Laying Foundations for Scalable Coaching for Data Storytelling: An Evidence-Centered Design Approach

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Abstract

As demand for data scientists has increased to inform decision-making across multiple fields of societal importance, postsecondary institutions have expanded data science course offerings. Despite such growth, educators struggle to teach students all the skills central to data science. They focus on programming and statistical tools and lack time for mentoring students in data storytelling. This working paper reviewed literature and interviewed experts to model the domain knowledge of data storytelling to inform the design of intelligent technology to support data storytelling instruction at scale. The paper closes with a recommendation of two ways that artificial intelligence tools can support the development of students' data storytelling knowledge and skills: "direct" feedback to students on routine data science tasks and "facilitated" summaries of students' data story progress to inform instructors' feedback. We intend to apply these insights to the design of intelligent coaching in an online platform to support the development of storytelling competency at scale.

CCS Concepts

• **Human-centered computing → Interaction design**.

Keywords

data storytelling, AI technology, evidence-centered design

ACM Reference Format:
Louise Yarnall, Hui Yang, Sophia Ouyang, and Lujie K. Chen. 2025. Laying Foundations for Scalable Coaching for Data Storytelling: An Evidence-Centered Design Approach. In *Proceedings of the Twelfth ACM Conference on Learning @ Scale (L@S '25), July 21–23, 2025, Palermo, Italy*. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3698205.3733928

1 Introduction

In business, government, medicine, military, and scientific contexts, decision-makers increasingly rely on data scientists to convert data insights into action [1, 6, 9, 14, 33]. To serve this role, data scientists need to engage in "data storytelling" practices that focus on communicating data findings effectively and accurately to inform solutions to societal and business problems [2, 12, 16, 29]. College educators find it difficult to develop students' data storytelling skills within courses already straining to cover the required technical and statistical competencies [4, 12, 15, 21, 24]. To address this challenge, learning scientists and data scientists partnered to develop and test a new web-based data storytelling application called Story Studio. To establish the foundation for this scalable learning technology, this paper presents the literature review and expert insights that have informed the development of a working domain model of data storytelling knowledge and skills. This working paper concludes with the initial approach to designing interactive queries, automated formative feedback, and learning analytics to support scalable learning and teaching of data storytelling.

L@S '25, Palermo, Italy

ACM ISBN 979-8-4007-1291-3/2025/07
https://doi.org/10.1145/3698205.3733928

2 Theoretical literature

Recent research integrating artificial intelligence (AI) into the data storytelling process [19, 23] identifies AI as potentially helpful for encouraging learners to engage in the kind of playful, iterative re-framing of problems useful in ill-structured domains [25]. Such visions draw on cognitive apprenticeship [5] from learning science, an approach that emphasizes the importance of providing learners with interactive supports, or "scaffolding" that fades as learners become more proficient. To achieve this vision, researchers can define a domain model of the knowledge and skills of data storytelling that breaks down storytelling development into a series of well-defined subproblems with clear problem-solving rules. For example, AI can provide background knowledge on demand, story exemplars and templates, and criteria to evaluate the accuracy of data interpretations, the comprehensibility of data visualizations, and the coherence of data stories. Sociocultural learning theorists have identified various challenges to AI-based coaching in education. They question the lack of real-world context of AI-based coaching, citing its limited integration of human mentoring, its reliance on predefined models and formulas, and its references to culturally biased underlying data [3, 31]. Keeping in mind both the promise and the cautions around leveraging AI technology to support data storytelling education at scale, we focus in this working paper on delineating the component storytelling knowledge and skills based on literature and expert interviews, and then lay out the roles and interactions for using AI technology to expand the capacity for college educators to teach data storytelling [8].

3 Instructional literature

Data storytelling standards and practices at both post-secondary and K-12 levels clarify the complexity of these skills. To develop them, post-secondary education experts recommend giving students repeated opportunities to use and consume oral, written, and visual communication modes with a variety of audiences [7, 30]. At the K-12 level, recommended instructional strategies draw on social-constructivist theory, which underscores the importance of providing experiences to engage learners in sense-making, visualization, data modeling, and communication processes [18, 27] and using datasets connected to students' interests and prior knowledge [22]. To define the knowledge and skills to be developed in college data science courses, our research team aimed to answer the following research questions:

RQ1. What are the distinct types of data storytelling skills that need to be learned by students?

RQ2. What challenges, instructional strategies, and helpful supports do instructors and students report around data storytelling?

RQ3. How can artificial intelligence tools support student learning of data storytelling?

4 Methods

We have employed an evidence-centered design approach to domain modeling [28, 38] to develop initial design patterns (DPs) that document in a structured way the knowledge, skills, and abilities (KSAs) that students need to learn. Design patterns document observable behaviors of competent performance, task features that elicit evidence of skills, and rubrics. We also sought to document common instructional challenges and coaching strategies. Design pattern development begins with scans of relevant literature; in this case, this scan was intended to quickly establish domain rapport with experts. We sampled literature from the 1990s through 2023, focusing on "data science," "education," and "instructional tools." Based on the analysis of the literature, we developed three DPs: DP1. Understand Audience and Communication Goals [21, 26, 32, 36]; DP2. Generate and Annotate Data [10, 11, 17, 20]; and DP3. Construct Data Story [30, 35, 39] (for abbreviated overview, see Figure 1). Next, drawing from small scale, in-depth expert judging practices used to validate content [13], the team purposively recruited and interviewed 5 post-secondary subject matter experts (SMEs) with experience teaching data storytelling in both academic and business contexts (one data storytelling expert and book author, two experts with industry and classroom teaching backgrounds, and two college-level instructors from a liberal arts college and community college) and 8 students reflecting a range of college contexts (6 from a 4-year research university and 2 from a 2-year college) and undergraduate levels (2 seniors, 3 juniors, 3 sophomores). Researchers interviewed both SMEs and students via Zoom for 45 to 60 minutes.

5 Data collection and analysis

Grounded in a qualitative thematic analysis approach [34], two education researchers collaboratively analyzed the transcribed interview data using an iterative coding process. The researchers independently conducted initial open coding on both SME and student interview transcripts to identify preliminary codes related to student needs in coaching and assessing data storytelling (e.g., learning to pose questions that guide exploration of a dataset, analyzing one or more datasets, gathering and applying additional knowledge about data, developing data stories, etc.). They then met to compare codes, resolve discrepancies, and refine the codes and categories, ensuring consistency and inter-coder agreement. They used axial coding [37] to group related codes into broader themes, map insights across the SME interviews, identify areas where students needed support, and refine and assess the focal KSAs within each of the three data storytelling design patterns. The team eschewed the use of formal rating metrics (e.g., kappas) since the primary goal was to rapidly elicit common instructional challenges and practical, actionable coaching strategies that experts used to develop such skills. The same analytic approach was applied to the student interview data, with researchers focusing on reported challenges, successful strategies, and students' suggestions for helpful intelligent supports. Themes from both datasets were then synthesized through focused coding to develop a consolidated inventory of desired AI-driven coaching supports for data storytelling projects. This is described in the results section.

6 Preliminary Findings

The experts endorsed the three design patterns as capturing the core knowledge and skills (See Figure 1), and confirmed having limited time to coach students around data storytelling.

In addition, experts emphasized differences in time, tools, and iteration for data storytelling in college courses and professional contexts. For example, one expert noted that real-world data scientists and analysts often need considerable time to understand what questions datasets can answer. This is a foundational data storytelling process that often takes more iterations in the professional context than is possible in a college course. Similarly, professionals have more time and tools to analyze data, while students work within the limitations of available software tools and the time required to learn them.

To cope, instructors simplify datasets and phase in different levels of difficulty. Instructors described how they scaffold students to handle increasingly difficult data science and storytelling tasks. For example, they described gradually expanding the types of statistical analyses, shifting students from working with cleaned to raw datasets, and increasing the difficulty of the communication tasks from accurately interpreting data to conveying messages for different audiences. See summary of basic versus advanced instruction in Table 1.

Despite such approaches, students described feeling overwhelmed. Students ranged from two who had little formal data science education or experience to those who studied programming and statistics. While students consumed journalistic media or participated in the visual and performing arts, few saw themselves primarily as storytellers. They sought guidance on what analyses to conduct, visualizations to use, and stories to tell. Both 4-year and 2-year students reported challenges related to all three DPs. For example, posing questions to be answered by the data (DP1) seemed easy at first, but once analysis (DP2) began, they encountered problems focusing

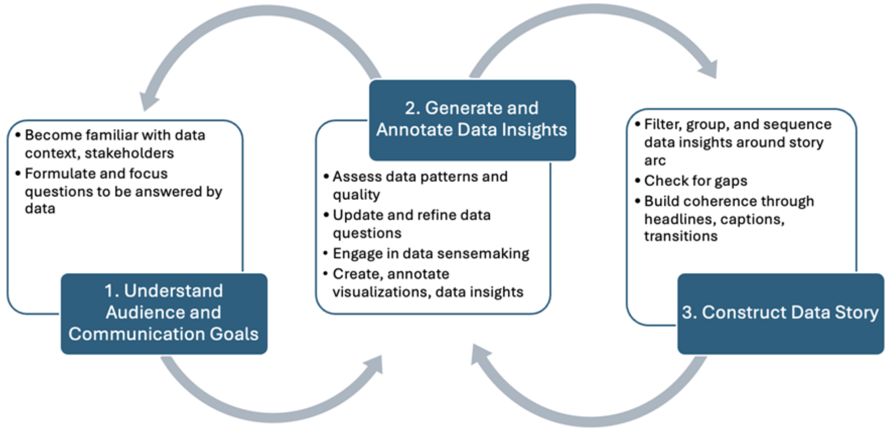

Figure 1: ***Data Storytelling Design Patterns***

their questions and developing clear answers. In some cases, these challenges stemmed from being overwhelmed by too many paths for data exploration. One student described having more questions than she could answer. In others, challenges emerged from a lack of familiarity with the real-world context of the data.

As students moved deeper into data analysis (DP2), they expressed concerns about dataset limitations, selecting analytic and visualization approaches, and executing programming and statistical procedures. When datasets lacked desired variables, students needed coaching support to shift their analytic approach. They wanted stepwise guidance and tips on programming syntax and visualization options.

When constructing their data stories (DP3), some students expressed enjoyment of the presentation process, but most described struggles to connect the disparate data visualizations into a coherent story. Sometimes this challenge stemmed from data analyses that produced equivocal findings. As one student said, "How can I make this memorable, or how can I really capture the audience?" Table 2 summarizes the challenges and coaching supports that students described.

Both experts and students desired two types of support from AI: "direct" supports where AI can shorten the time spent on low- level tasks and offer data story templates and coaching tips that facilitate iterative testing of different analyses and storytelling approaches, and "facilitated supports" where AI can assess student needs so that instructors can provide targeted and timely feedback. Such facilitated supports serve the additional role of continually updating and "ground truthing" the system. These AI supports are reflected in Table 3.

7 Discussion and Conclusion

This study affirms the potential educational utility of separating data storytelling into three types of knowledge and skills: posing questions to drive analyses, choosing statistical analyses and visualizations, and developing stories around findings. Given the limited time in college courses for data storytelling instruction, AI can provide automated templates, stepwise guidance, and case-specific tips to facilitate rapid iteration of questions, analyses, and story framings. For example, early in the process, AI prompts may assess or build students' knowledge of data science in varied domains; later, AI may invite students to try different analyses, visualizations, or story templates. With such features, AI can help guide student decisions and build student knowledge of options for analysis, visualization, and coherent story arcs. AI may also directly address low-level information requests from students on data science content and apply learning analytics to identify higher-level needs. Sharing such data with instructors can help them focus their time on mentoring students. To build on this preliminary work, future research might compare how AI can best mediate learning interactions between students and instructors or between peers, so the field can learn more about how AI can develop student storytelling using individual and collaborative learning methods. Such studies can build an understanding of the AI features that encourage students to review and refine data stories and help busy college instructors develop this complex skill.

8 Limitations

This study was based on a small set of expert and student informants. Further validation studies could expand to a larger number of participants using more formal content validation methods. This study focused on a limited geographic scope of participants, who were primarily from one Mid-Atlantic state in the United States. Future studies could include participants from more geographic locations.

9 Acknowledgments

We acknowledge help from Brent Dykes, Sara Stoudt, Rachel Saidi, and Lianne Wappett, and the student interviewees. This research was supported by the National Science Foundation under Grants Nos. 2302794 and 2302795. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the foundation.

Table 1: Expert Recommendations for Finalizing Data Storytelling Design Patterns

Design Pattern	Challenges	Basic Instruction	Advanced Instruction
DP 1: Understand Audience and Communication Goals	Learning about the data context is iterative	Provide datasets with familiar topics; support learners' decisions about appropriate data questions	Focus on deeper questions that data can answer; probe into audience needs
DP 2: Generate and Annotate Data Insights	Data cleaning, sensemaking, and visualization are iterative	Balance giving cleaned data with opportunities to build persistence around imperfect data; support learners' understanding of the emerging story arc	Discuss ethical data use (experts disagreed on when to introduce this—some preferred introducing it early, others later in advanced classes); provide practice transforming raw datasets
DP 3: Construct Data Story	It is tempting to describe the analysis process chronologically instead of creating a story	Focus on accuracy of insights, correctness of cause vs. correlation, and support learners' explanations of data insights and audience relevance	Consider how to shape stories for different audiences; emphasize engaging headlines and clear recommendations

Table 2: Student Challenges with Data Storytelling and Relevant Support Strategies

Design Pattern	Challenges	Desired Support
DP 1: Understand Audience and Communication Goals	Uncertainty about how to pose questions about larger datasets, and how to align questions with real-world context	Seeking guidance on how to frame goals of data analysis for specific audiences
DP 2: Generate and Annotate Data Insights	Uncertainty about best analyses to run and visualizations to use	Seeking social support from peers or instructor on when and how to clean data, share programming and statistical steps and visualization tools, and augment a limited existing dataset with larger relevant datasets
DP 3: Construct Data Story	Uncertainty about how to create a coherent story across findings	Finding templates to decide which visualizations and framings to use

Table 3: Suggested Supports for Data Storytelling Using AI and Automation

	Type 1: Direct Supports	Type 2: Facilitated Supports
DP 1: Understand Audience and Communication Goals	Summarize types of audiences and common questions in the data domain context. Pre-check datasets for the presence of categorical and continuous variables.	Provide structures to elicit student questions, inviting them to express concerns and seek instructor feedback.
DP 2: Generate and Annotate Data Insights	Provide guidelines, menus, and rules for data cleaning and selecting analytic procedures and visualizations. Provide automated monitoring of students' data cleaning and code markups.	Generate reports on students' data cleaning steps, analyses, and plots for instructor review and feedback.
DP 3: Construct Data Story	Provide access to story arc templates. Provide automated monitoring of students' inclusion of data labels and legends, use of colors, and types of headlines.	Generate reports on students' use of story arcs, headlines, and transitions for instructor review and feedback.

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