0.21) | 4.33 (0.26) | 3.35 (0.32) | 4.65 (0.25) |
| Overcome getting stuck | 5.41 (0.25) | 5.17 (0.30) | 4.67 (0.14) | 5.83 (0.17) | 5.21 (0.23) | 5.34 (0.28) |

expressed with less emotional weight, many participants still voiced concerns about data science, coding, and the associated technologies. Concern about using R was common; for instance, one participant explained, “Some of the programs, such as R, are a little intimidating. I usually can find my way through, but it takes several trials.” Another participant had experience with a different programming language but still commented, “I have tried coding before, just messing around, and I am definitely not a natural, so R is very intimidating to me.” Others, including those with substantial prior experience related to data science, expressed concerns with making sense of the data: “What if you interpret it wrong?” Another noted the challenge of analyzing data in a new context—and doing what they described as *true* data analysis: “Although having two degrees in mathematics-related fields, my experience with true data analysis is limited. As a classroom teacher, I analyze student data regularly, but rarely (really, never) with advanced statistical analysis.” Participants often used the word “fear.” For instance, one participant shared, “I am fearful I will not have enough time to fully understand the programming.”

A much smaller percentage (6.8%) indicated that social factors were a source of intimidation. For instance, social comparison seemed like a significant concern, with one participant worrying, “That I am up to speed with the rest of the class.” and another writing, “I am not confident in my abilities in this subject matter and do not want to put that on display for others.”

## RQ #2: How Did the Design of the Workshop Help Educational Researchers Overcome Barriers to Doing Data Science?

Our quantitative analysis of participants’ confidence in overcoming getting stuck and confidently working with data, measured by pre-post survey items, revealed that participants grew in confidence working with data through the workshop (Table 5). Across both years, the mean increase in confidence was 1.30 on the seven-point Likert-type scale. There was not a meaningful change in overcoming getting stuck, with an overall increase of approximately 0.13 on the seven-point Likert-type scale. We note that these values are only for students who completed both the pre- and post-survey and could be matched with a unique, anonymous key: 17 participants in Year 1 and six students in Year 2, for a total of 23 participants.

Qualitative analysis of workshop strengths (Table 6) showed that participants particularly appreciated pedagogical factors (65.9% of participants overall). One key pedagogical factor was coding as a group. One participant explained, “It was helpful to practice what we were doing together so we could ask questions of each other. I also really appreciated when you explained what the code was saying [by] reading it out loud.” Another participant noted, “Being able to work through together with different commands was beneficial.” Participants named additional strengths such as the instructor’s patience (e.g., “[The instructor] was very knowledgeable, patient, and flexible. He was able to adjust to meet the needs of the group.”) and tolerance of mistakes (e.g., “The laid back approach and the realistic way [the instructor] handled errors put me more at ease with R.”). One participant provided a detailed explanation of how the instructor’s facilitation was a strength:

> [The instructor] gave copious amounts of information and was able to explain it in layman’s terms when necessary. [The instructor] explained specific vocabulary terms as well as coding so that we knew what the data meant. [The instructor] made a “bunch of numbers” actually mean something. Although, I didn’t understand many things, [the instructor] stayed positive and never made me feel less intelligent.

Some participants in Year 1 (22.2%) named the software (R, RStudio, the web-based RStudio Cloud platform) as a strength of the workshop, but none of the Year 2 participants shared this appreciation.

Qualitative analysis showed that the most common suggested improvements for the workshop (Table 7) included adding pre-workshop work (22.7%) and changing the modality—that is, changing the online workshop to an in-person format (20.5%). Time issues (11.4%), clearer instructions (11.4%), and more opportunities to make meaning of the output generated (11.4%) were suggested as additional improvements. One

**Table 6** Strengths of the workshop

| Code | Year 1 *n* (%) | Year 2 *n* (%) | Overall *n* (%) |
|---|---|---|---|
| Pedagogical factors | 20 (74.1) | 9 (52.9) | 29 (65.9) |
| Software | 6 (22.2) | 0 (0.0) | 6 (13.6) |

**Table 7** Suggested improvements for the workshop

| Code | Year 1 *n* (%) | Year 2 *n* (%) | Overall *n* (%) |
|---|---|---|---|
| Pre-work | 8 (29.6) | 2 (11.8) | 10 (22.7) |
| Modality | 1 (3.7) | 8 (47.1) | 9 (20.5) |
| Meaning making | 3 (11.1) | 3 (17.7) | 6 (13.6) |
| Instructions | 5 (18.5) | 0 (0.0) | 5 (11.4) |
| Time Issues | 4 (14.8) | 1 (5.9) | 5 (11.4) |

participant summarized the need for more time: "It seemed like a lot of information for one day. I may have been able to mentally process it better if it had been broken up throughout our week."

## Discussion

The purpose of this study was to explore the design and effects of data science workshops for educational researchers and establish guidelines for the formative design of future EDS workshops. The following sections discuss key findings from this study in light of the literature and then note the implications of these findings for practice and research.

### Key Findings: Lessons Learned from EDS Workshops

The first research question asked how doctoral students (i.e., early career researchers) situate themselves concerning data science. Results show that participants are likely to be concerned and even fearful about the experience of learning EDS (Table 4)—similar to past research reporting experiences of professional development for new technological knowledge (Carlson & Gadio, 2002; Daniel, 2019)—even while they possess resources from their prior degrees, work experience, and substantive teaching experience (Table 3). These resources include experiences that participants, instructional designers, and instructors can each draw upon to increase the likelihood that participants will have a confidence-building experience that extends their capabilities.

Often, participants in this study reported being intimidated and fearful because of the technologies involved in doing EDS (Table 4)—technologies that are very different from the ubiquitous spreadsheet tools that have been and continue to be commonplace in educational research and other social sciences (Daniel, 2019; Slater et al., 2017). Programming tools are ubiquitous in data science-related educational research projects and data analyses, but participants mentioned that these tools are often a source of anxiety because of their unfamiliarity and perceptions that they are challenging for novices to use. Knowing this is important for researchers and providers of EDS workshops because it means that educational researchers are likely to have a different starting point—and, subsequently, require different motivation (Daniel, 2019)—than individuals in fields for which programming tools have been more commonplace, like statistics or physics. Hazzan and Mike (2023) found similar challenges among K-12 teachers preparing to teach data science, concluding that training must attend to technological knowledge (e.g., working in Python worksheets to practice data science) in addition to content and pedagogical knowledge.

Although anxious, participants in this study were not likely to start doing data science without *any* prior experience (Table 3). The novel methods and novel data sources that comprise two-thirds of McFarland et al.'s (2021) definition of EDS can thus be made more accessible by leveraging the knowledge that participants from education backgrounds are likely to have in the remaining one-third: educational issues. This suggests, too, that researchers and providers of EDS workshops should not assume that fearful participants completely lack a background in programming and data science tools: many do, but the different (educational research) context and the use of these tools to conduct what one participant referred to as "true data analysis" can be a scaffold to support participants. This finding is in alignment with recommendations for EDS-related *courses*—namely, that such learning experiences "include practical quantitative elements" and that they emphasize the relevance of the ideas and skills for individuals from a wide variety of backgrounds (Kizilcec & Davis, 2022). Another way this work aligns with such recommendations is by making materials open-access; all of the workshop materials used in this study are available via public GitHub repositories.[7]

Another key finding in this study is that participants reported growing through the workshops (Table 5) primarily due to pedagogical factors (Table 6). The design and implementation of the workshop were not carried out with wholly new strategies or approaches; instead, the workshops were designed, revised, and updated with situated and self-directed perspectives of learning in mind. This was reflected in a focus to help participants to gain confidence to be able to work to address and solve issues that arise when they independently conduct an analysis. We took pedagogical actions (e.g., expressing patience when errors by participants or instructors alike arose) and made decisions (e.g., using RStudio Cloud to avoid needing to muddle through software installation and navigate compatibility issues) to help participants have a positive initial exposure to EDS. While the instructors of EDS workshops and other learning experiences are likely considering both how to meet learners' needs as well as present EDS in a veridical manner (e.g., Rosenberg & Jones, 2022), participants in this

[7] https://github.com/jrosen48/data-sci-workshops-doc-students.

study reported that using pedagogical practices that make EDS accessible was a strength of the workshops (Table 6). Similar pedagogical factors that emphasize rigor and present a meaningful selection of data science skills while avoiding "talking down" to participants are likely to be a key for early career researchers (e.g., doctoral students) interested in learning EDS.

This key finding contributes to ongoing debates about the utility of workshops and other learning experiences for professionals that are relatively limited in duration (e.g., Feldon et al., 2017; Word, 2017). In this present work, results show how pedagogical factors helped participants to have positive experiences—experiences associated with gains in self-reported confidence in analyzing data (Table 5), suggesting that thoughtfully designed EDS workshops can be effective in meeting the targeted aim of making the domain more accessible to participants from a wide range of backgrounds. This approach offered low-stakes opportunities for workshop participants to engage in *legitimate peripheral participation* (Lave & Wenger, 1991) as they first enter and explore an EDS community of practice—learning skills as well as what it means to *be* and to *identify as* an educational data scientist.

## Formative Design Guidelines for Educational Data Science Workshops

The key findings described in the previous section—stated in terms of lessons learned from designing and updating EDS workshops—can be coalesced to form several guidelines for formative design. Understanding which specific elements of workshops for professionals interested in EDS are effective could offer useful insights to the designers and instructors of other such workshops and short courses. Feldon et al.'s (2017) study on the *absence* of effectiveness of workshops in achieving their stated aims raises questions about how—and whether—such brief learning experiences can matter. Nevertheless, the current study's findings align with Word's (2017) conclusions: workshops can be optimized for specific learning outcomes because they can be designed to meet participants where they are in terms of their experience and career stage. In the following paragraphs, we discuss implications for practice in terms of five emergent formative design guidelines that could help EDS workshops achieve the learning objective of increasing learners' confidence.

### Formative Design Guideline #1: Tailor EDS Workshops to Participants' Backgrounds

A first formative design guideline for EDS workshops is increasing learners' confidence, because this may indicate that significant barriers of learners' fearfulness and anxiety about EDS have begun to be overcome. Our experiences of designing, revising, and updating many EDS workshops over the years, and specifically the key findings from this study, have increased our emphasis on tailoring each workshop to its participants—and further adapting the learning design in the moment when needed. This guideline is bolstered by the low confidence some participants expressed at the outset of the workshops relative to at the end (Table 4) and similar experiences of technological intimidation expressed in past research (Carlson & Gadio, 2002; Daniel, 2019). Therefore, an implication of this study is to carefully tailor EDS workshops to participants' backgrounds (Fernández-Batanero et al., 2022)—especially by considering the resources that participants already possess. It is important to not over- or under-estimate how much participants know prior to a workshop. Educational researchers likely do not know as many EDS techniques (e.g., coding) as statisticians, but neither are they likely to be completely unprepared. Designers and facilitators of workshops should consider what can realistically be achieved within the limitation of a short time period, given the experiences and skills of participants—and focus narrowly on those elements. Thus, starting with participants' backgrounds, contexts, and interests can make EDS more accessible and can convey that EDS is not confined to isolated technical skills, but, rather, putting these skills into practice in complex and dynamic contexts that necessitate questions of how and for what purposes data are being used. In this way, workshop design could reinforce the self-directed learning principle of matching the difficulty of learning with learner readiness (Francom, 2010).

### Formative Design Guideline #2: Use Familiar, Educational Data Sources Rather Than Generic Ones

A second formative design guideline is to design, revise, and update workshops with participants in mind by using data that are already familiar to them, at least initially. For example, classroom data, including formative or summative assessments of students, would provide excellent workshop examples (Chikasanda et al., 2013). Familiar data may be key for making EDS more accessible to participants given the relatively low confidence our participants reported at the outset of the workshops: familiar data may present an access point (Table 4). This approach aligns with calls for a *humanistic*—rather than a solely technical—approach to data science education, a perspective that emphasizes the cultural, political, and personal bearings upon data analysis (Lee et al., 2021). These cultural, political, and personal factors likely matter at least as much, if not more, in education—a domain with cultural and political interests intertwined with the personal motivations and characteristics of teachers and learners—as in any other discipline.

### Formative Design Guideline #3: Emphasize the Relevance of Data Science to Participants' Research or Work

A third formative design guideline is to emphasize the relevance of EDS to workshop participants (Plair, 2008). Although many participants are likely to be interested in and motivated to learn data science because it could help with their research, others are likely to participate because it is required of them—as past research (Carlson & Gadio, 2002; Daniel, 2019; Gee, 2005) and our results showed (Table 2). These multiple purposes for participating in the workshop tie into the importance of the workshop design being flexible enough to accommodate the motivations of different learners. We designed the workshops to incorporate both situated and self-directed perspectives on learning. The *situated* perspective highlights how EDS is done by professionals working to solve real problems encountered by teachers and learners—emphasizing that doctoral students (i.e., early career researchers) are able to begin to engage in the work of and develop identities as educational data scientists (Lave & Wenger, 1991). The *self-directed* approach emphasizes that workshops can help participants make progress on the problems that matter most to them, even while the workshops are intended to serve only as a starting point for ongoing, independent learning (Francom, 2010; Louws et al., 2017). Using data familiar to participants (Formative Design Guideline #2) should help reinforce the relevance of EDS to participants (Chikasanda et al., 2013).

### Formative Design Guideline #4: Use a Set of Pedagogical Practices That Emphasize Support and Encouragement

A fourth formative design guideline is having a supportive set of pedagogical practices that emphasize support and encouragement—even more important to participants in this study than introducing and using EDS tools like R and RStudio (Table 6). Across many EDS contexts, more development and further research into tools for learning and doing data science are still needed (McNamara, 2018; Pimentel et al., 2022). There are likely tools that offer the capabilities of R and RStudio in an easier-to-use (and easier-to-learn) format, although, at present, simpler offerings may not support participants in carrying out the analyses they need or want to use for their research. Supportive pedagogical practices—especially those that emphasize the challenge of learning to program—seem to be especially important for the novice programmers who participated in these workshops. Encouragement and acceptance of coding errors were consistently mentioned as key practices by participants. These findings from the present study follow recommendations for improving technological knowledge from past research, such as ongoing support and feedback (Chikasanda et al., 2013; Fernández-Batanero et al., 2022; Plair, 2008).

### Formative Design Guideline #5: Balance Introduction of New Ideas with Opportunities to Practice

Last, a fifth formative design guideline is to design activities that balance introducing new ideas and techniques and providing opportunities for participants to immediately apply ideas (Chikasanda et al., 2013; Fernández-Batanero et al., 2022). Concretely, workshop activities should include multiple opportunities to practice using EDS techniques: (a) the brief introduction of new ideas through a presentation or demonstration of code, (b) an opportunity for participants to practice coding in a guided manner (e.g., through the instructor writing and running code, and then asking participants to do the same on their own), and (c) creating opportunities for participants to write and run code in a more independent manner (e.g., through starting with example code snippets and having participants use with new data or make small modifications to the code). Including some or all of these opportunities to practice EDS techniques can work in concert with supportive pedagogical practices (Formative Design Guideline #4) to meet participants' needs. Even if workshop participants cannot be expected to become fully proficient with many features of the R software and R Markdown documents, showing what can be done with the software can open participants' imaginations so that they will learn later how to accomplish tasks (Fig. 2) like creating complex, aesthetically appealing visualizations and conducting text and social network analysis. Providing such opportunities for immediate application also reinforces self-directed learning principles of practice (Francom, 2010) and immediately applicable information (Blaschke, 2012). Using RStudio Cloud—which does not require participants to download software or R packages—can also allow early and frequent practice of the data science skills at the core of the workshops.

## Limitations and Implications for Future Research

This study has several noteworthy limitations, namely a modest sample size and data collection that was focused on a very brief period of two short workshops for doctoral students. A larger sample of participants would provide benefits in terms of offering greater variation in participants' qualitative reports—and the potential for identifying common themes in participants' responses in a more generalizable manner. Despite these concerns, in the context of this study, the varied professional and demographic backgrounds of the participants are a strength. Additionally, data collection at a time far after the conclusion of the workshop—3 or 6 months, for instance, or longer still—would provide insight into the extent to which the observed changes in confidence are ongoing and sustained, demonstrating changed behavior in and tangible results for participants (Kirkpatrick &

Kirkpatrick, 2006). This longitudinal direction for future research would offer an opportunity to assess the degree to which workshops—with properly defined learning outcomes—meet their aims.

Although workshops are commonplace across educational research disciplines, empirical studies investigating workshops are far less common. Particularly considering ongoing initiatives to fund workshops in the use of newer computational methods and data sources (e.g., Institute for Education Sciences, 2022), the need for rigorous, creative research and evaluation of trainings remains. The present research is the first such study of a data science-related workshop for educational researchers, and the need for further work will likely increase with greater interest in applying data science, machine learning, and artificial intelligence techniques in educational research contexts.

To conclude, who learns EDS—who sees themselves as educational data scientists—matters because applying data science methods can equip educational researchers to answer new questions and address pressing educational challenges. However, progress will be hindered if EDS capabilities accrue only to a few researchers fortunate enough to be trained during graduate programs or through their social connections. Well-designed workshops and short courses can offer opportunities for a wide range of educational researchers to expand and extend their expertise with newer methods to carry out impactful work—in turn shaping the emerging field of EDS in a more accessible and democratic manner.

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## Declarations

**Conflict of Interest** The authors declare no competing interests.

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