Visualization mediates human-data interactions by representing data with abstract visual metaphors—e.g., encoding patterns in data as variations in color, position, and other graphical properties. The field of visualization research builds tools for constructing these representations and investigates what makes them meaningful and useful to human users. *However, prevailing notions of what makes a visualization meaningful or useful are divorced from context in ways that sometimes make them inadequate for guiding practice.* For example, consider the common usage of visualization in explanations of AI systems and in business intelligence dashboards, where the value proposition of visualization is that transparency will improve user understanding and agency in general. Understood in this way, the objective for visualization is to communicate clearly, and visualization research excels at comparing human interpretation errors for different representations to recommend generically optimal visualization techniques (e.g., [1, 2]). However, this approach *often fails to operationalize what makes a visualization meaningful in context* and *for what task a visualization is useful*. For instance, in a recent review article [3], we find many studies evaluating visual explanations of AI decision aids underspecify the participant's task or ignore what information would be relevant to visualize. In the field's focus on visual representation, visualization research emphasizes *how to visualize* data much more than *what data to visualize*, neglecting to systematize the messy relationships between people and data that define context in ways that would be actionable for guiding practice.

My research aims to create tools for helping people think with data, often using visualization as a medium. This requires contending with a *fundamental tension*: building tools requires formalisms that can align implementation with intended use, but these tools must be designed for people, relationships, and data that inherently resist such systematization. My research addresses this tension head on by triangulating with three epistemic approaches: By *theorizing* about data reasoning problems and adapting formal models from cognitive science and statistics, I develop new approaches to operationalizing performance and analytical intent with visualizations. Through *design inquiry*, I interview people about their contextually situated data problems, and engage them in user-centered software development. Using *experiments*, I conduct controlled evaluations of human data cognition with tools informed by theories and design methods. My research won multiple awards at IEEE VIS for contributing new theoretically-motivated ways to measure and model human data interpretation behaviors. Ongoing investigations leverage and stress-test these ideas by applying them to the development of domain-specific tools. For example, I received a grant from the Institute of Educational Sciences to reform the communication of scientific evidence to school leaders for the purpose of instructional decision-making. In combination, these efforts generate knowledge about visualization design that is both theoretically ground and contextually robust, pioneering a path toward a new generation of tools supporting personalized data communication.

ADAPTING THEORY FOR PRACTICE IN VISUALIZATION RESEARCH

Visualization as a discipline is inherently oriented toward practice. Whether a research project contributes a technique, evaluation, or toolkit, we seek knowledge about how visualization is applicable to real-world data problems. In a recent paper [4], I critique the *logic of generalization* by which we infer real-world usefulness from studies, focusing in particular on how we investigate the use of visualization as a decision aid. **I adopt decision theory as a lens for understanding the conditions for generalization about visualization as a decision aid.** Decision theory (Figure 1) posits that decision problems consist of several dimensions: an *action space* defining the possible actions a decision-maker might take; a *state space* defining possible states of the world that might be relevant to the decision-maker; a *signaling policy* representing a visualization technique by which information about states of the world is rendered as a *signal* shared with the decision-maker; a *signal space* defining the variety of distinct-looking charts that a visualization technique could produce; an *interpretation* by which the decision-maker infers the likely state of the world from a visualization; and a *utility* by which the decision-maker assesses the desirability of possible actions under likely states. **Utility plays a special role in the structure of decision problems by determining what states are relevant for the decision-**

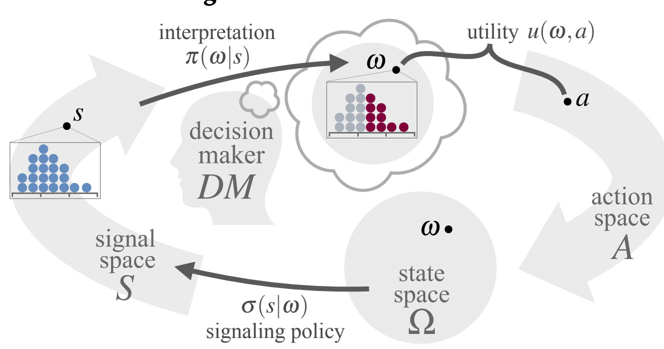

Figure 1. A diagram of the role of visualization according to decision theory.

maker to infer from a visualization. I argue that studying stakeholder values is key to systematizing variation in decision problems in order to enable more robust generalizations about decision support.

In contrast, most visualization research studies data interpretation and tool-building in ways that assume context is ignorable or inscrutable. I critique two extremes on an epistemic continuum [4]. V*isualization research focused on interpretation tends to assume context can be abstracted away*, that performance can be evaluated solely in terms of the "atomic" [5] perceptual operations involved in decoding data from an image. I call this logic of generalization the **optimistic atomicity assumption**, and it neglects decision context in ways that are undesirable. *Problem-focused visualization research attends carefully to context* through in-depth design studies [6], where researchers embed with a team of domain experts and develop software for them. However, this approach tends to be non-committal about systematizing context and views software abstractions as the primary research outcome, assuming that others will be able reason about generalization from truncated context descriptions. I call this logical move the **cautious indeterminacy assumption**, and it clearly hinders building generalizable knowledge from contextually situated design methods.

The juxtaposition of these two assumptions reflects an **epistemological rift in visualization research**, where the field ardently disagrees with itself about how to translate research into practice. *My research aims to step into this rift and reconcile it* by demonstrating the usefulness of both approaches in combination. I use theoretical frameworks like decision theory to *bind together* mechanistic accounts of data interpretation with the kinds of applied investigations that are needed to adapt these ideas for broader use.

FORMALIZING VISUALIZATIONS AS SIGNALING POLICIES

Decision theory frames visualization techniques as signaling policies [3, 4, 7], which *provide a mapping between states of the world and signal realizations* (i.e., charts with a particular appearance). In other words, a visualization technique induces a distribution of possible signals conditional on possible states. Recall that utility determines what states are relevant to a decision problem. **If we want to make personalized, context-aware visualization design recommendations, we need to formalize the different ways that visualization techniques can reveal, hide, or distort information about task-relevant states.**

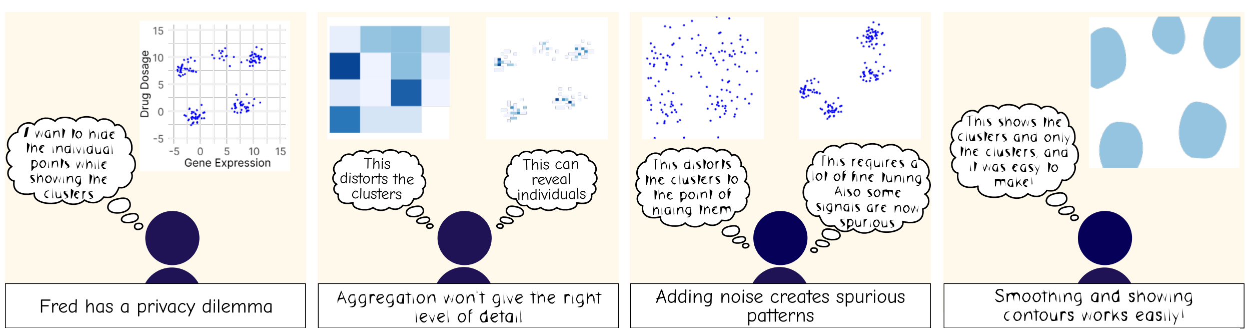

Figure 2. A data comic demonstrating the kind of privacy dilemma that can be more easily addressed with a vocabulary of disclosure tactics.

My lab is working to formalize visualizations as signaling policies. My PhD student, Krisha Mehta, led an investigation of **visualization as a mechanism for data disclosure** [8], contributing a taxonomy of distinct ways that data pre-processing operations involved in rendering visualizations can hide or distort information. We call these operations *disclosure tactics,* and we demonstrate how creating a vocabulary around visualization as a mechanism for data disclosure enables flexible solutions to selective data sharing problems (e.g., Figure 2). Such problems arise not only in applications where concerns about privacy, security, or intellectual property constrain data disclosure—the communicative bandwidth of a visualization must also be carefully rationed in contexts where the attentional capacity and data literacy of an audience limit what information a designer can hope to convey in an image. Thus, this work represents a *theoretical breakthrough* enabling a new way of conceptualizing solutions to a variety of core problems for visualization research and practice that until now were difficult to approach systematically.

In my NSF CAREER proposal, I describe anticipated future work developing **a new Domain Specific Language for data disclosure** that enables automated reasoning about information loss in visualization design. The intellectual advancements involved in creating this tool will extend accounts of visualization design as an algebraic process [9] and formally codify design objectives from decision theory about *what to* *show* in a visualization. Thus, formalizing visualization as a signaling policy bridges existing theories of data communication and enables weaving them together in software. The practical impacts of this tool are that it will enable, for the first time: (i) *automated visualization recommendations* based on the user's intent to communicate specific data signals; (ii) *interactive design explanations* unpacking for general audiences how a visualization might be misleading based on what data signals it can and cannot show by design; and (iii) *formal ethical guardrails for visualization design* reflecting agreed-upon data communication standards within an organization or community of practice about what forms of information loss are and are not permissible.

RETHINKING EMPIRICAL EVALUATIONS VISUALIZATIONS

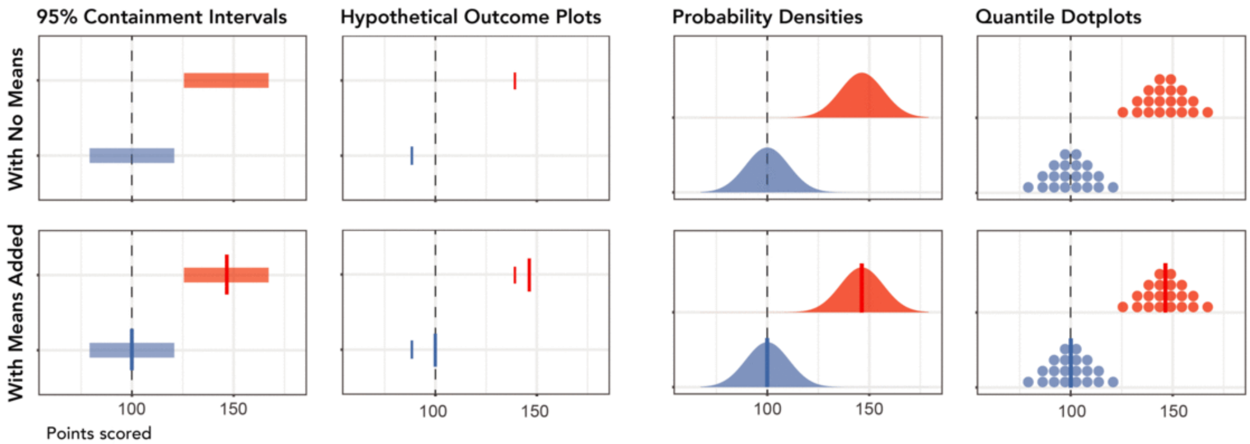

Figure 3. Uncertainty visualizations compared in a crowdsourced experiment on how heuristics influence decision-making behavior.

Even if we reject the optimistic atomicity assumption (see above) and instead try to make more context-aware design recommendations, visualization research still needs valid ways to measure and model user performance with visualization techniques. Unfortunately, the status quo for visualization evaluation relies on *atheoretical metrics of accuracy, response time, and user satisfaction* [10]. These measures are oversensitive to arbitrary variations in experimental design and undersensitive to the user's underlying cognitive processes. Further, *visualization research tends to underspecify tasks* [3], in the sense that we struggle to score accuracy in an unambiguous and credible way. As a corrective, my research creates and impels new approaches to visualization evaluation that **elucidate cognitive mechanisms underlying data interpretation** and **define benchmarks for human performance in the absence of a known ground truth**.

Data interpretation involves cognitive processes such as **the heuristics and strategies by which users selectively attend to and decode information from a chart** in order to perform a task. My research measures and models these cognitive mechanisms in novel ways. For example, I ran a crowdsourced experiment investigating how people use uncertainty visualizations (Figure 3) to make incentivized decisions, and I found that people often satisfice with visualizations by adopting oversimplified strategies which lead to suboptimal decision-making [11]. This work won the *InfoVis Best Paper Award at IEEE VIS 2020* for sparking a new style of evaluation drawing on cognitive science and behavioral economics to uncover cognitive mechanisms of data interpretation. In an ongoing collaboration with researchers at Northwestern, Tufts, and Columbia University, we seek to build on this idea of modeling mechanistic chart interpretation by statistically **identifying visual decoding operators** through bespoke modeling of behavioral data [12]. Future plans entail enumerating and modeling a library of decoding operators that can be used to *predict data interpretation in ways that will drive visualization recommendation* and query planning in database systems.

Part of the trouble with accuracy measures is that **the ground truth interpretation is hard to define for real datasets**. Imagine we want to measure the quality of causal inferences with visualizations. If we knew the correct interpretation of a dataset, there would be no need to visualize it, so in most use cases for visualization it is difficult to evaluate accuracy. This severely limits the rigor of systems evaluations. Drawing on theories from cognitive science [13], I devised a way to benchmark the quality of chart users' causal inferences based on the compatibility of a dataset with competing causal models [14]. This work won an *Honorable Mention Award at IEEE VIS 2021*, both for methodological innovation and for a surprising finding—none of the visualizations tested improved causal inferences compared to text contingency tables. This work offers a new **model-based operationalization of accuracy**, which can be extended to define the instrumental value of datasets or model outputs for answering inferential queries. Future work will use this formalism to evaluate systems for dataset search and summaries of scientific evidence for decision-makers.

VISUALIZATION IN REAL-WORLD DECISION-MAKING

The effectiveness of visualization as a decision aid is highly situationally contingent. It's natural to ask, "Effective for what and for whom?" As I argue in my theoretical work [4], the answers to these questions can only be resolved by studying a wide variety of decision problems and systematically characterizing how they differ both structurally and in terms of the values of stakeholders. At the University of Chicago, I am pursuing multiple **investigations of real-world applications of visualization as a decision aid** in an effort to **develop tools that make visualizations more portable across audiences and contexts**.

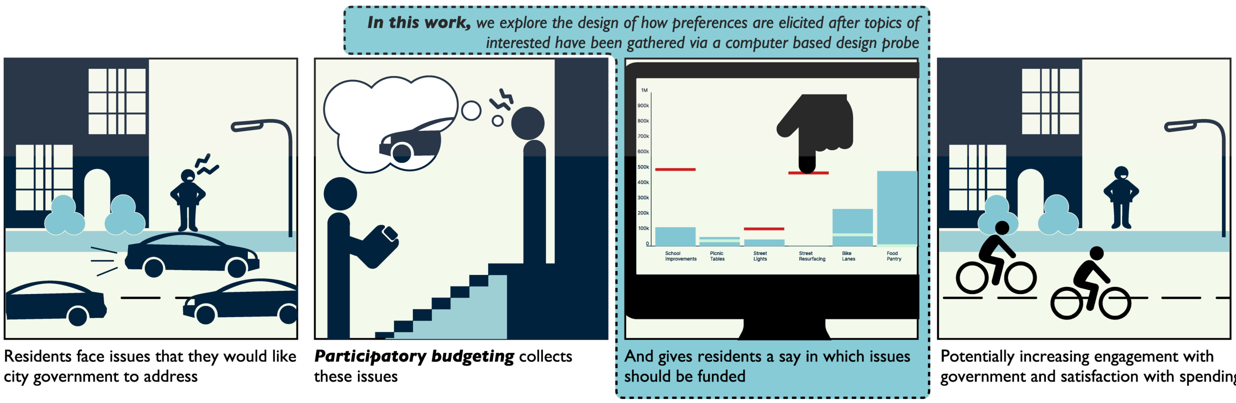

Figure 4. A comic-style depiction of participatory budgeting. We expore the role of visualization as an interface for voting and reporting results.

One such investigation focuses on **participatory budgeting (PB) in the City of Chicago**. PB empowers city residents to propose civic projects, have them vetted by domain experts, and then vote on the allocation of municipal funding to pre-approved projects. My research interest in PB is that it represents *a collective decision problem for which residents' values around and relationships to proposed projects should drive the design of voting interfaces*. With students at the University of Chicago, I led a design investigation into how visualization might benefit PB in Chicago as both (i) a voting mechanism where residents allocate funds to projects by drawing on a chart, and (ii) a transparency mechanism where residents can view voting results [15]. Through interviews with PB experts and organizers in Chicago, we found that *interactive visualization shows promise as a utility elicitation procedure* that might help residents deliberate about their values. However, we also find that *generic dashboards fail to speak to situated, individual priorities* that arise around voting, and *dashboards present access barriers* for people without high graphical literacy. This work suggests a **need for more flexible ways of summarizing data for different audiences**, echoing a design imperative that arises in ongoing collaborations on how experts and laypeople make different interpretations of epidemiological models [16] and how scientists and school leaders think differently about the mobilization of scientific evidence to support instructional decisions in schools.

Consider the problem of **evidence-based decision-making in K-12 education**. For the past two decades, the Department of Education has funded and coordinated research on "what works" in schools, focusing primarily on accumulating evidence from controlled experiments and meta-analyses in *online repositories of evidence called clearinghouses*. Although well-conceived, this effort was stymied by disconnects between research and practice [17], highly heterogeneous decision processes across school districts [18], and a sparsity of high-quality studies that can directly answer questions about a specific instructional decision. In 2024, the Department of Education funded a grant for collaborators at Northwestern, Villanova, and me to **redesign the summaries of scientific evidence** shared with school leaders via clearinghouses. Recent cuts at the Department of Education throw this system of evidence dissemination into crisis, replacing centralized knowledge repositories with more distributed and ad hoc systems of evidence sharing. This problem presents an urgent need and an opportunity to reform science communication for non-scientists, which will entail research into *how organizational decision processes drive demand for evidence* and *how to personalize evidence summaries with sparse data inputs*. Addressing these challenges will result in new ways of generating data summaries that both **selectively stage information based on relevance to the audience** and **explain how to interpret data according to scientific standards**. This ongoing and future work builds on my previous efforts developing tools for statistical analysis [19, 20] and research synthesis under scientific uncertainty [21, 22]. The envisioned mixed-initiative decision support tools can also make direct use of the Domain Specific Language for visualization as a data disclosure mechanism (described above).

VISUALIZATION IN DATA-DRIVEN DISCOVERY

The *looseness of discovery* as a target for data analysis presents *cognitive and technical challenges* for visual analytics tools. Cognitively, data scientists struggle to articulate their analytical intent to systems or to recognize whether visualized data supports valid statistical inference about a pattern of interest [23]. Technical challenges mirror these cognitive difficulties: system builders struggle to develop interfaces and algorithms that adequately reflect users' thinking or priorities in data analysis, and visual analytics tools lack affordances for detecting and mitigating false discovery [24]. I design new patterns of data interaction that **enable users to articulate their mental models about data** and **formally encapsulate analytical intent to improve the utility of data analysis while safeguarding against spurious inferences**.

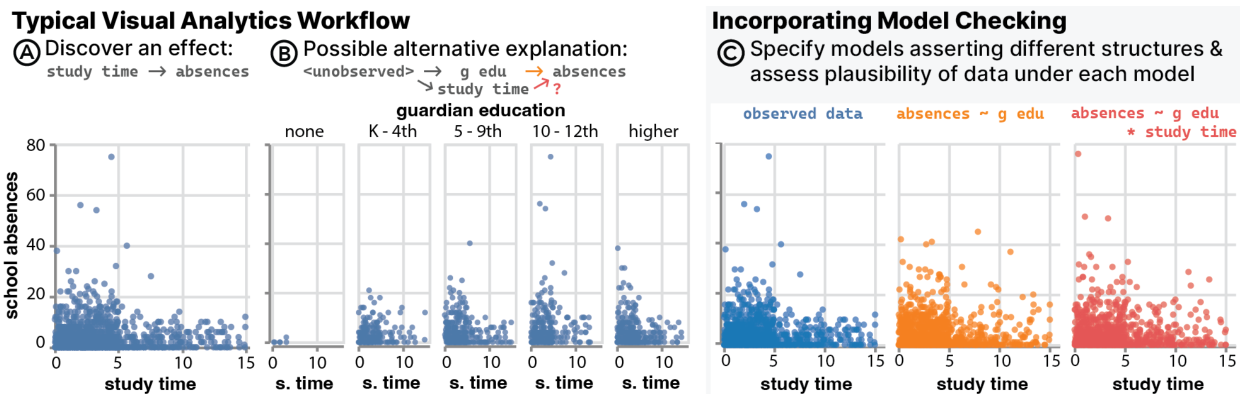

Figure 5. A visual explanation of how model checking benefits visual data exploration by formally encapsulating insights as statistical models.

To make mental models of data generating process explicit in visual analytics tools, I am leading an effort around **new systems that enable analysts to express provisional statistical models and visually check their compatibility with data**. Motivating this approach of using statistical models to encapsulate hunches about data generating process are (i) theories of statistical inference that suggest *model checking* (Figure 5) is a key activity for sensemaking [23], (ii) limited support for statistical modeling in many existing visual analytics tools, and (iii) empirical evidence from my own work showing that people struggle to reason about the compatibility of models with data without explicitly visualizing model outputs [14]. I led the design and development of a proof-of-concept system called EVM (exploratory visual modeling, Figure 6), which adds operations for specifying and comparing regression models in a Tableau-like interface [25]. Evaluating this tool with data scientists demonstrated the promise of **enabling analysts to build up explanatory models gradually while interactively exploring a dataset**, however, it also pointed to **challenges around model elicitation and the role of automation** in recommending models and comparisons. To address these challenges, I wrote an NSF Medium grant to initiate a collaboration with researchers at University of Illinois Chicago to investigate sketch- [26] and LLM-based *model elicitation techniques*, and to develop *automated recommendations over a model search space* that aim to guide discovery and advise caution against spurious insights. Additionally, with collaborators at Northwestern, we developed VMC (visualization model checks), *a grammar for specifying visual diagnostic checks for generalized linear model outputs* [27]. This work **formalizes visualization as a signaling policy for regression models**, enabling future systems to make visualization recommendations based on the traversal of model space.

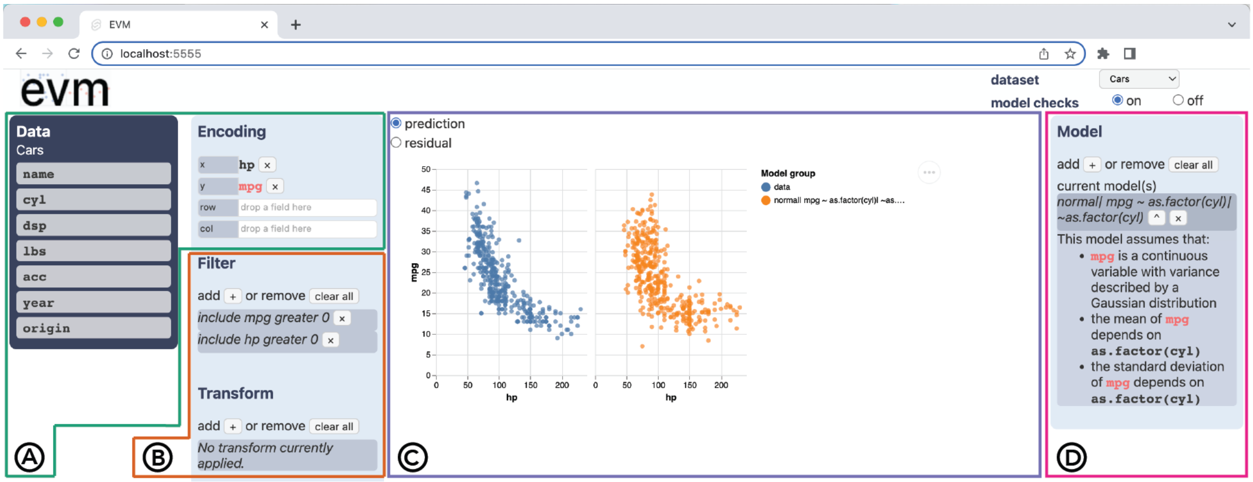

Figure 6. A screenshot of the EVM interface: (A and B) a shelf construction interface for specifying visualizations and data transformations; (C) a plotting canvas; (D) a novel model bar interface for specifying, editing, and exploring the assumptions of generalized linear models.

Difficulties operationalizing analytical intent present an even greater obstacle to dataset search, where data scientists provisionally assess the usefulness of a multitude of data sources, often retrieved algorithmically from large repositories. Visual analytics approaches do not scale well to the consideration of many datasets in parallel, yet interactive tools may be necessary for data scientists to refine their sense of *information need* well enough to articulate in search tools what they seek in a dataset. To better understand how data scientists conceptualize and express information need during dataset search, my PhD student, Danni Liu, and I initiated a collaboration with Raul Castro Fernandez's lab to run an ongoing and unpublished survey and interview study. Our initial findings suggest that **data seekers evaluate information need by proxy using criteria** regarding the *relevance* of a data source to their task, the *quality* and usability of a dataset, and *social signals* about the usefulness of the dataset or the trustworthiness of the data provider. Interestingly, participants report **using these criteria in a resource rational manner**—e.g., often limiting their search to trusted data sources rather than doing an open search in broad repositories—in part because of *difficulty matching with relevant and trustworthy datasets through search interfaces* and in part because data seekers operate under *constraints that select for criteria other than the instrumental value of data*. We envision that **dataset search systems would benefit from operationalizing information need explicitly as a model of economic utility**, driving search results based on elicited preferences over criteria like the ones that emerged from our investigation. In future work, we will (i) explore the use of LLMs [28] and methods from behavioral economics [29] for *eliciting preferences* over datasets, (ii) develop visualization recommendation systems that *generate summaries of search results that are personalized* based on an explicit model of the data seeker's utility, and (iii) integrate these interface components with model-based dataset matching algorithms from Fernandez's lab (e.g., [30]) into a proof-of-concept system. This work strives to reduce the cognitive costs of interacting with dataset search tools by increasing alignment with the way that data seekers naturally reason about and express their information need.

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