DATA LITERACY FOR CONCEPTUAL CHANGE: A MODEL WITH SPECIAL APPLICATIONS IN CLIMATE CHANGE EDUCATION

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The purpose of this theoretical paper is to synthesize evidence and theory at the intersection of data literacy and science education and propose a model describing the role of data literacy in conceptual change: The Data Literacy for Conceptual Change (DLCC) model. The DLCC positions data literacy skills identified in the mathematics education literature in terms of models of conceptual change. Notably, we elaborate on key critical data literacy skills that serve to help students make personal meaning of data, and account for the role of affective dimensions (e.g., motivation, emotion, and beliefs) that promote scientific conceptual change. Incorporating affective pedagogical goals from mathematics education, which emphasize the emotional dimensions of learning about issues of injustice, the DLCC model adapts such goals to support students' emotional processing of data, with specific applications for climate change learning.

Keywords. Data Literacy, Climate Change, Conceptual Change, Data Visualization

Now more than ever, people need to be skeptical of the information that they encounter online. Unregulated, self-authored content is being published and circulated online at an alarming rate, a large fraction of which contains misleading or incorrect statistical information (Aïmeur et al., 2023; Kata, 2012; Treen et al., 2020). Internet searches for controversial science topics like vaccinations and climate change reveal millions of articles, and about 45% of which include misinformation (Kortum et al., 2008; Treen et al., 2020)—and much of this incorrect information relies on misleading data. Additionally, when learners encounter conflicting or alarming data about pressing issues like climate change, emotional responses such as anger, worry, or hopelessness are common (Herrick et al., 2025a). These emotions can intensify if learners collaborate in small groups, underscoring the need for explicit socioemotional regulation strategies (Lobczowski et al., 2021b) to sustain constructive engagement with complex data.

Numerical data (e.g., statistics) and data visualizations found in the news are powerful tools for conceptual change, whether that change be for better or for worse. On the one hand, presenting people with data on topics such as climate change can shift their attitudes, beliefs, and misconceptions to be more aligned with those of scientists (Ranney & Clark, 2016; Thacker, 2023, 2024; Thacker & Sinatra, 2022). On the other hand, presenting students with *misleading* statistical information can shift their scientifically correct conceptions and attitudes to be less aligned with those of scientists (Ranney & Clark, 2016). Taken as a whole, this research suggests that data can be used as a catalyst for conceptual change, though students require unprecedented levels of data literacy to identify and make sense of trustworthy information. If left unaddressed, the emotions evoked by this complexity—such as fear, anxiety, or hopelessness—can limit learners' ability to reason deeply and even lead them to reject scientific explanations (Sinatra & Hofer, 2021). Recent studies in science education have demonstrated that acknowledging and guiding these emotional responses from hopelessness or anxiety toward constructive hope can foster deeper processing of data (Herrick, 2023; Herrick et al., 2022; Herrick et al., 2025a). Additionally, research in socioemotional regulation (Lobczowski et al., 2021b) points to the importance of supporting students not just cognitively but also emotionally, particularly when data evoke strong feelings or highlight local injustices. This underscores why it is essential to consider not only the cognitive but also the emotional dimensions when learning from data.

The purpose of this theoretical paper is to synthesize evidence and theory at the intersection of data literacy and science education and propose a model describing the role of data literacy in conceptual change: The Data Literacy for Conceptual Change (DLCC) model. The DLCC positions statistical literacy skills identified in the mathematics education literature in terms of models of conceptual change. Notably, we elaborate on key critical data literacy skills that serve to help students make personal meaning of data, and account for the role of affective dimensions (e.g., motivation, emotion, and beliefs) that are crucial to consider when learning about issues of injustice and for promoting conceptual change. The DLCC model adapts such goals to support students' emotional processing of data, with special emphasis on applications for climate change teaching learning (Herrick et al., 2025a). Specifically, the goals of this paper are:

1. Provide a comprehensive overview of conceptualizations of *conceptual change* and how people revise their science-specific conceptions based on data and data visualizations. This includes processing numbers, visualizations, and data-specific evidence and negotiating the plausibility of multiple scientific claims, and conceptual change.
2. Reconcile these conceptual change processes with the literature on data-literacy skills required to make meaning of data which includes consideration of data properties and data pre-processing factors.
3. Highlight evidence-based strategies for promoting deep engagement with data to enhance scientific learning, with a focus on applications for promoting climate change learning.
4. Discuss principles to guide future scholarship and future areas of research on the topic of data literacy for conceptual change; including how explicit attention to students' emotional pathways (Herrick et al., 2025a) during group socioemotional regulation (Lobczowski et al., 2021b) can enhance or impede engagement with data.

To frame how relevant data literacy skills can support science learning, we integrate theories of Conceptual Change, Magnitude Knowledge, and Data Visualization Literacy. In addition to these theories, we draw on recent work examining students' emotional processes around data depicting climate change and socio emotional regulation strategies in collaborative learning. These studies highlight how emotions emerge, are shared, and can be guided toward productive data engagement, which are pivotal considerations for conceptual change around socioscientific topics in classroom settings.

Conceptual Change

When individuals encounter data or data visualizations in the news or online that conflict with their prior conceptions,[1] conceptual change may occur. Conceptual change represents a particular kind of learning that occurs when new information conflicts with a learners' background knowledge, leading to a restructuring of conceptual knowledge (Dole & Sinatra 1998; Murphy & Mason, 2006). Conceptual change researchers tend to describe concepts as either consistent or inconsistent with the understanding of experts and many define conceptual change as a correction of inconsistent conceptions, or *misconceptions.* For example, if an individual holds the misconception that scientists believe that humans are not responsible for

[1]A concept can be defined as "units of mental representation" such as the notion of "object" or "climate change" (Carey, 2009). Further, concepts are constructed from prior knowledge and experiences. Beliefs, in contrast, are structures of concepts that are taken to be true (Carey, 2009).

climate change and reads a statement that "97% of scientists agree that climate change is caused by humans," then there might be potential for the learner to question their misconceptions and shift them to be more consistent with scientists. In this way, numbers have the potential to instigate conceptual change, though there are many additional contributing factors and processes illustrated across prominent models of conceptual change theory. Recent scholarship suggests that these factors include not only individual reactions (e.g., surprise), collective emotional responses in group contexts (e.g., collective concern), and the need to manage socioemotional dynamics when new data contradicts learners' prior conceptions (Herrick et al., 2025a; Lobczowski et al., 2021b).

Developmental Models of Conceptual Change

Many perspectives exist regarding the nature of conceptual change including those from developmental psychology (Carey, 2009), science education (Posner et al., 1982; Strike & Posner, 1992), and educational psychology (Dole & Sinatra, 1998; Murphy & Mason, 2006; Sinatra, 2005). For example, the *Framework* approach is a developmental model of conceptual change postulates that new information is filtered through a unified body of knowledge called a "framework theory." When new information is not compatible with that framework, it may get neglected or distorted, leading to misconceptions or synthetic conceptions that are developed as new information is added, while the background assumptions of the framework theory are maintained (Vamvakoussi & Vosniadou, 2004, 2007, 2010; Vosniadou & Skopeliti, 2014). Another classic conceptual change model was posited by Posner et al., (1982) which posits that conceptual change occurs in a manner similar to *scientific revolutions* (Kuhn, 1970). Learners may initially hold conceptions that are consistent with earlier scientific ideas (e.g., that the earth is flat) but conceptual change may occur if the learner is *dissatisfied* with their existing conception, and they find a new conception to be *intelligible*, *plausible,* and *fruitful* for leading to new insights (Posner et al., 1982). If these conditions are met, conceptual change may occur.

Warm Models of Conceptual Change

Although these earlier models articulate cognitive factors and rational processes involved in conceptual change, they do not include motivational, affective, or contextual factors (Pintrich et al., 1993; Sinatra, 2005). Motivational and affective factors such as emotion, self-efficacy, interest, attitudes, and goal setting—termed *warm constructs* (Pintrich et al., 1993; Sinatra, 2005)—have come to characterize modern approaches in educational psychology. These constructs are important because they are closely linked with student engagement, learning, achievement, and conceptual change (e.g., Linnenbrink-Garcia & Patall, 2015; Sinatra, 2005). Furthermore, when learners work in groups, emotional responses can escalate or subside collectively (Lobczowski et al., 2021a), shaping whether they process deeply or disengage. Recent work points to "emotional pathways" that emerge in classroom settings (Herrick et al., 2025a), through which students' initial anxiety or skepticism about local data depicted climate issues can be processed into curiosity and hope, reinforcing the "warm" dimensions of conceptual change.

For example, Dole & Sinatra's (1998) *cognitive reconstruction of knowledge model* (CRKM) of conceptual change takes into account information characteristics (e.g., whether soil data is *comprehensible*, *compelling*, and *relevant*) and learner characteristics (e.g., their *beliefs*, *motivation*, and *emotions*), which interact to determine students' levels of cognitive engagement. Higher levels of engagement, in concert with people's shifting motivational and emotional states, then predicts more serious consideration (or reconsiderations) of whether scientific ideas are *plausible* (Lombardi et al., 2016). More explicit plausibility considerations then predict a higher likelihood that people reconsider their stance and exchange scientifically accepted ideas with their prior conceptions (i.e., experience conceptual change). Guiding students in a classroom setting to name and interpret the emotions arising from new data could help sustain an explicit plausibility appraisal, rather than letting anxiety or confusion derail them. These models frame conceptual change as a process that involves motivation, beliefs, and motivation.

Indeed, theory and evidence suggest that *motivational factors* such as a learners' *individual interest* in STEM (a stable disposition), their *situated interest* (interest triggered by the environment), and *utility value* (perceived utility of learned information) are important process mechanisms involved in the use of interventions that support learning and conceptual change (Hidi & Renninger, 2006; Hulleman & Harackiewicz, 2021; Hulleman et al., 2010; Seyranian et al., 2023). *Belief factors*, such as epistemic dispositions—people's relatively stable beliefs about knowledge and processes of knowing—are also thought to predict explicit engagement with new claims (Lombardi et al., 2016; Richter & Maier, 2017; Stanovich & West, 1997), and potential for conceptual change (Emlen Metz et al., 2020; Thacker, 2023, 2024; Thacker & Sinatra, 2022). *Emotional factors* are also hypothesized to direct learners' explicit attention to plausibility appraisals (Lombardi et al., 2016); for example, *epistemic emotions*—emotions that arise during learning, such as surprise and curiosity—can drive attention and mediate motivational, affective, and learning processes (e.g., Jacobson et al., 2021; Linnenbrink, 2007; Muis et al., 2018; Thacker et al., 2020). As such, the warm models of conceptual change (Dole & Sinatra, 1998; Lombardi et al., 2016) assume that emotion, motivation, epistemic dispositions are mechanisms that support conceptual change. Further, *group-level socioemotional regulation* can sustain or amplify these mechanisms (Lobczowski et al., 2021b). For example, if a group collectively reappraises frustrations about complex climate data as a shared challenge, individuals may remain more motivated to reconcile discrepancies and engage in deeper conceptual analysis. Such findings align with the propositions that warm constructs, when managed collectively, can drive more robust conceptual change.

Reconciling Conceptual Change with Data Literacy Frameworks

Conceptual Change from Quantitative Data

Across all models discussed so far, novel information catalyzes cognitive, affective, and motivational processes that increase potential for conceptual change. How might things change when that information is quantitative? Are there particular challenges people encounter when evaluating and interpreting quantitative data and data visualizations? Theory on magnitude knowledge and numerically driven inferencing suggests that, indeed, some people may require support in making sense of numbers they are presented with, and that emphasizing specific data literacy skills may facilitate sensemaking processes.

Magnitude Knowledge. Making meaning of number magnitudes is considered to be a core competency in mathematics and science and involves several skills that develop over time (Booth & Siegler, 2006; Cheuk, 2012; Sasanguie et al., 2012; Siegler & Booth, 2004; Siegler & Opfer, 2003). Siegler's (2016) Integrated Theory of Numerical Development provides an explanation for how this development occurs, positing that people develop accurate understandings of number magnitudes and their relationships as they connect numbers (e.g., representing rising temperatures) to the things that those numbers refer to (e.g., global climate change). As learners develop, they learn new ways to make meaning of numbers by connecting and comparing them to other numbers, ideas, and representations through processes of *association* and *analogy*, both of which are activities that are considered crucial for both mathematical and scientific learning (Siegler, 2016). Yet, while this theory offers useful insight into how people coordinate meaning and number, one consideration left out of this perspective is when real-world magnitudes refer to socio-political issues. For example, what happens when magnitudes point to real-world issues, such as disproportionate access to ecosystem services across an urban landscape? We seek to develop a model that incorporates learners' experiences of strong emotions that can influence how they incorporate new numerical insights. An initial step in this direction is to account for the role of learners' *attitudes* and *beliefs*.

Numerically-Driven Inferencing. Numerically-driven inferencing (NDI) is a framework of conceptual change that investigates how peoples' understanding of numerical information is connected to their knowledge, attitudes, and beliefs about larger issues (Ranney et al., 2001; Thagard, 1989). Rather than asking someone their stance on particular issues, one would ask what they would prefer the *numbers* to be. Numbers are thought to be the "tip of the iceberg" in a person's thinking, and are connected with beliefs, attitudes, and conceptions in such a way to bring "coherency" to their worldview (Ranney & Thagard, 1988; Thagard, 1989). NDI operationalizes conceptual discrepancies in terms of the differences between estimates of numbers and their actual values and conceptual change in terms of changes observed in individuals' re-estimates and number preferences after reading new information (Ranney, 2001; Ranney & Thagard, 1988). According to NDI, numerical evidence that is *critical*, *germane*, and *credible* will catalyze conceptual change (Ranney et al., 2001; Ranney & Thagard, 1988). NDI also posits that *the emotion of surprise* plays a central role in learning from novel statistical information, it is elicited when an individual encounters discrepant information and is thought to lead to questioning and discovery (Munnich et al., 2007; Thagard, 2005). Beyond individual surprise, evidence shows that *groups* may collectively navigate or dismiss surprising statistics depending on their ability to co-regulate emotions (Lobczowski et al., 2021a; Vea, 2020), suggesting that NDI processes might be amplified or stalled by group-level emotional dynamics.

NDI and Numerical Development theories have some commonalities with the CRKM. They assume that conceptual change is initiated with exposure to discrepant information, leading to revision of knowledge and beliefs. The models also assume that knowledge, attitudes, and beliefs are interconnected, and in the case of NDI, incorporates emotion (surprise) and message characteristics. However, unlike the CRKM, the NDI framework and other models leave out important learner characteristics (e.g., motivation and engagement) and message characteristics (e.g., plausibility and comprehensibility). It is precisely these properties that we believe deserve attention. Indeed, we believe that understanding how people make sense of quantitative data requires considering the confluence of motivational, emotional, and cognitive properties—while at the same time considering the particularities of the data that they are learning from.

Data Literacy Models (and What Conceptual Change Models can Gain From Them)

We believe that literature on data literacy and statistical literacy offer strengths for inclusion in an integrated model of data literacy for conceptual change. Though there is no consensus on a definition, the term "data literacy" can be defined as the statistical competencies, methods, and techniques that facilitate decision-making (Gould, 2017). Because decision-making with data can be complex, data literacy frameworks often include many interrelated core competencies that range between about 5 to 20 different categories. Such data literacy frameworks often include competencies such as *understanding*, *acquiring, reading, interpreting, evaluating, managing, visualizing,* and *using* data (Börner et al., 2019; Carlson & Johnston, 2014; Kim et al., 2023; Prado & Marzal, 2013; Ridsdale et al., 2015), which are critical for driving advancement and insight in fields of science more broadly (Qiao et al., 2024). Prompting students to express how the data makes them feel can open emotional pathways that lead to an individual or collective openness to deeper data analysis and processing (Herrick et al., 2025a, Herrick et al., 2023).

Research on learning with data visualizations also offers ideas that may improve conceptual change models. Advances in the study of visualizations for STEM learning suggest that imagery has potential for helping students to ground abstract concepts in perceptions of scientific representations (Schwartz & Hiezer, 2006). There are a number of properties of data visualizations that are related to their efficacy for learning and communicating science content. For example, according to the Data Visualization Literacy Framework (DVL-FW), different types of visualizations can be designed to fulfill information needs of the learner, and each visualization type requires specific skills for interpreting them (Börner et al., 2019). According to this framework, a central process required to interpret data from visualizations is *translating* relevant problems of interest into problems of data. That is, before acquiring, analyzing, and visualizing data, individuals must first understand how the data relates to a relevant situation. As such, to improve students' interpretation of data visualizations, they may need support in translating real-world situations and problems into data. However, at the same time, research also suggests that data visualizations revealing local phenomena can evoke anger or worry within groups which in turn influences how students scrutinize or accept the underlying evidence (e.g., Phillip et al., 2016).

In sum, the data literacy skills identified in the literature offer important nuances and affective considerations that might be integrated into warmer models of conceptual change. Specifically, when considering the *comprehensibility* of data, data-literacy research offers specific data interpretation skills and critical literacy skills that might be applied to initially interpret them. For example, some models consider key *properties* of data and/or how it is visualized (such as data scales, analyses, graphic symbols, and how variables are visualized; Börner et al., 2019; Shaw & Hoeffner, 2002) and the *mathematical skills* learners must acquire to comprehend them (such as proportional reasoning, understanding of conventions of diagrams, Börner et al., 2019; Cromley et al., 2013; Shaw & Hoeffner, 2002; Vahey et al., 2012). An implication of this research is that it offers useful principles to take into account when presenting data to support student comprehension of data and data visualizations—such as, by reducing *working memory* demands, avoiding *three dimensional graphs*, using *multiple formats* to communicate data, and helping craft a *narrative* around what the data communicates.

While these models offer useful tools to support comprehension, other models of data literacy offer more in the way of promoting *critical data literacy* skills. For example, Rubel et al. (2021) identify three key skills needed to critically *read* properties of data: formatting (questioning what and how data is quantified), *framing* (questioning relationships depicted and visualized), and *narrating* (questioning the stories authors tell). Other models, such as Weiland (2017) consider both critical reading of data and critical *writing* of data. Critical writing of data centralizes student agency and attends to critical statistical literacies such as to encourage students to identify untold stories, statistically investigate and resolve sociopolitical injustices, and use statistical investigations when communicating and arguing efforts to broad audiences for a more just world. Integrating emotional processing into these critical readings can further empower students to question, react to, and potentially reframe data narratives that evoke strong affect, ensuring that frustration or anger become opportunities for more rigorous engagement with data. Focusing on emotional awareness can help educators anticipate and guide the affective responses that arise when students confront unsettling or surprising data (Ojala, 2023).

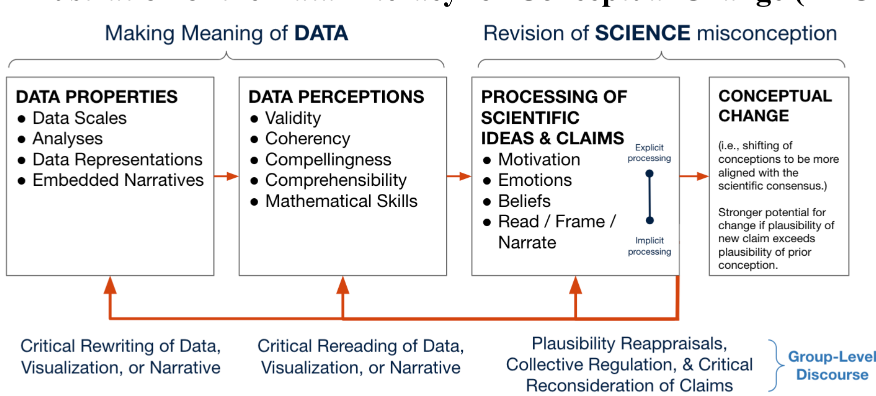
In sum, while there are many useful data literacy and critical data literacy frameworks that exist in the literature (e.g., Qiao et al., 2024; Rubel et al., 2021; Vahey et al., 2012; Weiland, 2017), currently none take into account motivational or affective constructs that are crucial in understanding the unique challenge of preparing students with skills needed to make sense of data related to socio-scientific topics such as climate change. Conversely, educational psychology models for socio-scientific learning (e.g., Dole & Sinatra, 1998; Lombardi et al., 2016; Sinatra & Hofer, 2021) rarely incorporate data literacy or the justice-centered perspectives crucial for understanding climate impacts (Morales-Doyle, 2024). Our theory of Data Literacy for Conceptual Change attempts to reconcile these perspectives by foregrounding both individual-level and collective socioemotional processes that drive whether or not learners ultimately revise their prior conceptions.

The Data Literacy for Conceptual Change Model (DLCC)

The DLCC positions data literacy skills identified in the mathematics education literature in terms of models of scientific conceptual change. Notably, our model explicitly assumes that key critical data literacy skills (e.g., such as proportional reasoning, formatting, framing, reading, writing, and narrating data context and visualizations**;** Rubel et al., 2021; Vahey et al., 2012; Weiland, 2017) serve to help students comprehend and make personal meaning of data, and also intersect with the affective dimensions (e.g., motivation, emotion, and beliefs) that promote conceptual change at the individual level. Incorporating affective pedagogical goals from mathematics education (Kokka, 2022), which emphasize the emotional dimensions of learning about issues of injustice, the DLCC model adapts such goals for science learning with special emphasis on supporting students' emotional processing of climate data (Herrick et al., 2025a).

Namely, our model assumes that the format of data and data visualizations predict learners' initial framing and perceptions of the data (in terms of its validity, coherency, compellingness, and comprehensibility), which then predicts learners' processing of the plausibility of scientific ideas, claims, and explanations represented by the data (including how emotional reactions can be co-regulated within groups), and ultimately learners' negotiation of whether to adopt such scientific conceptions at the individual level. More specifically, we assume that plausibility appraisals are more thoughtful and explicit depending on learners' motivational and affective states, and more explicit processing is associated with higher likelihood for conceptual change. Lastly, we propose that group-level discourse can prompt students to negotiate and reconsider the plausibility of scientific claims, engage in critical re-readings of scientific ideas, or even re-write data and narratives. In this way, the DLCC acknowledges that conceptual change emerges when individual cognitive conflict and motivational factors converge with collaborative emotional support and critical data literacy skills. The model pertains across socio-scientific topics, with special applications of data literacy for climate change teaching and learning, given that the evidence for this model stems from this topic which we elaborate on in the next section.

Figure 1: An Illustration of the Data Literacy for Conceptual Change (DLCC) Model



Evidence for the DLCC with Applications for Climate Change Learning

Evidence supports relationships posited in the DLCC. For example, engagement with climate change numbers in game-based learning settings can support conceptual change and highlight relevant relationships posited in the DLCC. Namely, prompting secondary and undergraduate students randomly assigned to estimate key climate change numbers before being shown the consensus value improved their climate change knowledge compared with a control group by about a third of a standard deviation (Ranney & Clark, 2016; Thacker 2023, 2024; Thacker & Sinatra, 2022). Additional qualitative and experimental evidence demonstrates that these learning outcomes are bolstered with targeted support of proportional reasoning strategies, conventions around interpreting number-line data visualizations, and compelling and contextualized data narratives (Thacker, 2023; Thacker et al., 2024). Further, these efforts to support data comprehensibility, validity, and compellingness which promoted student learning were found to be moderated or mediated by learners' adaptive beliefs about knowledge, positive emotion, and motivational factors (Thacker, 2023, 2024; Thacker et al., 2024; Thacker et al., 2025). These studies reveal the importance of attending to both mathematical and scientific learning properties when designing instruction and begin to illustrate the benefits of intentionally mitigating negative emotion and climate hopelessness when discussing climate change (see Stoknes, 2015).

Indeed, explicit attention to learners' emotional responses can bolster students' engagement with climate-related data and support conceptual change. For example, in Herrick et al. (2025a), teachers led brief, repeated *Community Science Data Talks* (CSDTs)—a pedagogical tool that integrates traditional data literacy skills with affective processes around locally relevant climate impact data (e.g., data depicting disproportionate tree canopy coverage in a city) and prompt students to share how the data made them feel. This invitation opened "emotional pathways" that encouraged learners to share personal experiences, express surprise or concern, and collectively process emotions toward curiosity and constructive hope around the implications of the data they examined (Herrick et al., 2025a, 2025c). On a practical level, CSDTs demonstrate two pivotal strategies for data literacy around local socio-scientific topics (1) structuring small, regular, open-ended data-discussion routines that highlight learners' sense of place and (2) prompting students to narrate their emotional responses to support the technical elements of their data interpretation. By weaving affective dialogue into data literacy instruction, teachers create a shared sense of urgency and curiosity around local climate impacts, which support the DLCC model's emphasis on individual learners revisiting and revising their prior conceptions.

Principles For Future Scholarship Areas of Research

While the empirical research is relatively conclusive in demonstrating that levers improving students' comprehension of data is linked to motivational and learning gains, there are several factors that need more research. Namely, educational psychology and mathematics and science education have complementary strengths that could be leveraged more effectively through cross-pollination of ideas and methods. On the one hand, data literacy research can more frequently consider affective and socioemotional dimensions of student learning (emotion, motivation, attitude), including how group co-regulation of emotion fosters or hinders deeper analysis of data at the individual level. On the other hand, conceptual change research could do a better job of incorporating critical data activities, specific skills needed to make sense of data, and especially in data depicting localized socioscientific topics. Ultimately, increased collaboration and partnership among educational psychology, math, and science education research would only lead to improved integration of data-literacy research and affective dimensions of learning that promote conceptual change.

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