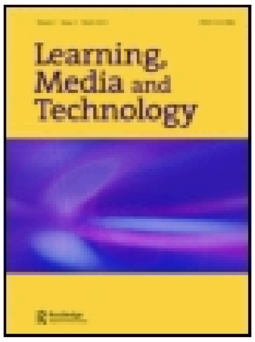

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High school students' data modeling practices and processes: From modeling unstructured data to evaluating automated decisions

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ABSTRACT
It's critical to foster artificial intelligence (AI) literacy for high school students, the first generation to grow up surrounded by AI, to understand working mechanism of data-driven AI technologies and critically evaluate automated decisions from predictive models. While efforts have been made to engage youth in understanding AI through developing machine learning models, few provided in-depth insights into the nuanced learning processes. In this study, we examined high school students' data modeling practices and processes. Twenty-eight students developed machine learning models with text data for classifying negative and positive reviews of ice cream stores. We identified nine data modeling practices that describe students' processes of model exploration, development, and testing and two themes about evaluating automated decisions from data technologies. The results provide implications for designing accessible data modeling experiences for students to understand data justice as well as the role and responsibility of data modelers in creating AI technologies.

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Data modeling; machine learning; unstructured data; model development processes

1. Introduction

Artificial Intelligence (AI) has become a ubiquitous facet of our daily lives. We see it in spam filters, personalized search, and the many recommender technologies we encounter in our everyday activities on the Web. In addition, we are bombarded with the news about the role of AI in every sector of our lives, most recently chatbots, like ChatGPT, becoming more prevalent in customer service, virtual assistants, and other applications that require human-like communication. Meanwhile, there are concerns about the ethical implications of AI and the potential impact on employment and society as a whole. It features as well in the research of our field (e.g., Csanadi et al. 2018; Erkens, Bodemer, and Hoppe 2016; Holtz, Kimmerle, and Cress 2018; Williamson and Eynon 2020). Our young generation should be given high-quality academic training that empowers them to participate in the public discourse about AI (AI4K12 2019). It is a challenge to position youth to be thought leaders in this public discourse without fostering an in-depth understanding of what exactly AI is, how AI works, and why and where AI is used.

Efforts have been made to engage youth in understanding AI through developing machine learning models, a branch of AI that is concerned with learning patterns from data and making predictions based on the patterns. For instance, Zimmermann-Niefield and colleagues (2019)

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provided an embodied learning experience for youth to make machine learning models for recognizing their own physical activities. They found that youth developed an understanding of how machine learning models learned patterns of body movements and this could contribute to the understanding of the iterative process of machine learning. In addition, Google developed web-based tools (e.g., Teachable Machine) to make machine learning accessible to the public, including youth (Carney et al. 2020). These studies stressed the cultivation of data literacy among youth as modeling data is a core concept in machine learning.

It's important to promote data literacy and support the youth to explore the social and ethical implications of data and data technologies, including data-driven AI technologies. Being data literate entails the ability to use data effectively in diverse situations, including skills such as locating, evaluating, analyzing, and applying data to support decision-making and problem-solving (Pangrazio and Sefton-Green 2020; Perrotta 2013). A growing area of study, known as critical data studies, investigates learning designs that engage youth in understanding the procedures for collecting, analyzing, and using data, as well as the power structures that underlie these procedures (Philip, Olivares-Pasillas, and Rocha 2016). As part of critical data studies, researchers suggest that two key elements that learning designs should cover are data justice, which involves addressing issues such as bias, discrimination, and power imbalances that may arise from the use of data (Dencik et al. 2019); and data ethics, which involves addressing ethical issues such as privacy, informed consent, and transparency in the handling of data (Shapiro et al. 2020). These elements are essential for preparing young students to become responsible consumers and creators of data technologies in the future (Philip, Schuler-Brown, and Way 2013). The growing body of work on data literacies, critical data studies, data justice, data ethics, and more broadly data science reflects a growing awareness of the importance of data in our society and the need to help youth develop the skills and literacies necessary to navigate, make sense of, and shape this datafied world (Pangrazio and Sefton-Green 2020).

In data-driven AI technologies, data modeling is a core concept as computers gain their 'intelligence' by learning from data. The growing attention to data literacy in pre-college education (e.g., Haldar et al. 2018; Pangrazio and Sefton-Green 2020) has partially responded to this learning goal. However, the data literacy community has primarily focused on structured data, which are already in rows and columns, ready for modelers to manipulate and analyze. What has been neglected are those unstructured and semi-structured types such as text, image, and video. While humans can comprehend and enjoy these raw materials, they mean little to nothing to machine learning algorithms. Modelers must extract features and create structures from the raw data so that machine learning algorithms can detect meaningful patterns (Witten et al. 2016). Identifying these structures, applying appropriate domain knowledge, and creating computable representations – these human processes are inseparable from the machine learning processes and largely determine the nature of the intelligence being created. These foundational data practices are currently missing in pre-college education. Integrating unstructured data into pre-college data science education will serve a dual purpose of equipping youth with the essential data literacy skills to handle such data and also providing them with an understanding of how humans use creativity to develop computable representations. By doing so, they will not view AI as a mystical concept (a common belief that views machines acquire knowledge without any human involvement and in a manner that is incomprehensible; Long and Magerko 2020) but rather as a result of human endeavors.

To address the research gap in K-12 data science education, our work focuses on advancing students' understanding of structures in seemingly unstructured data, a fundamental concept cutting across all AI fields that exploit unstructured data such as text, image, audio, and video. In particular, engaging students in building models with unstructured data is important, for one to address the gap in building data literacy skills and the other, critically evaluate automated decisions from data-driven AI technologies.

2. Theoretical framework and literature review

This study was guided by two theoretical perspectives: technical democracy (Callon, Lascoumes, and Barthe 2011) and situated learning (Lave and Wenger 1991). By using the theoretical framework of technical democracy, we closely observed how students responded to the societal implications of data technologies during data modeling processes. The theoretical lens of situated learning emphasizes that learning is situated in social and physical contexts and occurs through participation in authentic activities. We drew on this perspective to explore how students engage in data modeling practices through authentic activities (in this study, developing data models using real-world datasets). Specifically, the situated learning lens of data modeling guided us to concentrate on contexts that may impact data modeling practices and processes. Together, these two theoretical perspectives provided a comprehensive framework for investigating how students can develop the necessary skills and knowledge to understand the societal implications of data technologies and to engage with them responsibly. In the following section, we first introduce the two theoretical lenses and then provide an overview of the literature review on data modeling.

2.1. Technical democracy

Technical democracy is a theoretical framework that highlights the importance of democratizing the development and use of technologies. At its core, it is concerned with creating an environment in which the public have the knowledge, skills, and opportunities to participate in decisions about technological systems (Callon, Lascoumes, and Barthe 2011). This framework challenges the notion that technological development should be left solely to experts, and instead emphasizes the importance of including diverse perspectives and experiences in the design and use of technology (Landström et al. 2011). In other words, technical democracy emphasizes the need for democratic participation in the decision-making processes surrounding technology.

Technical democracy also recognizes the role of power and inequality in shaping technological systems, with an emphasis on addressing power disparities that may result from the application of technology (Thompson et al. 2022). This perspective includes addressing issues such as digital divide, access to technology, and ensuring that technology is used in ways that benefit everyone in society.

We drew on this theoretical perspective to explore instructional and technological strategies to support youth in understanding the societal implications of data technologies. This approach seeks to equip students with knowledge and skills needed to engage critically and thoughtfully with data technologies, and to prepare students to create more equitable and just data systems that serve the needs of society. Overall, this perspective provides a valuable framework for designing effective strategies to support data literacy and the development of awareness in responsible data use and technology development among youth.

2.2. Situated learning

The situated perspective of learning values that participation in meaningful practice primarily engenders learning (Johri, Olds, and O’Connor 2014; Lave and Wenger 1991). Goodwin describes situated learning as a ‘practice-based theory of knowledge and action’ (1994, 606). Central to this practice-based view is an emphasis on a process of constructing knowledge and negotiating meaning in an authentic and meaningful context (Brown, Collins, and Duguid 1989). The impact of context is pervasive in situated theories (Brown, Collins, and Duguid 1989; Greeno, Collins, and Resnick 1996). Jonassen (2011, 159) describes that, in situated perspectives, learning occurs as ‘a product of activity, context, and culture’. For Lave and Wenger (1991), learning is a socially mediated process in a community of practice where individuals participate in meaningful practices and grow from peripheral to legitimated members in the community.

We adopt this situated perspective to understand students' data modeling experiences and practices. Modeling, a process of developing representations of phenomena being experienced in order to engender conceptual change, has been an effective learning strategy for knowledge construction in mathematics and scientific domains (Jonassen 2011). For example, mathematical modeling allows students to engage in a cyclical process to represent authentic problems and their internal relations into mathematical languages and then discover solutions using mathematical knowledge and concepts (Haines and Crouch 2007; Verschaffel, Greer, and Corte 2002). Erbas et al. (2014) also indicate this process prompts students to construct their understanding of mathematic concepts in an authentic context. The study involved having students work on data modeling tasks that were based on real-world datasets, providing them with an authentic experience. Additionally, this type of task closely mirrors the workflow in professional settings (Medhat, Hassan, and Korashy 2014). We expect that this authentic task could provide valuable insights into students' data modeling experiences and practices from a situated perspective. By adopting this perspective, we aim to gain a deep understanding of how students engage in the process of developing representations of real-world phenomena.

2.3. Literature review: data modeling

Data modeling is defined as practices wherein learners formulate, structure, and represent data into a solution in response to the variability of a problem (Kazak, Fujita, and Turmo 2021; Lehrer and English 2018). Modeling has been a primary practice in data science education, but limited research has specifically shed light on data modeling. A unified understanding of student practice of data modeling is needed.

Existing research on students' practices of working with data mainly addressed mathematical modeling. Mathematical modeling has been integrated into the curriculum as one critical skill for K-12 students (Pfannkuch, Ben-Zvi, and Budgett 2018). Garfield and Ben-Zvi (2008) also investigated students' practices of using statistical models to solve mathematical problems. Students may identify appropriate statistic models and use them to represent the problem in data and deal with the variation of the data. Alternatively, students may determine the model use based on the dataset in order to articulate the variability in the data (Garfield and Ben-Zvi 2008). Modeling practices allow students to work with data and its variation, but the importance of connecting data with the context has been overlooked. Students' interaction with data has been viewed as a socio-technical practice (Jiang and Kahn 2020) in which context, technology, and learning intertwine to impact students' knowledge construction. Effective data modeling practice should end up with solutions that fit the context where the modeling practice occurs (Pfannkuch, Ben-Zvi, and Budgett 2018).

Specifically, Pfannkuch, Ben-Zvi, and Budgett (2018) reviewed three types of contexts that may impact data modeling practices, including data context, learning experience context, and designer context. Data context, described as the original context that the data is stemmed from, establishes the social-cultural phenomenon that the data may interpret. Data usually contains rich information beyond just numbers. For example, Eberendu (2016) outlines unstructured data that may comprise various formats of data such as images, texts, audio, and videos. When modeling the variations of the data, students are expected to attend to the unstructured data and translate them into numbers for analysis. In addition, learning experience context addresses the context in which students participate in modeling practices, including learning environments and students' prior knowledge or experience, which may affect students' performance in data modeling (Pfannkuch, Ben-Zvi, and Budgett 2018). Furthermore, designer context describes the context that the technological tool or software affords for data modeling (Wilkerson and Laina 2018). The context for students to interact with technology may be constrained by the designer's perspectives on data science practices (Pfannkuch, Ben-Zvi, and Budgett 2018).

More recently, researchers argue that it is critical for students to understand how artificial intelligence (AI) technologies gain their 'intelligence' and evaluate automated decisions from these technologies (Tatar et al. 2021; Long and Magerko 2020; Ruppert et al. 2023). For this reason, efforts have been devoted to supporting students' AI understanding through engaging them in data modeling practices. As an example, Lee and colleagues (2021) held a summer AI workshop in which secondary school students built image classification models. They found that students' AI understandings and knowledge about biases in data increased significantly at the end of the workshop. Similarly, Sakulkueakulsuk and colleagues (2018) organized a workshop in which secondary school students were introduced to machine learning concepts by classifying fruits using different features (e.g., length, color, and shape). At the end of the workshop, students gained an in-depth understanding of fundamental machine learning topics such as training and testing data. Collectively, these studies showed that engaging students in building data models could promote a critical understanding of the working mechanism of model decision-making. However, the focus of the studies is mostly on the learning outcomes rather than the students' learning processes. By studying the learning processes, researchers and educators can gain a deeper understanding of how to support and enhance students' learning experiences, leading to effective educational practices. To fill the research gap, this study examines students' data modeling processes in classrooms. Specifically, we address the following research questions (RQ):

RQ1: What are the practices that describe students' data modeling processes?

RQ2: What learning opportunities emerge from classroom discussions that could support students' critical evaluation of automated decisions from data technologies?

3. Method

3.1. Context and participants

This study took place in a high school Journalism class at a magnet school in the Northeastern United States. In the school, approximately 47% of the students were eligible for free or reduced-price lunch. Twenty-eight students from a journalism class participated in this 15-day study (45 min each day). A journalism and English Language Art teacher from the school, Ms. Smith (all names are pseudonyms), taught the class. The class was an elective course and was open to any students from any grade. Therefore, we had a diverse student population in terms of grade level (Table 1) and race and ethnicity (sixteen, African-American; six, White; six, Latinx; one, prefer not to answer; one student self-identified as both African-American and Latina). Among them, nineteen were female and nine were male. 22 students expressed their intention to enroll in a 4-year college after graduation. Regarding prior knowledge about AI, three students shared that they never learned about AI, and twenty-five of the students explained that they heard about AI

Table 1. Backgrounds of the participants.

Characteristics	Number of Participants
Gender	
Female	19
Male	9
Grade	
10th	3
11th	9
12th	16
Race/Ethnicity	
African American	16
White	6
Latinx	6
Prefer not to answer	1

Note: One student identified herself as multiracial.

through media such as TV shows and movies. None of the students received any formal training related to AI.

Students engaged in activities in a curriculum with seven learning modules. The first three modules were designed for students to get familiar with AI concepts with a focus on building machine learning models with text data as well as being aware of ethics and bias in the process of developing data models and deploying these models for use in different fields. In the next two modules, students used StoryQ (a web-based text-mining platform developed by the research team, as shown in Figure 1 in the findings section; Jiang et al. 2022) to build models using a dataset from ice cream restaurant reviews on Yelp (i.e., an American company that publishes crowd-sourced reviews about businesses). The reason we selected this particular learning task is because it involves classifying reviews, which is a task that is commonly performed in professional fields like marketing and customer service (Medhat, Hassan, and Korashy 2014). By engaging in this task, students could gain an authentic learning experience that is relevant to real-world scenarios. Specifically, in the module of ‘sentiment analysis’, students were introduced to concepts related to building models to classify negative and positive reviews. In the module of ‘features and models’, students were required to improve the model accuracy to 80% by changing the features (i.e., computable representations) used to build the model. In the module of ‘all the words as features’ (sixth module), students explored a unigram model that considers all unique words in the dataset as features. In the last module, students reflected on human responsibilities in developing AI models for social good. In this class, there was one desktop computer for each student, one teacher computer, and one projector to display the teacher’s computer screen to the whole class. Other than activities involving hands-on practices of building models, students worked individually on their own computers.

Before incorporating the project into her classroom, Ms. Smith participated in a one-month professional development workshop (1.25 h per week) for teachers. During this workshop, she was introduced to the project and provided feedback on its components such as the curriculum and technology. She was motivated to bring the project to her journalism class as she believed that AI technology, including its use in detecting fake news, was important for the field of journalism. After the workshop, the research team met with Ms. Smith to go over the curriculum and plan the data collection procedures. The team provided her with cameras for video recording and set up

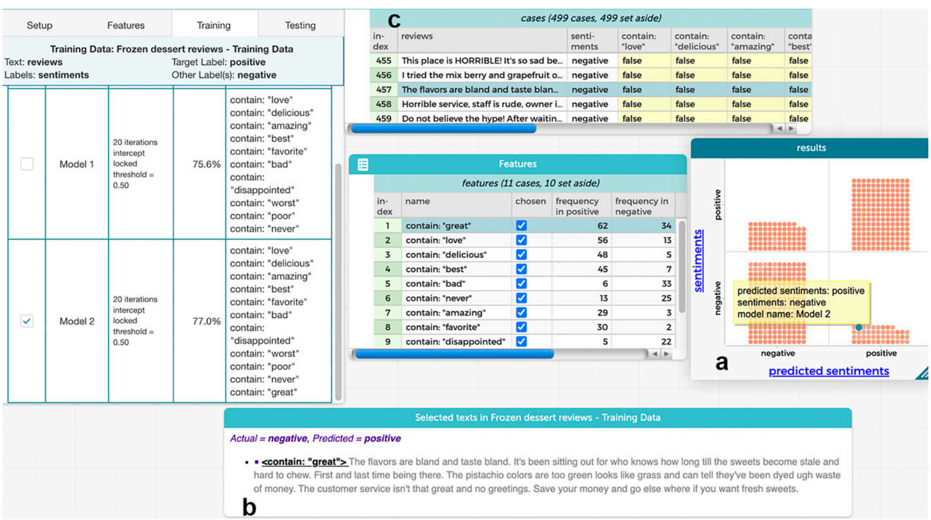

Figure 1. Zuri’s screen. Her mouse was on a dot in the confusion matrix (a), which is a performance measurement for machine learning classification that compares human-labelled and predicted ratings in a two-dimensional array. In StoryQ, the representations were dynamically linked. Thus, the corresponding instance was highlighted in the dataset (c) and the review was shown in the selected text window (b).

screen recording accounts using Screencastify. During the implementation, the research team supported the class through Slack (i.e., an online messaging program) when Ms. Smith had questions or needed help. Also, the technology development team stood by remotely for any emergent technology issues in all classroom sessions. In addition, the research team followed up with Ms. Smith twice a week through remote meetings via Zoom (i.e., a video conferencing tool) and constantly checked data collection processes and results with Ms. Smith through emails after each-day implementation.

3.2. Data collection and analysis

We collected multiple sources of data to understand the students' data modeling practices and processes, including video and audio recordings of students' screens and classroom activities, teacher's written reflections, and activity reports. To capture students' data modeling processes, we randomly selected five focal students for screen recording. These recordings captured both students' actions on the screen and their discussions with peers and the teacher (1295-minute recordings). In addition, the classroom was both audio and video recorded with one camera (534-minute recordings of classroom activities). Since the school was not in the state where the researchers lived, Ms. Smith helped the research team to record students' screens and classroom activities and uploaded these recordings to a shared cloud drive with robust privacy protection measures after each-day implementation. Furthermore, Ms. Smith wrote reflections after each class in a shared Google document. She answered six open-ended questions to reflect on classroom implementation. For example, one question was: what is your biggest takeaway from today's implementation? The research team reviewed the document and recordings after each class session to understand the progress in the implementation as well as to identify places for improvement. While completing the activities in the curriculum, students answered activity-related questions (30 questions in total). For instance, they wrote down features that they created when building models. Some students left certain questions unanswered, therefore we received a total of 685 responses for these 30 questions. These questions were designed to scaffold students' learning throughout the activities. Their responses were recorded as an activity report.

Data from each source were analyzed using different strategies to address the research questions. To address the first research question about practices that describe students' data modeling processes, we took an interactionist approach (Greeno 1994) to analyze screen recordings. We used interaction analysis methods (Jordan and Henderson 1995) to understand participants' data modeling strategies. We first developed analytic memos around what appeared to be – through continuous or constant comparisons (Glaser 1965) of individual participants – conceptual and technical practices to describe participants' data modeling. We then selected episodes for microanalysis, in which we analyzed gesture, discourse, and tool use as sources of knowledge and learning. After reviewing and comparing the students' records, we finalized the emerged categories (Strauss and Corbin 1998) of data modeling practices.

To answer the second research question regarding learning opportunities emerging from classroom discussions, we engaged in the following three phases of qualitative data analysis (Derry et al. 2010; Patton 1990): discussing teachers' written reflections on classroom implementation, content-logging video recordings, coding hotspots and generating themes. First, we read and discussed teachers' written reflections to identify learning challenges and opportunities as well as gain a general view of the classroom implementation. Second, four researchers were assigned videos to watch and write content logs. In content logs, we highlighted the following aspects: summary of the video segment, learning challenges and opportunities, and students' discussions with peers and teachers. After we finished the content logs, every week, we held research meetings to discuss these logs. Our discussions mainly focused on how students engaged with the activities, in which activities students had rich discussions and how, and how we can improve the activities to support student learning of machine learning concepts and evaluations of automated decisions. We constantly revised content logs based on feedback from the research team. Third, we identified hotspots in content logs. In these hotspots, multiple students joined the classroom discussion and the discussion covered the evaluation of automated decisions. Afterward, we transcribed the hotspots for in-depth analysis. Specifically, we coded these hotspots and discussed emerging themes related to learning opportunities.

Furthermore, we employed open-coding strategies (Strauss and Corbin 1998) to activity reports to triangulate data and strengthen our interpretations in the data analysis process. To ensure the credibility and trustworthiness of the analysis, we engaged in a systematic process to ensure that the research findings are credible, authentic, dependable, and transferable by following these standards: credibility, transferability, dependability, and confirmability (Erlandson et al. 1993; Lincoln and Guba 1985; Shenton 2004).

4. Findings

4.1. RQ1: what are the practices that describe students' data modeling processes?

We identified nine data modeling practices in the process of developing and exploring machine learning models with text data from a real-world restaurant review dataset: 1) using connotative words as features, 2) making hypotheses about patterns, 3) analyzing confusion matrix, 4) identifying patterns in training data, 5) noticing the gap between hypothetical patterns and patterns from training data, 6) using trial and error to improve model accuracy, 7) pursuing feature surprises, 8) generating 'thoughtful' testing data, and 9) reasoning about model decision making.

Specifically, *using connotative words as features* refers to the practice of creating features with words that have positive and negative connotations in describing experiences of visiting ice cream restaurants. Examples of words with positive connotations were great, awesome, love, fabulous, and delicious and examples of words with negative connotations were terrible, horrible, dirty, rude, and ignoring. The reason why students used these words as features might be due to the fact that the learning task was building models to classify negative and positive reviews. In this practice, students usually positioned themselves as review writers, instead of paying close attention to reviews in the dataset and the characteristics of review writers who generated this dataset.

Making hypotheses about patterns represents the practice of explaining hypothetical patterns before building models. A hypothetical pattern could be: A review with the feature 'like' is more likely to be a positive review. These hypothetical patterns might be aligned with or contrary to actual patterns in the dataset and reflect students' knowledge of how people like them would use words to describe positive or negative experiences, without careful consideration of how people from other backgrounds would use these words. These hypotheses might be overly influenced by the students' own perspectives and experiences, potentially leading to biased models that fail to adequately account for the diverse range of perspectives that exist within the larger community. Without further in-classroom guidance, this practice could undermine efforts to promote technical democracy among youth as students might not be aware that making hypotheses from a single perspective could result in machine learning models that are not sufficiently inclusive.

After building models, students were guided to perform the practice of *analyzing confusion matrix*, in which they examined correctly and incorrectly classified reviews systematically. As an example, using the confusion matrix (Figure 1), Zuri observed that after adding the feature 'great' into a model, the model was more accurate in predicting positive reviews. She wrote in the activity report, 'I think that the feature 'great' affected the model by model 2 having more positive reviews being recognized. Model 1 has fewer positive reviews being recognized because it's less accurate.' Meanwhile, she recognized that 'great' was not as effective as she would expect as there were many negative reviews containing the word 'great.' Thus, she looked closely at the misclassified reviews and found that 'great' was also commonly used in ways such as 'is not that great' and 'flavor is great but the service is super slow.' We described this practice as *identifying patterns* *in training data*. Through systematically analyzing reviews, students engaged in exploring and explaining patterns in training data.

After identifying patterns, they noticed that some patterns were different from their hypotheses in the practice of *noticing the gap between hypothetical patterns and patterns from training data*. For example, Jennifer considered 'like' as a good feature for positive reviews (i.e., if a review has the feature 'like', most likely it's a positive review), but the model showed that over half of the reviews having the feature 'like' were negative reviews. After reading negative reviews containing the feature 'like', she found that 'like' were commonly used in negative reviews such as 'don't like' and 'taste like soap.' The gap could motivate close reading of reviews in the dataset and reasoning about different contexts of using the same word.

In the practice of *using trial and error to improve model accuracy*, students iteratively revised the feature space for better model accuracy. They added more connotative words as features and deleted added features if these words led to a decrease in model accuracy. Students were expected to improve model accuracy by addressing misclassified reviews after analyzing confusion matrix and close reading of reviews in the dataset. Without explicit guidance, students usually ended up in the trial-and-error strategy, without connecting the process of improving model accuracy with other practices, such as the practice of *analyzing confusion matrix*.

When exploring the unigram model, students picked features that showed unexpected patterns in the practice of *pursuing surprising features*, such as exploring why feature 'die' had a positive weight (0.07) and why feature 'ordered' had a negative weight (−0.39). The features were assigned weights on a scale of −1–1 to indicate their relative importance. If a feature is more frequently present in negative reviews compared to positive reviews, it will have a weight closer to −1. For example, in Figure 1, the word 'disappointed' has a negative weight as it appears 5 times in positive reviews and 22 times in negative reviews. On the other hand, if a feature is more frequently present in positive reviews compared to negative reviews, it will have a weight closer to 1 (e.g., the word 'great' has a positive weight as it appears 62 times in positive reviews and 34 times in negative reviews; Figure 1). The use of the phrase 'to die for' in food reviews typically carries a positive meaning, rather than a negative one, according to the dataset that students explored in this project. Thus, 'die' has a positive weight (4 times in positive reviews and 0 time in negative reviews). In terms of 'ordered' having a negative weight (13 times in positive reviews and 42 times in negative reviews), it could be that people tend to associate the word 'ordered' with negative experiences when it comes to food, such as receiving cold or incorrect orders.

These surprising features were usually different from features that they considered connotative words. As explained by Paula, 'the weights of 'chocolate', 'even', and 'everything' surprise me because neither word has an inherently positive or negative leaning.' In the unigram model, both 'chocolate' and 'everything' had positive weights (0.21, 38 times in positive reviews, 15 times in negative reviews and 0.19, 22 times in positive reviews, 5 times in negative reviews respectively) and 'even' had a negative weight (−0.32, 20 times in positive reviews, 47 times in negative reviews), indicating that 'chocolate' and 'everything' appeared more often in positive reviews and 'even' appeared more often in negative reviews. Through exploring surprising features, some students reasoned about proxies for contexts in positive and negative reviews. For example, Jennifer explained that 'going' (the weight of this feature was −0.17, 12 times in positive reviews, 22 times in negative reviews) could be a proxy for not being satisfied with some aspects of the restaurants or suggesting people not visit the restaurants. She shared, 'possibly because 'going' is used to say I am never going here or going back again.' Overall, in the practice of *pursuing surprising features*, students explored words in different contexts and most importantly, reasoned about proxies for contexts. This type of analysis could help students build a nuanced understanding of how language is used to convey meaning and sentiment in different settings. Consequently, they could scrutinize data with discernment and attentiveness to context, leading to a comprehensive and precise interpretation of model decisions.

When testing a model with self-generated reviews, students modified reviews so that the model could make correct predictions after realizing that the model only used single words as features and could not understand contexts. We described this practice as *generating 'thoughtful' testing data*. For instance, Zuri tested a unigram model with the following positive review that she wrote,

> I once went to Rita's. It was a very nice place. The ice cream was heavenly. To this day I have dreams of their ice cream and crave its sweet wonder. The only problem is that I hate spending 30$ on a single ice cream. I mean it is worth every cent. But I don't just have 30 bucks to blow on ONE ice cream. That's my only complaint. Please come back to Rita's, your ice cream is the one that got away. (Responses from activity report)

The model predicted her review as negative, which was different from her actual intention. She found that 'heavenly' was not considered by the model. Thus, she made two changes to help the model to classify the review correctly: changing 'heavenly' to 'amazing' and 'got away' to 'you love'. She made these changes as 'amazing' and 'love' had big positive weights from the training data. The changes demonstrated students' understanding of the limitations of machine learning models built from single words and the importance of creating features that could capture the nuances of language contexts.

In the practice of *reasoning about model decision making*, students shared both correct understandings and misconceptions about how models make decisions. As an example of correct understanding, Isabella explained that 'a classification model tries to draw some conclusion from the input values given for training.' This statement reveals that Isabella understood that the model learns patterns from handcrafted features and was using the word 'conclusion' to refer to a model's classification decision. Other students, however, were confused about how the unigram model made decisions. For example, Serenity stated that 'features are single words or punctuation that help a model differentiate between a positive and negative category, while a unigram is more of a sentence.' From Serenity's perspective, the reason why a unigram model had much better accuracy than models with handcrafted features was that a unigram could read sentences instead of single words. In fact, a unigram model also uses words as features but uses all unique words in the dataset. In general, while students were mostly able to explain the importance of and process for feature selection as well as model learning patterns from training data, they had difficulty describing how texts were turned into features when the feature space was big (e.g., a unigram model has hundreds and thousands of features or unique words).

4.2. RQ2: what learning opportunities emerge from classroom discussions that could support students' critical evaluation of automated decisions from data technologies?

We found two themes describing learning opportunities emerging from classroom discussions that could support students' critical evaluation of automated decisions from AI technologies: the conflicting emotions surrounding AI technology and learnersourcing activities for model development and testing. In the following, we illustrate the themes using in-depth and nuanced video analysis from representative classroom discussions.

4.2.1. The conflicting emotions surrounding AI technology: fear and hope

Consistently, we witnessed that students demonstrated emotional reactions and mixed feelings (fear and hope) towards AI technologies in classroom discussions. In particular, they were deeply concerned about automating the process of giving people access and opportunities. We elaborate on this aspect using a classroom discussion about AI technologies for college admission. In the pre-survey, students answered questions related to the following scenario: A college is developing an AI application to identify prospective students for admission. The scenario was designed for students to understand the context easily as it was highly related to this population (a large portion of the students in the class decided to attend college as their next step and some of them just submitted their college applications), without any intention of causing tension or debates in classrooms.

Unexpectedly, the class had rich discussions about the idea of developing AI applications for college admission. Excerpt 1 shows how students responded to the scenario after Ms. Smith asked them to share their thoughts on the pre-survey. Students used words such as ‘horrible’, ‘scary’, ‘offended’, and ‘threatening’ to express deep concerns about applications for automating decisions on getting into colleges.
Excerpt 1.

1 Imani	Yeah, we (*referring to classmates*) are gonna talk about it. I guess it was the college thing, umm just, but that was **horrible** (*laughing*). I guess for me it was, umm, it was like, I guess, the computer is getting too (*not able to hear the word*). I think, for me, it was also a job thing. I think that’s **scary** because we already have an issue. I think it, the computer, is taking on what humans do and I think it is kind of **scary**.
2 Ms. Smith	Okay, so you are seeing, like you’re bringing the term automation as you see, jobs being automated. Why you and the other people, why you are concerned about college admission, why did that make you feel type of what, tell me what type of feelings and why?
3 Camillia	I was gonna say, because we are all humans, and we worked really hard to get into the school and get into colleges. So, like and especially being with personal essays like that, it is like, I don’t know, I feel like it should be reviewed by humans because that is what we deserve.
4 Ms. Smith	Okay, you’re bringing your human side into the table, you also want the others to bring their humans’ side into the table.
5 Camillia	Yeah, right!

In turn 1, Imani expressed concerns about giving computers the power to decide who to admit to colleges. Not just concerned, she felt scared. In turn 2, Ms. Smith invited more students to share their feelings and emotions towards this type of AI technology. Camillia was also opposed to the development of technology for college admission (Turns 3 and 5). It could be due to the fact that she wrote her essays with humans as audiences. Thus, she would expect humans to read them. Then, the class started to have multiple students talk at the same time. Ms. Smith had to call a stop and asked individual students to continue sharing their feelings (Turn 6). More students expressed concerns and sometimes anger towards developing such kind of AI technology.

6 Ms. Smith	(*Cross-talking in the classroom*) Alright! Jennifer first and then Maya.
7 Jennifer	Yeah, I pretty much agree with Camillia. Like I think we all got so **offended** because we just went through the process. And umm, like we are still waiting or already heard some college decisions and it is like Camillia was saying like our essays are not type of personal information of the college applications. Like all the clubs we’ve done over the years, like you put your heart and soul on that stuff, and it is pretty much all about humanity. Like what you are writing about, like what you experience, so it is like ironic and irritating that a robot would be reading my work instead of another human being and seeing that hard work, understanding, you know, the trials and tribulations that you have to go through rather than some computer not see some good works and being like ‘oh, you’re rejected.’ It is like I think it is **threatening** but it is also kind of **offensive**.
8 Ms. Smith	Mmm, okay. Thank you for sharing, it is kind of, in my stage of life or it reminds me of college, all my friends or myself included putting resumes up. And, mm, from my knowledge and experience, the college application is not heavily automated. Because I know people who work in the college admission office and they are human beings and not using these tools. But not to say it is not possible. But, my experience with the job market is that, like when you are applying huge databases of jobs, there is a certain amount of automation, etc. I mean these possibilities are valid. Anyone else wants to share? I think, Maya.
9 Maya	I have all kinds of emotions, if I am putting my heart and soul and the computer is just saying nope, next, nope, next, nope, next (*using hands to show actions of turning pages and talking in a frustrated voice;* Figure 2).

Jennifer echoed Camillia that as college applicants, they put lots of effort into preparing application materials (Turn 7). She used words like ‘offended’ and ‘offensive’ to express anger at the idea of having computers or robots make important decisions that would affect their life significantly. To calm students down, Ms. Smith explained that at the current stage, their application materials would not be evaluated by computers only (Turn 8) and then Maya shared similar concerns (Turn 9). The class continued with the discussion with the societal impacts of AI technologies for college admission such as bias and discrimination, as well as potential solutions to these issues,

Figure 2. Maya used gestures of turning pages to express frustration with having computers make decisions on college admission.

such as increased transparency and accountability. With reference to the whole-class discussion, Ms. Smith documented her thoughts in her reflection notes:

> The questions about AI replacing the college admissions process, hit a nerve for students, it seemed. Most of the class are seniors awaiting admissions decisions as they take the survey, so the prospect of being analyzed and given a decision without the benefit of human nuance was intimidating. In one student's words 'those questions pissed me off.' This means, however, that the topic will be ripe for discussion when we talk about the impact, dangers, and benefits of AI. (Ms. Smith' written reflection)

She recognized the opportunity of turning the discussion into in-depth conversations about the societal impacts of AI technologies in the coming sessions. Despite not addressing the topic in later discussions, it was evident that the teacher saw the students' apprehension regarding the automation of providing access and opportunities to individuals, particularly those that pertained to students themselves.

In the coming sessions, the class shared hope for AI technologies. For instance, they discussed problems that AI technologies might be able to solve and new challenges that might emerge. As an example, after watching videos showcasing the capabilities of AI technologies, Paula highlighted, 'I found that the impact of replacing real animals in marine parks will save money over time and its ability to be a more ethical solution the most interesting.' Bailey shared a similar concern regarding animal rights, and at the same time, she was concerned about emerging challenges after sending animals back to the sea, 'I wonder how they were going to get the real animals back into their habitat, which is the sea like the killer whales. The dolphin might not be ready for predators.' Mixed feelings and tensions about AI technology were popular topics of discussion in the classroom. These discussions provided rich opportunities for students to critically evaluate what should be automated and prepare our students to be active citizens in shaping the development of AI technologies in the future. By taking part in these discussions, students developed the ability to form their own opinions and viewpoints on the subject, which would help them become informed and responsible citizens who can make informed decisions about the future of AI.

4.2.2 Learnersourcing activities for model development and testing

Learnersourcing is a form of crowdsourcing in which learners in a community collectively produce content that can be leveraged to create novel learning opportunities (Wang et al. 2019). We observed that students were guided to generate and discuss datasets collectively for model development and testing. These discussions provided rich opportunities for introducing fundamental and complicated machine learning concepts in an engaging and accessible way. As an example, Ms. Smith asked students to test a model with reviews that they wrote in StoryQ. She used reviews from students as a testing dataset to evaluate the performance of the model and explained that

the current model made eight correct classifications and ten incorrect classifications (Turn 1; Excerpt 2).
Excerpt 2.

1 Ms. Smith	Raise your hand if it (*referring to the model*) categorized your review correctly, like if it is a positive review and categorized correctly (*as positive*). (*Counting raised hands*) Let's see, 1, 2, 3, 4, 5, 6, 7, 8. Um, so let's hear, let me hear now if your review was categorized incorrectly. So, we have eight correct, and (*counting raised hands*) we have 1, 2, 3, 4, 5, 6, 7, 8, 9, 10. 10 incorrect. So, is this a good model, okay model? What are we thinking? (*Shaking her hands to demonstrate the model's performance was not good.*)

Then Ms. Smith commented that the model needed to be improved for better accuracy. She emphasized that to improve a model, they should first identify features that were indicators of positive or negative reviews in the current model. To engage students in identifying features, instead of showing students the ten features in the model, she asked students to look closely at features that the model picked up in their own reviews to identify these ten features (we called this activity, deciphering the model).
Excerpt 3.

1 Ms. Smith	So, raise your hand again if the model predicted your word correctly, your review correctly. So then, click your review. And let's think about what the model is picking up. (*Amir raises her hand*) So maybe Amir, yours is correctly predicted, right? Yours is a positive review or negative review?
2 Amir	Positive.
3 Ms. Smith	So, Amir, read your review. As you guys are listening, I want you to predict what you think of the words that the computer is focusing on in Amir's review. So, Amir, would you give it to us, nice and loud?
4 Amir	(*Reading the review that she wrote*) A local Ice cream shop near me is Hersheyś Ice Cream. My experience there is pretty **good**, the people are really **nice** when kids come over, they let them taste the flavors to see if they **like** them. The food is really good. Each holiday, they would have a new flavor to go with the season and I **love** that because I always know that it is going to be really good.

In turns 2 and 4 (Excerpt 3), Amir was invited to share her review, which was correctly predicted as a positive review. After that, Ms. Smith asked the class to identify features that the model considered when making predictions on Amir's review (Turn 5).

5 Ms. Smith	Oh, okay, so your review is positive and predicted as positive. So, what are some words that you've heard from Amir that maybe the model is picking up?
6 James	Nice.
7 Ms. Smith	What else?
8 Easton	Good.
9 Ms. Smith	Others?
10 Paula	Like.
11 Ms. Smith	So, Amir, when you click on this feature graph right here, this Christmas tree-looking thing (Figure 3), what numbers light up?
12 Amir	Nine.
13 Ms. Smith	Okay, feature number nine, which we know or might be 'love', right? Are there any others?
14 Amir	Seven.
15 Ms. Smith	Oh, it may be, so maybe seven is one of these words, nice, good or like, etc. Um, let's see who had a negative review predicted correctly.

Three students shared that the features might be words with positive connotations, including 'Nice', 'Good', and 'Nice.' As the model considered two features in the review (Turns 12 and 14), Ms. Smith prompted that the seventh feature might be words that the class came up with (Turn 15). Ms. Smith continued this process of sharing reviews and guessing features until they found the ten features from the model as a whole-class activity. Overall, students contributed to this process of deciphering the model by testing reviews that they wrote. In the end, Ms. Smith reemphasized machine learning concepts such as training data, testing data, features, models,

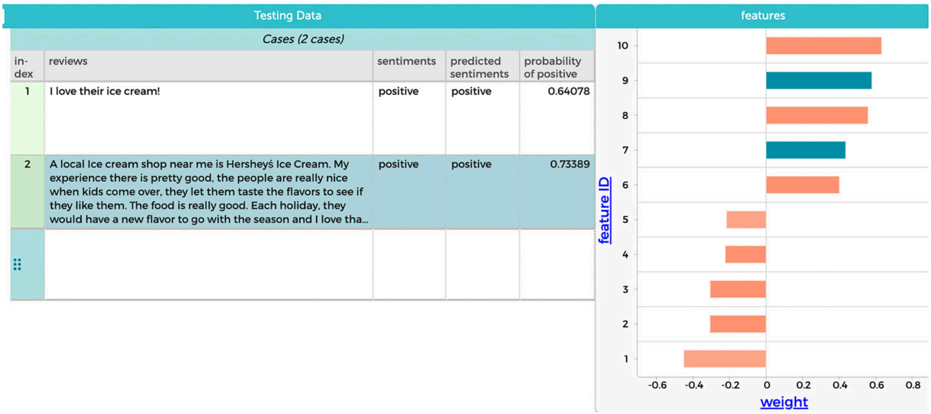

Figure 3. In StoryQ, two features were highlighted when the model made predictions on Amir's review.

and patterns. She referred back to this deciphering the model activity when emphasizing those concepts in later sessions.

There are other kinds of learnersourcing activities that could support the learning of machine learning concepts. For example, the majority of students wrote negative reviews. This was a good opportunity for students to discuss sampling, imbalanced datasets for training models, and the consequences of using imbalanced datasets for model development. In summary, working with datasets that were crowdsourced from learners in the classroom could provide opportunities for concrete and meaningful learning about machine learning concepts and evaluating machine learning models.

5. Discussion and implications

In this study, we provided a close-up look at data modeling practices and classroom discussions that could support students' critical evaluation of automated decisions from AI technologies. Specifically, we identified nine data modeling practices that students engaged in when exploring, developing, and testing predictive models built from text data and two themes that demonstrate learning opportunities for students to critically evaluate automated decisions from predictive models. Based on these findings, in the following, we discuss challenges and opportunities in supporting students to understand fundamental and complicated machine learning and data modeling concepts to prepare them to be critical creators and consumers of data-driven AI technologies.

First, we found that students tended to draw on their prior experience and knowledge, a component of the learner experience context (Pfannkuch, Ben-Zvi, and Budgett 2018), in building models with text data, such as in the practices of using connotative words as features and making hypotheses about patterns. Thus, often, they did not pay close attention to the dataset itself or the data context (Pfannkuch, Ben-Zvi, and Budgett 2018) in model development. It has pros and cons. On the positive side, leveraging students' prior experience and knowledge would help them to gain some preliminary understanding of model development (Lee et al. 2021; Wilkerson and Laina 2018). However, purely drawing on prior knowledge, students would miss the opportunity of actively asking questions about the sources of the data, such as when the data was generated, how it was generated, who generated it, for what purposes, and whose perspectives it represented. These questions would help students critically evaluate bias in the dataset (Lee et al. 2021). In addition, students will be empowered to understand data justice (e.g., challenging transparency, justice and fairness) (Dencik et al. 2019) and data ethics (e.g., reflecting responsibility, and privacy) (Shapiro et al. 2020) in developing data-driven AI technologies. To develop inclusive and representative models that reflect the needs and preferences of all members of society, we need to promote the awareness of technical democracy (Callon, Lascoumes, and Barthe 2011) among youth. To this end, it is essential to guide students to consider the data context in which data is generated and the potential biases that may exist within the data.

Second, in some practices (e.g., noticing the gap between hypothetical patterns and patterns in training data), students were motivated to close read instances in the dataset (in this study, reviews). The literature describes this phenomenon as gap or misalignment between learner experience context (e.g., personal experience) and data context (e.g., data trends and patterns) (Enyedy and Mukhopadhyay 2007; Philip, Schuler-Brown, and Way 2013). Discussing the gap allows students to develop a deeper appreciation for the importance of inclusivity and diversity in the development of machine learning models, and can become more adept at identifying and mitigating potential sources of bias and injustice. When designing data modeling tools or learning environments, we should create spaces for students to discuss the gap in order to teach fundamental and complicated concepts such as feature, pattern, and training data. In this study, the linked representations in the technology could help students to navigate between an aggregate view of word frequency in positive and negative reviews and a detailed view of instances in the dataset. Thus, designing representations and ways of connecting representations to support reasoning about data and patterns from the data would be another promising future research direction.

Third, in the effort to address technical democracy in data mdeling practices, designer context cannot be overlooked. In particular, students in our study encountered some misconceptions about the context that the tool afforded during their hands-on model development, evaluation, and testing activities. For instance, when the feature space was large (this is a characteristic of text data; Witten et al. 2016) and the predictive model was accurate, they had the misconception that the model was intelligent and could read sentences like humans. Future research should devote efforts to identifying such misconceptions and developing instructional and technological strategies to help students to overcome these misconceptions. In this manner, they would be better prepared to reason about the working mechanisms of data-driven AI technologies in daily life and evaluate the impacts of such technologies.

Fourth, we found that trial and error (Liu et al. 2017) was a common strategy that students used to develop models. We expected that students would analyze misclassified reviews and then create new features based on the analysis, especially features that could be proxies for contexts. In such a way, students would gain an in-depth understanding of the role of human insights in developing predictive models. However, we found that students engaged in the process of trying out features that they considered connotative words. An important area for future work is examining ways of fostering diverse strategies of developing models (in particular strategies that highlight human responsibility and creativity in creating features such as using single words as proxies for contexts) and developing technologies to support the exploration of different features, such as two words as features and the number of words in a sentence as features. Encouraging this approach could promote technical democracy since students would realize that the features utilized in constructing models are rooted in human perspectives.

Fifth, we found that students had conflicting emotions (fear and hope) toward AI technologies. On the one hand, they were concerned about the potential negative consequences of automation, but on the other hand, they were optimistic about the possibilities that AI technologies bring, such as increased efficiency and advancements in various fields. This duality of emotions highlights the complexity of the relationship between students and AI technologies. In particular, they had deep concerns about technologies (e.g., college admission technology) that automate the process of giving access and opportunities to people. This finding is consistent with Sadler and Zeidler's (2004) research which revealed that students had emotional responses to socioscientific topics such as cloning technology. Furthermore, it suggests that future designs should consider turning discussions about this kind of technology into productive reasoning about how we can shape the way technology functions in society. We should carefully consider students' emotions when designing learning experiences related to AI technologies. Understanding the emotional landscape of students will help create an inclusive and supportive learning environment that addresses their concerns while fostering their hope and excitement. By doing so, learning designers can help students understand and embrace the potential of AI technologies while also considering the ethical and social implications of their use, which could promote their responsible development and effective utilization (Landström et al. 2011) of AI technologies in the future. Furthermore, learning designers can play a critical role in helping students develop the critical thinking and problem-solving skills necessary to navigate the complex and rapidly evolving field of AI. In such a way, we can support the development of informed and responsible citizens who are equipped to make informed decisions about the future of AI and its impact on society.

Sixth, this study indicates that learnersourcing activity might be able to support the learning of data modeling concepts in an engaging and accessible way. For instance, imbalanced datasets, a typical challenge in the field of machine learning (Witten et al. 2016), can lead to biased models that are not representative of the entire population, which is an important issue for promoting technical democracy. By engaging in discussions around imbalanced datasets, learners could gain insights into the potential pitfalls of relying on biased data to develop AI models, and learn to evaluate the fairness and accuracy of these models. This could help them become more informed consumers and developers of AI technologies, and promote the responsible and equitable use of these technologies (Philip, Olivares-Pasillas, and Rocha 2016). Continuing with this line of research, future work could investigate the impact of learnersoucing activity on knowledge acquisition.

Last, this study holds implications for teachers to support students' critical evaluation of automated decisions. Teachers should engage students in discussing the impact of automated decisions on individuals and groups, the ethical implications of automated decision-making, the potential biases that may be built into automated decision-making processes, and the impact of automated decisions on society as a whole. For example, students can be guided to explore the potential biases that may be built into automated decision-making systems by looking at the output of a system and trying to understand how the data is being used. Teachers can also support students in evaluating the impact of automated decisions on individuals and groups by using case studies or real-world examples, such as studies showing AI facial recognition disproportionately misidentifying people of color (Harwell 2019).

In conclusion, this study sets exciting first steps for exploring students' learning processes in building predictive models with text data. We argue that having a solid comprehension of how AI functions is vital for students to engage in democratic discussions about AI technologies and make informed evaluations. Findings from this study are deeply situated in the activity of building machine learning models for classifying reviews with specific tools and in a journalism class. Much more needs to be understood about data modeling practices and processes with differing students, contexts, and tools.

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References

AI4K12 (Artificial Intelligence for K12). 2019. *Five big ideas in AI* (Poster). Retrieved from https://bit.ly/ai4k12-five-big-ideas.

Brown, J. S., A. Collins, and P. Duguid. 1989. "Situated Cognition and the Culture of Learning." *Educational Researcher* 18: 32–42. doi:10.3102/0013189X018001032.

Callon, M., P. Lascoumes, and Y. Barthe. 2011. *Acting in an Uncertain World: An Essay on Technical Democracy*. Cambridge, MA: The MIT press.

Carney, M., B. Webster, I. Alvarado, K. Phillips, N. Howell, J. Griffith, J. Jongejan, A. Pitaru, and A. Chen. 2020. "Teachable Machine: Approachable Web-Based Tool for Exploring Machine Learning Classification." In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–8. doi:10.1145/3334480.3382839.

Csanadi, A., B. Eagan, I. Kollar, D. W. Shaffer, and F. Fischer. 2018. "When Coding-and-Counting is not Enough: Using Epistemic Network Analysis (ENA) to Analyze Verbal Data in CSCL Research." *International Journal of Computer-Supported Collaborative Learning* 13 (4): 419–438. doi:10.1007/s11412-018-9292-z

Dencik, L., A. Hintz, J. Redden, and E. Treré. 2019. "Exploring Data Justice: Conceptions, Applications and Directions." *Information, Communication & Society* 22 (7): 873–881. doi:10.1080/1369118X.2019.1606268.

Derry, S. J., R. D. Pea, B. Barron, R. A. Engle, F. Erickson, R. Goldman, R. Hall, et al. 2010. "Conducting Video Research in the Learning Sciences: Guidance on Selection, Analysis, Technology, and Ethics." *Journal of the Learning Sciences* 19 (1): 3–53. doi:10.1080/10508400903452884.

Eberendu, A. C. 2016. "Unstructured Data: An Overview of the Data of Big Data." *International Journal of Computer Trends and Technology* 38 (1): 46–50. doi:10.14445/22312803/IJCTT-V38P109.

Enyedy, N., and S. Mukhopadhyay. 2007. "They Don't Show Nothing I Didn't Know: Emergent Tensions Between Culturally Relevant Pedagogy and Mathematics Pedagogy." *Journal of the Learning Sciences* 16 (2): 139–174. doi:10.1080/10508400701193671.

Erbas, A. K., M. Kertil, B. Çetinkaya, E. Çakiroglu, C. Alacaci, and S. Bas. 2014. "Mathematical Modeling in Mathematics Education: Basic Concepts and Approaches." *Educational Sciences: Theory and Practice* 14 (4): 1621–1627.

Erkens, M., D. Bodemer, and H. U. Hoppe. 2016. "Improving Collaborative Learning in the Classroom: Text Mining Based Grouping and Representing." *International Journal of Computer-Supported Collaborative Learning* 11 (4): 387–415. doi:10.1007/s11412-016-9243-5.

Erlandson, D. A., E. L. Harris, B. L. Skipper, and D. S. Allen. 1993. *Doing Naturalistic Inquiry: A Guide to Methods*. London: Sage.

Garfield, J. B., and D. Ben-Zvi 2008. "Learning to Reason About Statistical Models and Modeling." In *Developing Students' Statistical Reasoning*, edited by J. B. Garfield and D. Ben-Zvi, 143–163. New York: Springer.

Glaser, B. G. 1965. "The Constant Comparative Method of Qualitative Analysis." *Social Problems* 12 (4): 436–445. doi:10.2307/798843.

Goodwin, C. 1994. "Professional Vision." *American Anthropologist* 96: 606–633. doi:10.1525/aa.1994.96.3.02a00100.

Greeno, J. G. 1994. "Gibson's Affordances." *Psychological Review* 101: 336–342. doi:10.1037/0033-295X.101.2.336.

Greeno, J., A. Collins, and L. Resnick. 1996. "Cognition and Learning." In *Handbook of Educational Psychology*, edited by R. Calfee and D. Berliner, 15–46. New York: Macmillan.

Haines, C., and R. Crouch. 2007. "Mathematical Modelling and Applications: Ability and Competence Frameworks." In *Modelling and Applications in Mathematics Education*, edited by W. Blum, P. L. Galbraith, H.-W. Henn, and M. Niss, 417–424. New York: Springer.

Haldar, L. C., N. Wong, J. I. Heller, and C. Konold. 2018. "Students Making Sense of Multi-Level Data." *Technology Innovations in Statistics Education 11*(1). doi:10.5070/T5111031358.

Harwell, D. 2019. "Federal Study Confirms Racial Bias of Many Facial-Recognition Systems, Casts Doubt on Their Expanding use." *Washington Post*. Retrieved from www.washingtonpost.com/technology/2019/12/19/federal-study-confirms-racial-bias-many-facial-recognition-systemscasts- doubt-their-expanding-use/.

Holtz, P., J. Kimmerle, and U. Cress. 2018. "Using big Data Techniques for Measuring Productive Friction in Mass Collaboration Online Environments." *International Journal of Computer-Supported Collaborative Learning* 13 (4): 439–456. doi:10.1007/s11412-018-9285-y.

Jiang, S., and J. Kahn. 2020. "Data Wrangling Practices and Collaborative Interactions with Aggregated Data." *International Journal of Computer-Supported Collaborative Learning* 15 (3): 257–281. doi:10.1007/s11412-020-09327-1.

Jiang, S., A. Nocera, C. Tatar, M. M. Yoder, J. Chao, K. Wiedemann, W. Finzer, and C. P. Rosé. 2022. "An Empirical Analysis of High School Students' Practices of Modelling with Unstructured Data." *British Journal of Educational Technology* 53 (5): 1114–1133. doi:10.1111/bjet.13253.

Johri, A., B. M. Olds, and K. O'Connor. 2014. "Situative Frameworks for Engineering Learning Research." *Cambridge Handbook of Engineering Education Research*, 47–66. doi:10.1017/CBO9781139013451.006.

Jonassen, D. H. 2011. *Learning to Solve Problems: A Handbook for Designing Problem-Solving Learning Environments.* 1st ed. New York, NY: Routledge.
Jordan, B., and A. Henderson. 1995. “Interaction Analysis: Foundations and Practice.” *Journal of the Learning Sciences* 4 (1): 39–103. doi:10.1207/s15327809jls0401_2.
Kazak, S., T. Fujita, and M. P. Turmo. 2021. “Students’ Informal Statistical Inferences Through Data Modeling with a Large Multivariate Dataset.” *Mathematical Thinking and Learning*, 1–21. doi:10.1080/10986 065.2021.1922857.
Landström, C., S. J. Whatmore, S. N. Lane, N. A. Odoni, N. Ward, and S. Bradley. 2011. “Coproducing Flood Risk Knowledge: Redistributing Expertise in Critical ‘Participatory Modelling’.” *Environment and Planning A: Economy and Space* 43 (7): 1617–1633. doi:10.1068/a43482.
Lave, J., and E. Wenger. 1991. *Situated Learning: Legitimate Peripheral Participation*. Cambridge: Cambridge University Press.
Lee, I., S. Ali, H. Zhang, D. DiPaola, and C. Breazeal. 2021. “Developing Middle School Students’ AI Literacy.” In *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education*, 191–197. doi:10.1145/3408877.3432513.
Lehrer, R., and L. English. 2018. “Introducing Children to Modeling Variability.” In *International Handbook of Research in Statistics Education*, edited by D. Ben-Zvi, K. Makar, and J. Garfield, 229–260. Dordrecht: Springer.
Lincoln, Y. S., and E. G. Guba. 1985. *Naturalistic Inquiry*. (Vol.75). London: Sage Publications.
Liu, Z., R. Zhi, A. Hicks, and T. Barnes. 2017. “Understanding Problem Solving Behavior of 6–8 Graders in a Debugging Game.” *Computer Science Education* 27 (1): 1–29. doi:10.1080/08993408.2017.1308651.
Long, D., and B. Magerko. 2020, April. “What is AI Literacy? Competencies and Design Considerations.” In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16. doi:10.1145/3313831.3376727.
Medhat, W., A. Hassan, and H. Korashy. 2014. “Sentiment Analysis Algorithms and Applications: A Survey.” *Ain Shams Engineering Journal* 5 (4): 1093–1113. doi:10.1016/j.asej.2014.04.011.
Pangrazio, L., and J. Sefton-Green. 2020. “The Social Utility of ‘Data Literacy’.” *Learning, Media and Technology* 45 (2): 208–220. doi:10.1080/17439884.2020.1707223.
Patton, M. Q. 1990. *Qualitative Evaluation and Research Methods*. 2nd ed. Newbury Park, CA: Sage.
Perrotta, C. 2013. “Assessment, Technology and Democratic Education in the age of Data.” *Learning, Media and Technology* 38 (1): 116–122. doi:10.1080/17439884.2013.752384.
Pfannkuch, M., D. Ben-Zvi, and S. Budgett. 2018. “Innovations in Statistical Modeling to Connect Data, Chance and Context.” *ZDM* 50 (7): 1113–1123. doi:10.1007/s11858-018-0989-2.
Philip, T. M., M. C. Olivares-Pasillas, and J. Rocha. 2016. “Becoming Racially Literate About Data and Data-Literate About Race: Data Visualizations in the Classroom as a Site of Racial-Ideological Micro-Contestations.” *Cognition and Instruction* 34 (4): 361–388. doi:10.1080/07370008.2016.1210418.
Philip, T. M., S. Schuler-Brown, and W. Way. 2013. “A Framework for Learning About big Data with Mobile Technologies for Democratic Participation: Possibilities, Limitations, and Unanticipated Obstacles.” *Technology, Knowledge and Learning* 18 (3): 103–120. doi:10.1007/s10758-013-9202-4.
Ruppert, J., D. Velazquez-Ramos, R. Roque, and R. B. Shapiro. 2023. Taking Play and Tinkering Seriously in AI Education: Cases from Drag vs AI Teen Workshops. Learning, Media and Technology, 1-15.
Sadler, T. D., and D. L. Zeidler. 2004. “The Morality of Socioscientific Issues: Construal and Resolution of Genetic Engineering Dilemmas.” *Science Education* 88 (1): 4–27. doi:10.1002/sce.10101.
Sakulkueakulsuk, B., S. Witoon, P. Ngarmkajornwiwat, P. Pataranutaporn, W. Surareungchai, P. Pataranutaporn, and P. Subsoontorn. 2018, December. *2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE),* 1005–1010. doi:10.1109/TALE.2018.8615249.
Shapiro, B. R., A. Meng, C. O’Donnell, C. Lou, E. Zhao, B. Dankwa, and A. Hostetler. 2020, April. “Re-Shape: A Method to Teach Data Ethics for Data Science Education.” In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–13. doi:https://doi.org/10.1145/3313831.3376251.
Shenton, A. K. 2004. “Strategies for Ensuring Trustworthiness in Qualitative Research Projects.” *Education for Information* 22 (2): 63–75. doi:10.3233/EFI-2004-22201.
Strauss, A., and J. M. Corbin. 1998. *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory*. 2nd ed. Thousand Oaks, CA: SAGE.
Tatar, C., M. M. Yoder, M. Coven, K. Wiedemann, J. Chao, W. Finzer, S. Jiang, and C. P. Rosé. 2021. “Modeling Unstructured Data: Teachers as Learners and Designers of Technology-Enhanced Artificial Intelligence Curriculum.” In *Proceedings of the 15th International Conference of the Learning Sciences - ICLS 2021*, edited by E. de Vries, Y. Hod, and J. Ahn, 617–620. Bochum, Germany: International Society of the Learning Sciences.
Thompson, G., K. N. Gulson, T. Swist, and K. Witzenberger. 2022. Responding to Sociotechnical Controversies in Education: A Modest Proposal Toward Technical Democracy. Learning, Media and Technology, 1-13.
Verschaffel, L., B. Greer, and E. d. Corte. 2002. “Everyday Knowledge and Mathematical Modeling of School Word Problems.” In *Symbolizing, Modeling and Tool use in Mathematics Education*, edited by K. Gravemeijer, R. Lehrer, B. van Oers, and L. Verschaffel, 257–276. Berlin: Springer.

Wang, X., S. T. Talluri, C. Rose, and K. Koedinger. 2019, June. "UpGrade: Sourcing Student Open-Ended Solutions to Create Scalable Learning Opportunities." In *Proceedings of the Sixth (2019) ACM Conference on Learning@ Scale*, 1–10. doi: 10.1145/ 3330430.3333614.

Wilkerson, M., and V. Laina. 2018. "Middle School Students' Reasoning About Data and Context Through Storytelling with Repurposed Local Data." *ZDM* 50 (7): 1223–1235. doi:10.1007/s11858-018-0974-98-018-0974-9.

Williamson, B., and R. Eynon. 2020. "Historical Threads, Missing Links, and Future Directions in AI in Education." *Learning, Media and Technology* 45 (3): 223–235. doi:10.1080/17439884.2020.1798995.

Witten, I. H., E. Frank, M. Hall, and C. J. Pal. 2016. *Data Mining: Practical Machine Learning Tools and Techniques*. fourth edition. Elsevier: San Francisco.

Zimmermann-Niefield, A., M. Turner, B. Murphy, S. K. Kane, and R. B. Shapiro. 2019. Youth Learning Machine Learning Through Building Models of Athletic Moves." In *Proceedings of the 18th ACM International Conference on Interaction Design and Children*, 121–132. ACM. doi:10.1145/3311927.3323139.