

Project Description

1 Overview

My long-term career goal is to examine statistical graphics with the goal of *helping people use data more effectively*, and to apply this research to educate and inspire a new generation of scientists while supporting science literacy among the general public.

Rationale and Critical Need: Scientific graphics transform quantitative data into images to leverage the human visual system’s ability to take in and process huge quantities of information with minimal cognitive effort. However, unlike mathematical data transformations, the transformation to visual space incurs loss when rendering data to an image and when transitioning between image and cognitive representation. That is, when creating data visualizations, we have to be concerned with the accuracy of the rendered image and with how the image is perceived by the viewer. Entire books document misleading transitions from data to image [1–3]; identifying scenarios where the transition from image to cognitive representation is suboptimal is more challenging and requires user studies. There have been empirical studies of graphics for at least 100 years [4–6], but the foundational work in graphical perception is Cleveland & McGill [7], which established our ability to accurately estimate information from simple visual displays. This work, while important and valuable, has been synthesized into recommendations and rankings which go far beyond the original experiments [8, 9] with limited empirical verification, though in some cases these extrapolations are based on general cognitive research. It is easy to forget that [7] examined charts with respect to the direct numerical accuracy of quantitative estimates; the results do not necessarily apply if we are interested instead in determining whether differences between quantities can be perceived [10, 11], ordered, remembered [12], or used to reach a reasonable real-world decision [13]. The design space of visualization user studies is incredibly large [14, 15] and spread across different fields with different preferred experimental methods; it is only natural that studies use different measures to address the same basic question. As a result of this complicated design space, it is extremely difficult to synthesize existing literature to derive empirically driven guidelines for creating graphs that are both accurate and effective, however, such efforts are essential for effectively disseminating scientific results and ensuring that scientific data can be used to make well-informed decisions at the individual and societal level.

Goals and Objectives: To that end, the **overall research goal** of this CAREER proposal is to address the fundamental research question underpinning this problem: *How do design decisions impact the perception and use of data visualizations?* Three research objectives (ROs) support this goal:

- **RO1:** Create a framework for comprehensive graphical testing across multiple levels of user engagement.
- **RO2:** Assess the impact of measurement methods on statistical graphics experiments.
- **RO3:** Empirically validate common chart design guidelines, measuring the impact of design decisions on task performance.

We focus our investigation on user engagement represented by the integrated cognitive complexity and temporal evolution of the user-chart interaction, which is roughly illustrated in Figure 1. Previous hierarchies have focused on the complexity of graphical tasks [7, 16, 17]; while this is a useful way to determine which chart to use to display data, it does not approach different ways users engage with a specific chart: are they perceiving the graphical forms without engaging with the underlying symbolic meaning? Using the chart to understand the underlying natural phenomenon? Doing statistical inference (visually estimating parameter

values)? Making decisions based on their understanding of the data? Each of these use cases involves different cognitive tasks; as a result, different graphical testing methods must be used to assess the effectiveness of charts for each level of engagement.

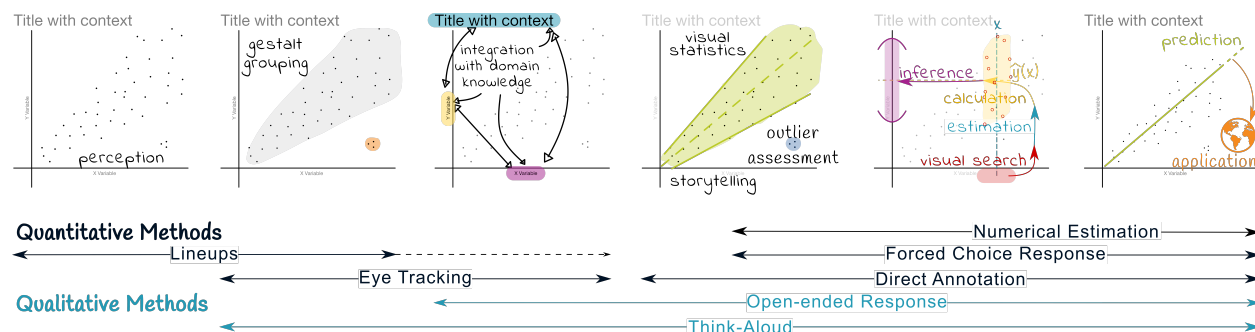


Figure 1: Levels of cognitive engagement with charts, roughly ordered by complexity, time, and effort. Methods which effectively measure (or could be extended to measure) each stage are shown below the charts. Text annotations show examples of the types of operations which involved in each stage.

Integrated with these research efforts, the overall **education goal** is to leverage visualization research to motivate statistical learning and improve data-driven decision making in society. Three education objectives (EOs) address this goal:

- **EO1:** Implement experiential learning activities in graphics for undergraduate introductory statistics courses.
- **EO2:** Create graduate course modules for educators that connect ongoing graphics research to hands-on STEM classroom activities.
- **EO3:** Improve the dissemination of visualization research by incorporating summaries of empirical research into resources used by data scientists, industry analysts, and researchers.

Expected Impact: Taken together, these objectives build a user-focused foundation for measuring and assessing the design and use of data visualizations. The focus on multiple simultaneous measurement methods within an experiment separates this project from almost all previous graphical research studies, which typically use one evaluation method per experiment. This CAREER proposal will develop methodology for measuring the functional cognition underlying data driven decision making using statistical graphics. The results from this research will facilitate integration of conflicting historical results, generating a robust set of empirical evidence that can be leveraged to produce more nuanced, task focused, accessible design guidelines for data visualization.

Experiential learning activities will connect graphics research to critical concepts within statistics courses at the undergraduate level as well as in secondary education STEM courses. Incorporating research summaries into general visualization resources will connect practitioners with research results, improve teaching materials for statistical computing, and involve undergraduates in the research process. Ultimately, proposed activities have the potential to improve how scientists communicate results to each other and to the general public, increasing the accessibility of scientific results and facilitating data-driven decision making.

Relation to the PI's Career Trajectory and Department Goals: This CAREER proposal extends the PI's ongoing research program in data visualization, building a strong foundation for studying the perception of statistical graphics and data. In addition, the research and educational objectives extend ongoing work, using graphics to connect with students and motivate development of statistical logic and computational thinking. The objectives will support the UNL statistics department's new undergraduate programs in statistics and

data science and will contribute to the wider university objectives of integrating experiential learning into undergraduate courses and supporting knowledge transfer from the university to Nebraska residents.

2 Background

In the 100 years since the first experimental graphics studies, the quantity of charts created, the methods available for creating charts, and the technology available for measuring and evaluating comprehension have evolved in remarkable ways. Vanderplas et al. [18] provides a comprehensive review of studies that experimentally examine the use of statistical graphics as well as related research in cognitive psychology (perception, memory, attention, executive function) that relates to our ability to use charts effectively.

Narrow Empirical Support, Broad Guidelines What is remarkable given the ubiquity of statistical graphics in scientific communication is that even after a century of empirical graphics research, we still have relatively little empirical evidence to support some common design guidelines and heuristics; where there are empirical studies, they often conflict or have been over-extrapolated from the design and goal of the original experiments. For example, Tufte’s data-ink ratio [19] has been thoroughly tested [16, 17, 20–22], but results have been decidedly mixed, suggesting that the data-ink ratio is too simplistic; even so, it is still part of the common vernacular and makes its way into many different design guidelines [23]. Another common recommendation is to locate the most important variables along position axes (e.g. x and y in a scatterplot) rather than encoding quantitative information in color; this is because Cleveland & McGill [7] found higher levels of accuracy in these comparisons, but estimation accuracy is not an important metric for many use cases [24]. In fact, it is relatively uncommon for individuals to directly estimate one specific numerical quantity from a chart: for these tasks, a table would be much more appropriate [25].

Need for Integrated Testing Methods Fundamentally, we know that graphics are useful for exploring data and communicating scientific results; whether the target audience is ourselves, peers, or the public, graphics are a critical tool. So why do we assess graphics based solely on measures like estimation accuracy or response time [26], and then extrapolate the results to tasks and situations that do not revolve around estimation accuracy or speed? What is needed instead is a testing framework focused on the user’s engagement with a chart. Lam et al. [27] divides evaluation scenarios into several user-focused task-based methods for both visualization and data analysis, assessing the utility of several methods for testing these empirically, but stops short of performing experiments evaluating the same graphics using multiple different methods. This component of the proposed work is essential because it provides control that is not present when aggregating results across experiments: the same participants, data (or data generating model), and testing conditions can be used across multiple testing methods, as a result, experimenters can draw stronger conclusions. In this work, we propose a comprehensive, multi-modal experimental framework for evaluating graphics that provides a novel alternative to the patchwork testing of individual questions using single methods. Instead, we empirically assess how specific charts (or design decisions) function under multiple tasks and measurement methods to gain a more complete, user-focused perspective on the utility of different design choices.

Need to Understand Input Method Choice Impacts There are multiple factors that must be considered and evaluated to achieve the broader goal of empirically testing design guidelines: the measurement methods and variables used to assess charts are of obvious interest, but other factors are also important. Consider the relatively simple case where a participant is asked to estimate the length of a specified bar in a bar chart: the experimenter must determine how this estimate is recorded. Modern UI toolkits provide multiple options: the user can directly enter a number in a text box or indicate the number on a slider (with or without anchor points). The former requires translation into an explicitly numerical domain, where the latter requires that the participant map the chart onto a spatial domain but does not require explicit formation of a numerical estimate. Direct entry is subject to rounding effects that increase with participant uncertainty [28, 29]; while

these effects can be mitigated [30] through modeling, it might be preferable to use a continuous slider input, which might not trigger rounding. Unfortunately, slider inputs are not entirely simple either: they can contain anchor points (or not) that participants may latch on to; the inclusion of these additional annotations may reduce cognitive load, but may also introduce anchoring effects. Research in this area has examined sliders as inputs for categorical variables [31–35] and suggests that using sliders instead of radio button inputs changes the observed distribution of responses in important ways; while the comparison to radio buttons is not relevant to continuous data, the results of these studies indicate that there is a need to explicitly examine the effects of input methods on participant responses. This is just one example of the series of decisions experimenters make when eliciting and recording data from participants that do not directly relate to the hypotheses under investigation but which may impact the results.

Empirical Evaluation of Design Guidelines Validating a toolbox of methods for testing graphics at different levels of user engagement and assessing the impact of measurement decisions will provide a stronger foundation through which to address the fundamental goal of this research: **using comprehensive empirical testing to validate common design guidelines**. Many books and papers provide design guidelines along with examples, redesigns, and sometimes, supporting references to empirical studies [19, 27, 36–49]. Kandogan & Lee [50] summarize the structures and types of guidelines in many of these sources. There have also been empirical assessments of broad themes common to different sets of guidelines: Ajani et al [23] experimentally evaluated two themes (“declutter” and “focus”), finding that focused designs were preferred over decluttered designs, which were preferred over cluttered designs. What is lacking is a series of tests of design guidelines across the different levels of user engagement; the experiments referenced above typically examine one type of user engagement using one assessment method. Another major gap in the existing research is an assessment of how well different guidelines serve different groups of individuals. We know that disorders such as dyslexia, dyscalculia, and ADHD affect perception, numeracy, and other processes involved in graph comprehension [51–53], yet when we consider accessibility in charts, we mostly consider colorblindness. Designers try to consider audience and accessibility [54] but have little empirical support when assessing the impact of design choices on these populations.

This project builds a foundation for the next generation of empirical graphical testing by developing a robust set of measurement methods, assessing the impact of different experimental design factors, and leveraging this foundation to experimentally and inclusively examine design guidelines.

3 Preliminary Studies

In previous work [55], we have seen that simultaneously collecting quantitative and qualitative data provides the opportunity to gain rich and nuanced insight into how participants respond to graphical tests. A significant proportion of participants evaluating a visual hypothesis test committed a Type III error: the right answer to the wrong question [56]. This study’s results inspired a desire to obtain a more nuanced insight into participants’ responses which is reflected throughout more recent work.

Use of Log Scales with Exponential Data In a more recent series of studies, we expanded this approach, examining the use of log and linear scales to assess exponential time series data across multiple different user tasks: perception, estimation, and prediction. This series of studies, inspired by the COVID pandemic and the lack of empirical research assessing the effectiveness of log scales, used three different graphical testing methods: statistical lineups, which test whether users can perceive differences, direct numerical estimation, which assess whether users can read data off of a chart, and “you-draw-it”, which measures whether users can predict exponential growth. The “you-draw-it” task is a modernized form of hand-drawn regression lines [57] and one example of a direct-annotation method which provides quantitative information and predictions without requiring participants to convert graphical information to a numerical, real-world domain. We ran

this three-part experiment on the same set of participants, and are in the process of publishing the results [58, 59], though initial results from each part of the experiment were published as dissertation chapters [60].

Phrasing of Estimation Questions One challenging part of the estimation task in this series of studies was phrasing the estimation questions and record participants' responses. We asked participants to answer five different types of questions requiring estimation of quantities off of an exponentially increasing time series of points. Easy questions required estimation of the conditional value of y given x (or vice versa), intermediate questions required a calculation on either the additive or multiplicative scale, and a third intermediate question required estimating the time until the population doubled in size. In addition, participants were asked an open-ended question ("describe the data shown in this graph") before being asked to estimate values. Figure 2 shows the calculations required for one of the intermediate difficulty questions; participant results are shown in Figure 3. In addition to requiring the numerical input value, we provided participants with a scratchpad and basic calculator applet, providing details of how participants solved the problem as well as ways to assess logical and estimation errors for participants who used the scratchpad. We are currently developing methods for integrating the analysis of this additional layer of user data with more direct numerical estimates.

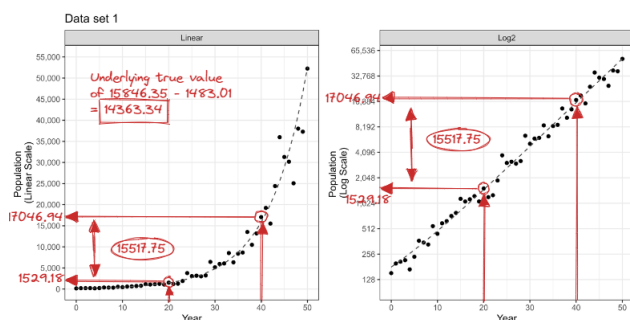


Figure 2: Steps to estimate additive population change.

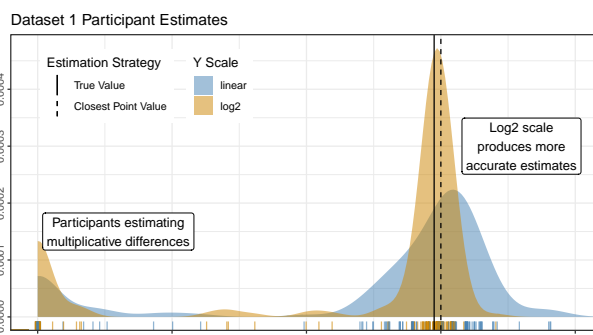


Figure 3: Distribution of participant estimates.

Manipulating Input Type In another study, we assessed the probability of perceived guilt or innocence of a defendant based on the type of testimony presented by a forensic examiner. To establish a baseline, we began with a calibration study examining the different ways we could record participant input, using free response, forced binary choice, categorical and numerical input sliders, and numerical inputs for numerator and denominator that calculate a probability of guilt; results in Figure 4 show that the results are different for different input types, with blank numerical slider inputs biasing results more towards 0.5 and ratio inputs showing evidence of rounding effects. Clearly, the input method has an impact on the observed results.

Measures of Probability of Guilt in Jury Studies

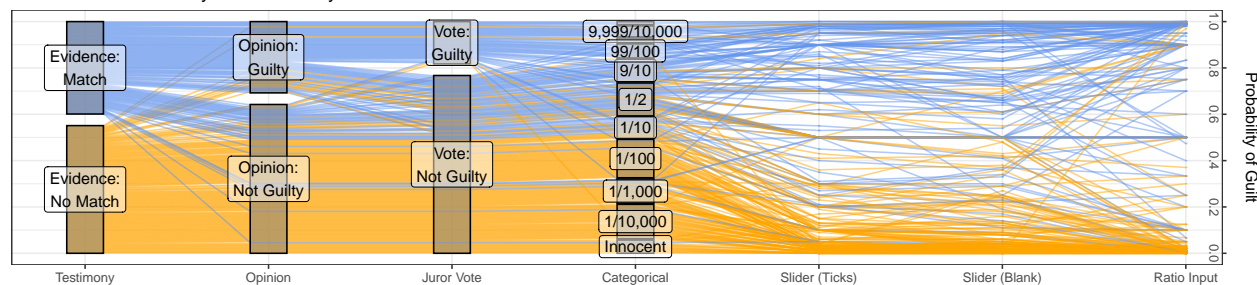


Figure 4: Input methods for assessing defendant guilt probability. Some category labels have been omitted due to space.

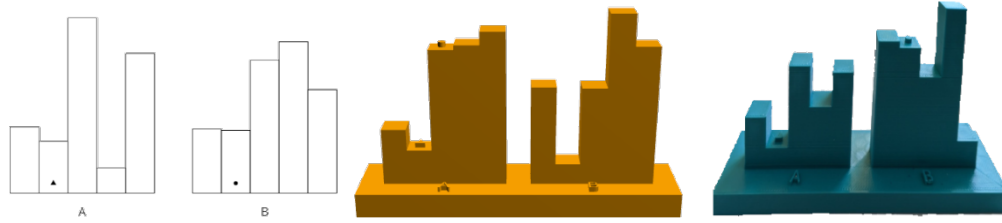


Figure 5: Three renderings of bar charts: 2D (left), 3D digital render (middle), and 3D printed (right).

Examining 2D vs. 3D Design Guidelines Another preliminary experiment supporting the importance of this research is a study reexamining Cleveland & McGill [7] in light of modern 3D rendering and printing technology. We created charts shown in Figure 5 rendered using modern 2D graphics software, 3D digital renderings [61], and 3D-printed graphics [62]. Our initial investigation found few differences between 2D, 3D digital, and 3D printed charts in comparison accuracy; this could be due to limited power, but an alternate explanation is that the 3D virtual rendering environment is not comparable to the fixed-angle 3D plots used in the original study; we will assess this in a followup study. It is entirely possible that interactive 3D charts can be accurately perceived while artificial 3D fixed-angle projections into 2D space lead to inaccurate perceptions. If this is the case, the guidelines to avoid 3D graphics may be entirely misguided given the interactive rendering environments available today.

Previous experiments make conflicting recommendations about the use of 3D projections, but these conclusions may arise from conflicting estimation procedures as well as different data and sample populations. Spence [17] had participants “position the cursor (along a number line) so that the horizontal line is divided in proportion to the apparent sizes of the elements”, which is essentially estimating the proportion $A/(A+B)$, while Cleveland & McGill [7] asked participants to “judge what percentage the smaller was of the larger”, which is A/B , using a numerical estimate (rather than a slider). This difference may explain the conflicting findings between the two papers; more importantly, this is a factor that must be investigated both to assist with the interpretation of past studies and to inform the design of future studies.

4 Research Plan

This CAREER proposal will lay a critically needed foundation for robust experimental evaluation of statistical graphics by simultaneously developing and validating methods focused on practical evaluation of chart use. In addition, we will empirically evaluate design guidelines to identify nuanced, user-focused guidelines that have empirical support and address accessibility. The results of these studies will directly tie into outreach activities that will inform data visualization practitioners about best practices based on empirical results.

While related, each of the below objectives can be completed independently from each other. The project is designed to allow results from the first two objectives to enrich our approach to the third, but there are already sufficient methods in the literature for testing graphics to allow us to complete a task-focused evaluation of design guidelines. In addition, while a critical examination of methods for numerical input in graphics studies will be useful, it is not essential to empirically assess design guidelines.

4.1 Research Objective 1: Create a framework for comprehensive testing across multiple levels of user engagement

The first research objective is to create a framework for comprehensive graphical testing across multiple levels of user engagement. Our **overall hypothesis** is that by *combining multiple methods of user testing*

within the same experiment, we can gather information which spans multiple levels of user engagement with acceptably small impact on participant cognitive load.

Method Combination Rationale We will conduct a series of experiments that incorporate multiple testing methods into empirical assessments of statistical graphics. Many methods commonly employed for testing graphics can be combined in the same experiment; think-aloud protocols can be combined with eye-tracking and other assessment methods to provide qualitative information about the user experience in combination with more quantitative assessments [63–65]. There are two fundamental limits to the combination of multiple methods: method incompatibility and what a single participant can reasonably be asked to do in a single experiment. For instance, statistical lineups involve multiple sub-plots, of which only one is composed of real data; this is incompatible with direct numerical estimation, because the framework for statistical inference under a randomization test necessarily removes the focus from the “real” data. We can also expect that asking participants to complete too many tasks with a single plot will result in poorer results than optimizing the methods to maximize information gain while minimizing participant effort. However, because this type of multi-method research is relatively rare (other than collection of open-ended opinions after quantitative data is recorded), we do not know where this limit is.

Participant Considerations and Sample Size As the primary goal of these experiments is to assess the measurement methodology, here we focus on describing the set of experiments and methodological comparisons; we will use data and graphical design comparisons from past experiments in the field or generate new data when necessary to push the limits of the measurement methodology. In general, we will conduct in-person experiments with a target participant sample size of 50 undergraduate students from the SOMA psychology student pool; this sample size will be calibrated as the PI gains experience with eye-tracking studies and the sample size needed for statistical power using the appropriate analysis methods for eye-tracking data. Online experiments will typically be conducted using a platform such as Prolific, with a target sample size of 300 participants; we have successfully conducted previous multiple-method studies with sufficient power at this sample size. We will attempt to recruit participants online who are demographically representative of the US population with respect to age, sex, race, and/or education where the collection platform allows. Explicit power calculations are reasonable for studies that can be evaluated with a statistical model or hypothesis test, however, with multiple testing and evaluation methods, some of which are qualitative, direct power calculations are less useful. Compounding this problem, we have very little prior information about the relevant effect sizes, which would be expected to change with chart type and the particulars of each experiment. Instead, we rely on past experience and have planned for as many participants as possible while limiting experiment costs and data collection time; this approach has worked successfully for the preliminary studies.

Eye Tracking Metrics In experiments where eye trackers are utilized, we will assess dwell time (time spent on each fixation area), both in total and on the first run, first fixation time for each fixation area, run count, and order of interest areas, both across and between participants. As the PI becomes more familiar with the eye-tracking software and collected metrics, additional measurements may be incorporated where they can provide valid insights, subject to the experimental design parameters.



Figure 6: Methods used in each proposed experiment along with targeted level of engagement from Figure 1.

Figure 6 provides a high-level pictographic summary of the different methods which will be used in each proposed experiment contributing to this aim.

Augment Lineups The first collection of experiments will assess expansions and augmentations of the statistical lineup protocol. **Part A1** will examine whether there is value in adding contextual information (axis scales, labels, titles) to lineups, expanding lineups beyond basic perception and grouping. Lineup studies typically do not include contextual information that would require participants to evaluate the plots using domain knowledge; instead, lineups in most studies lack axis labels and even titles [55, 66–68]; participants are encouraged to pick the plot which is the most different (which does not require understanding any data context). We will manipulate axis scales (which are usually controlled) to determine whether viewers use this information; we will also analyze user explanations to see if information in the plot and axis titles are referenced. While lineups have been used with eye tracking before [69], the technology used in those studies samples at a low rate and does not allow for collection of measures such as fixation length, time to return, and other quantities of interest. During **Part A2**, we will examine the lineup perception and decision-making process using eye tracking, with and without cognitive load, mimicking conditions where people use graphics in daily life with distractions. **Part A3** will expand upon part A2, asking participants to directly annotate [70] interesting features in a lineup using JavaScript-based web tools while in an eye-tracker. There is the possibility that this additional task will add too much cognitive load, as well as that the additional motion required for the annotation will disrupt the eye tracking results; both of these outcomes provide useful information. **Part A4** will validate the use of lineups with direct annotation, establishing if there is added value in including direct interaction with lineups in a more typical setting for visual inference studies (online).

Augmenting Single-Plot Studies As visual inference with lineups is qualitatively different than experiments examining a single plot, the second collection of experiments (A5-A9) will focus on methods for examining single plots, which allows us to test graphics in ways that directly mimic how they are used for decision support. **Part A5** will combine eye tracking, numerical estimation, and direct annotation: users will answer a set of questions requiring estimation of data from the chart, but the direct annotation component of the task will be varied across three levels (no annotation, annotation without numerical feedback, annotation with numerical feedback). This will allow us to assess the flow of attention during the estimation process as well as the effect that direct annotation has on the participants. Providing numerical feedback from the direct annotation will allow us to assess how much of the participant’s estimation accuracy is due to the transformation from spatial to numeric information; this is a more natural source of information than the “scratchpad” used in [60, Ch 4]. Think-aloud protocols, which ask participants to talk through the process of making a decision, have been proposed as an alternative to eye tracking for usability studies [63]; this is intriguing for experimental evaluation of graphics because think-aloud tasks can be performed through a web browser with minimal experimenter labor using APIs to automate transcription [71] and response coding [72]. In **Part A6** we will examine the overlap between direct annotation and think-aloud protocols using an online platform; automatic transcription APIs will be validated using manual transcription performed by undergraduate research assistants.

One major focus of this CAREER program is exploring how people use charts to support real-life decision making. **Part A7** adds forced-choice questions to the battery of methods for examining graphics, examining numerical estimation, forced-choice questions, and open-ended responses, with the potential to include or substitute the use of direct annotation or think-aloud methods based on the results of previous experiments. Participants will be directly asked to make a decision based on data and real-world consequences, such as “is X product safe for consumer use” or “do levels of Y meet the threshold for regulatory action” based on a scenario and sample data. Participants will be asked to estimate a relevant numerical quantity that should inform the decision making process and then use open-ended responses to explain their reasoning on the forced-choice decision task. Follow up experiments may be used to explore the effect of uncertainty [73, 74]

and other important factors on this decision-making process, but the primary goal of this experiment is to compare empirical results for the different measures used to assess this real-world decision-making process. Graphics also support inferential processes in the visual domain (distinct from visual inference using lineups). **Part A8** (in-person, eye-tracking) and **Part A9** (online, direct annotation) will examine the process of using graphics to support visual statistical inference calculations; these experiments will also include forced-choice real-world decisions supported by these inference calculations.

Visual vs. Statistical Inference The primary difference between visual and statistical inference is that in visual inference, the null model is embedded in the lineup generation process, where in statistical inference, the null model is embedded in the scenario description. The cognitive demands of the two inferential procedures are different: in visual inference, the participant must infer the null model; in statistical inference, the participant must work out the graphical and real-world interpretation of the model. The final planned experiment, **Part A10**, directly compares results from these two tasks through a head-to-head comparison of lineups and graphical inference, where both tasks are observed through direct annotation or think-aloud protocols. Participants will be provided with multiple scenarios and will be given either a visual inference (lineup) or a statistical inference (single graph) task that requires evaluation of the same hypothesis. We will examine not only the power of each method in a statistical sense, but also the richness of the additional information provided through annotation or think-aloud protocols.

The results of the proposed experiments will validate these methods for observing and evaluating how users leverage graphs for decision support by examining each stage of engagement while accounting for different tasks. While we have provided limited details about data sets and types of graphs tested using these methods, we will leverage past studies extensively to construct scenarios that balance the desire to assess real-world processes with the need for experimental control.

Expected Results and Significance: The lineup augmentation experiments will validate lineups for assessing contextual information, leverage eye-tracking to examine attention and feature comparison during lineup evaluation, and explore use of direct annotation with lineups. These methods will provide rich ways to gain additional information from lineup studies conducted in person or online. The single-plot augmentation experiments will allow us to assess the flow of attention during the estimation process, examine the information provided by direct annotation and think-aloud protocols, and explore the different components that contribute to estimation accuracy. We will also be able to examine the inferential process and compare the relative benefits of lineups, eye tracking, and direct annotation methods within this context. Even if these experiments indicate that some data collection methods cannot be effectively combined, we will still gain a better understanding of the cognitive demands of lineup and single plot evaluation, and we will be able to determine what combination of measurement methods best covers the range of user tasks. Taken together, these experiments will establish the limits of using multiple graphical evaluation methods in parallel when assessing charts experimentally.

We will produce an R package which implements Shiny modules for including direct annotation capabilities in graphical testing (x-axis estimates, y-axis estimates, drawn regression lines, and interval estimation), recording these annotations and think-aloud audio inputs as data, and transcribing audio inputs to text. Additional functions for analysis of eye-tracking data and use of Shiny apps with eye trackers will be included where functionality is not available in the existing software stack. Development of this software will provide graduate and undergraduate statistics students with the opportunity to learn open-source software development practices and to contribute back to the community.

In addition to making these methods available for other experimenters through open-source software, we will be able to compare the types and quality of information gained using each method through statistical and

qualitative analyses. Each experiment will also include questions designed to assess the cognitive load of participants through user reflection questions, to establish any limits on concurrent measurement methodology imposed by working memory and attention resource constraints.

Potential Pitfalls and Alternative Strategies: As this aim is specifically designed to examine the limits of the use of multiple testing methods simultaneously in graphics studies, we will either confirm the utility of combinations of testing methods, or we will gain information about the limits of participant working memory and comprehension. However, there are a few components of this plan which contain potential obstacles.

I have not previously used eye tracking to explore how we use graphics; most of my previous studies have been conducted using online tools. I have enlisted Dr. Michael Dodd at UNL, an expert in eye tracking, attention, and cognition, to mentor me as I become familiar with eye tracking equipment and methodology (see letter). This collaboration will also allow me to access the undergraduate psychology participant pool, which will ensure that I can recruit students for the eye tracking studies, as these cannot be conducted over the internet.

Another obstacle is that the direct annotation software framework does not yet accommodate some of the annotations required for the described experiments. Currently, direct annotations can be used to draw trend and smooth lines and extrapolate beyond provided data points [59], but additional functionality will have to be implemented to allow participants to highlight individual data points or regions of the plot, select positions along the x or y axis, and indicate regions for inferential purposes. Much of this functionality exists in other interactive software [70, 75], which should ensure that we can borrow from those implementations to create a similar interactive toolkit in Shiny. Some of the desired features are in the process of being added to the `youdrawitR` package under development through Google Summer of Code 2023. I expect that additional functionality can be added during this proposal’s review cycle, but if not, the schedule allows for time to implement the necessary features before they are needed. In addition, if direct annotation is not effective during Part A6, additional methods for assessing inferential processes in online usability testing may be explored in Part A9.

Finally, while there are packages for audio recording using JavaScript, I am not aware of any dedicated Shiny implementation, so we will need to write code to interface between an appropriate JavaScript library and Shiny. I have experience connecting similar JavaScript libraries to Shiny (including the JavaScript code used to implement the `youdrawitR` package), so this is not expected to be a significant obstacle, but in previous studies, there have been issues with browser permission conflicts causing Shiny to crash. We address potential issues like this during the pilot study before an experiment is officially deployed, but we will need to take special care that both the participant recruitment and the Shiny application are set up properly to ensure that we can successfully record this information.

4.2 Research Objective 2: Assess the impact of measurement methods on statistical graphics experiments.

The second research objective is to thoroughly examine the impact of experimental design factors, such as question phrasing and user input, on the results of graphical testing experiments. The history of experiments evaluating the effectiveness of graphics is filled with sequences of studies that approach a problem from different perspectives while producing mixed results [4, 5, 7, 17]. What is fundamentally lacking is a systematic examination of the different measurement methods and prompts that can influence the results of a study without being the focus of the experiment. This decision space is extremely large: Hullman et al [73] diagrammed 384 different paths taken by 82 uncertainty visualization papers through different goals, measures, input types, analysis methods, and other design decisions. While such explorations are useful, this aim does not just seek to record the different languages of the world; instead, **our goal is to assemble a Rosetta**

stone by which we can compare and interpret historical studies while guiding the design of future visualization evaluation studies. In this objective, we examine the impact of different ways of obtaining numerical estimates from participants, as well as the impact of different methods for prompting participants to provide a specific estimate.

Experiment B1 will examine input methods for continuous estimates. Continuous numerical estimates are more complicated than one might expect: in some problems, there is a defined $[A, B]$ input range that is relevant, while in other problems, estimates may be located along the entire real line (though typically, there is a range within that where the experimenter expects most values to fall). We sometimes want participants to generate high-precision estimates, but on other occasions we need them to estimate quantities over several orders of magnitude (e.g. multiplicative or “by a factor of” estimation) where precision on a log scale is more important than on a linear scale. Providing participants with appropriate cues that indicate which characteristics apply to the problem at hand is important, but we do not want to waste valuable participant cognitive resources on understanding and manipulating the user interface. This first series of experiments will be conducted by 1-2 new researchers and will examine the factorial combination of input range, desired type of precision, and use of different input technologies. We will start with the assessment of segmented scales, unsegmented scales, numerical range inputs that can assess uncertainty, numerical estimates (e.g. typing in 98.7 to a text input field), and direct annotations on charts that we would expect to lessen cognitive load. The new researchers will design scenarios across the different conditions described above (defined range, whole real line, order of magnitude precision, linear precision) and develop simulated data appropriate for testing the different input measures. We will execute the designed experiment and participants will clean, process, visualize, and model the data to assess the relative benefits of each input method.

Experiment B2 will examine the impact of question phrasing for comparative judgments and fractional estimation, such as those in [7, 17]. Students will complete an assessment of the different studies that have examined this question and will assemble a list of commonly used methods for assessing comparative judgments. We will then work together to design and execute an appropriately controlled experiment that allows us to compare the accuracy of these methods on both a raw accuracy scale and using appropriate psychophysical models (e.g. Stephens’ law as used in [17] compared to the corrected log2 midmeans method in [7]).

Incorporating New Researchers *Experiment B3*, *Experiment B4*, and *Experiment B5* will be selected by summer research students from a curated list assembled as part of the study summaries described in Section 5.4. The list will contain topics selected to be accessible to new researchers and such that the design, data collection, and analysis can be completed with 10-12 weeks of work. Students will pick a topic of interest, and I will work directly with the students to design and execute the study, similar to the approach I use to mentor graduate students. This “scaffolded” approach [76] provides students with greater insight into how research occurs by focusing on the process of inquiry; students learn the skills necessary to complete the tasks because they are interested, rather than as a prerequisite to doing research.

Future Directions One potential topic for subsequent years’ explorations is the effect of cognitive load manipulations (distractions, working memory tasks, etc.) to simulate graphical estimation and decision-making under the more chaotic conditions where we typically use graphics in daily life. Experiment A2 will briefly explore this within the context of lineup studies in an eye tracker, but cognitive loading manipulations are not common in most empirical studies of real-world chart usability and comprehension; if A2 is successful, then further exploration may be warranted.

Expected Results and Significance: When combined with the methodological research in the first objective and the design guideline based research discussed in the next section, these studies form a critical part of the foundational research necessary to critically assess historical studies while accounting for their methodological differences. In addition, because this is basic research that is essential to interpreting conflicting

studies, it provides a gentle introduction to the scientific process for new researchers, leveraging a domain that most people find interesting at a basic level (“how do we make decisions?”) in a scientific field that is accessible to almost everyone (data visualization). While this is basic research, it has all of the messiness of the scientific process baked in: the whole goal of these studies is to assist with interpreting conflicting historical results. As such, it not only forms a critical component of the research aims of this project, but also is a critical part of the education plan.

Potential Pitfalls and Alternative Strategies: Even if this portion of the project does not produce results which clarify historical studies, we will still gain greater insight into the ideal design of inputs for user testing, which will facilitate better study design in the future.

4.3 Research Objective 3: Empirically validate common chart design guidelines, measuring the impact of design decisions on task performance.

Hypotheses We expect that overall, many of the commonly repeated design guidelines will bear up in practice; while derived from extrapolated experiments or opinion, they have been honed over time and experience. We expect that there may be some differences in effective design guidelines for the general population compared with neurodiverse subpopulations with specific challenges. Statistical comparisons examining the effect of neurodiversity are primarily exploratory; our goal is to ensure that any design guidelines we empirically validate consider this dimension of human diversity. Additional follow-up studies will be necessary to explore how guidelines should be adapted to accommodate individuals with specific cognitive challenges, but these studies will at least identify the most promising avenues for future investigation.

Participant Recruitment These studies will be integrated with experiential learning activities in introductory statistics courses, with participation from at least 200 students per semester. In addition, we will work with Disability Services to recruit an additional group of 50-60 participants per experiment who are receiving academic accommodations for conditions expected to impact numeracy, executive function, or visual processing; these participants will be demographically similar to the students participating in the studies as part of statistics coursework. Experiments C4 and C6 may be conducted online with samples of approximately 300 participants; in these studies, we will recruit our neurodiverse sample using through posts on condition-related message boards so that we are recruiting participants with similar characteristics (online presence) in both general and neurodiverse populations. These measures are not perfect for demographic parity, but this research is the first step towards full consideration of neurodiversity in graphics research.

In **experiment C1**, we will examine guidelines that address the use of a third dimension in statistical graphics through multiple experiments integrated into educational objective 1. In **experiment C2**, we will experimentally evaluate guidelines that address the use of additional annotations beyond those strictly necessary to represent the data (sometimes called ‘chartjunk’), focusing not on completely minimalist graphs, but on the impact of design choices such as dual-encoding that have been hypothesized to provide more visually discriminable signal for all users and better accessibility for users with visual or cognitive impairments [55]. In **experiment C3**, we will examine the effectiveness of different ways to address overplotting, comparing solutions such as alpha-blending, binning, and density estimates to determine which solutions are most appropriate in which contexts and for which user tasks. In **experiment C4**, we will experimentally assess the effect of plot aspect ratio, revisiting the bank to 45° guideline in light of interactive and adjustable modern graphics where the aspect ratio may change at the user’s discretion. In **experiment C5**, we will conduct a series of smaller studies, using multimodal evaluation methods to revisit the relative merits of different representations of the same data (e.g. pie vs. bar, violin plot vs. boxplot vs. beeswarm plot). In **experiment C6**, we will examine guidelines relating to ribbons, stacked bars, and the line-width illusion, looking

specifically for users’ awareness (or lack thereof) of the difficulty of estimating these quantities. In **experiment C7**, we will experimentally evaluate guidelines relating to polar transformations, including guidelines recommending against the use of spider or radar charts, pie charts, and circular bar charts.

Expected Outcomes and Significance: Through these experiments, we will add to the body of literature empirically assessing design guidelines, specifically contributing studies which address multiple levels of user engagement via multiple measurement methods. This multi-modal engagement will allow us to evaluate guidelines in a more nuanced manner, providing designers with guidance that extends beyond “do this” to explain when and why. In addition, we will systematically screen for common design guidelines that are ineffective for neurodiverse subpopulations; this screening will provide empirical support for previously proposed explanations [55] and will also identify areas for future research, with the goal of making visualization guidelines more inclusive and accessibility focused.

Potential Pitfalls and Alternative Strategies: One of the potential challenges in this objective is the plan to assess design guideline effectiveness for neurodiverse individuals as well as the general population. There is relatively little guidance for recruitment of individuals with disabilities in this space: many conditions, such as ADHD and dyslexia, are commonly diagnosed together; in addition, every individual has a different level of severity and two individuals with the same condition may have different levels of impact in a specific cognitive domain. We acknowledge these complexities: this objective is designed to screen for promising areas of future investigation while providing some functional assessment of the impact of current design guidelines.

Multiple data collection methods used together provide a rich set of information which can be analyzed qualitatively as well as quantitatively; while we may find differences in the qualitative comparisons (e.g. significant statistical tests showing population differences), we expect that if there are differences in the impact of design guidelines between neurodiverse and general populations, we will be able to see evidence of that in the qualitative responses before we see significant hypothesis test results. Paradoxically, if there are no differences between neurodiverse and general populations, this is actually a good thing: it would mean that our design guidelines are at least not overtly creating inaccessible graphics. We expect that as a result of these experiments, we will be able to contribute new information focused on design for accessibility to a field where very little guidance currently exists and designers are left to guess about the impact of decisions on accessibility.

5 Education Plan

5.1 Education and Mentorship Philosophy

Graphics are a uniquely unassuming method of presenting scientific data to the public: almost anyone can read and understand a bar or line chart and use that information to draw conclusions from the data. Immediately after graduating with my Ph.D., I took a data science position in the power industry, working with engineers and business analysts to increase their use of available data. Many people I met were intimidated by my statistics degrees, but visibly relaxed when I would explain that my expertise was in data visualization. Data visualizations are less “scary” than the raw data or statistical models, not only to my former coworkers, but more generally.

I left industry for academia because I started training others in data science, and discovered that I enjoyed teaching and mentoring others. I avoided academia initially because my graduate school teaching experiences were not particularly enjoyable, but once I discovered that I enjoyed teaching, the final barrier to pursuing academia disappeared. As a professor, I knew I would have the opportunity to interact with and mentor students, do self-directed research, have an impact on the next generation of students, and create

knowledge that could impact scientific research for generations to come. I make every effort to equip students and trainees with the tools and mindset to conduct rigorous, ethical, reproducible, well-documented, and open science, whether they are headed to industry or academia.

This proposal leverages graphics research to demonstrate statistical concepts and improve data-driven decision making through activities targeted at undergraduate introductory statistics students, K-12 educators taking graduate courses for continuing education, and data visualization practitioners. The educational objectives are designed to use graphics to reach groups who are left out of the picture in one way or another: some target individuals who do not ‘see themselves’ in STEM, while others target industry analysts who may not have opportunities to engage with the newest research. As my career has spanned industry and academia, and reconsidering first impressions opened new and exciting opportunities for me, I want to prioritize engaging with these groups in order to expand reach of scientific results as well as the breadth of the population doing science.

5.2 Education Objective 1: Implement experiential learning activities in graphics for undergraduate introductory statistics courses.

The first educational objective targets students in undergraduate introductory statistics classes; these classes, which are often part of the core curriculum or required for STEM students, can be seen by students as something to ‘get through’ rather than as courses offering vital (and interesting) information. At UNL, our introductory courses follow the 2016 ASA GAISE recommendations [77], which emphasize statistical thinking over computations and rote memorization, as well as the importance of hands-on activity-based learning in statistics classes. Even with the incorporation of these guidelines, many students still struggle to make the connection between statistical concepts and the real-world implications when evaluating or designing scientific studies, interpreting data, or thinking critically about claims made in the media. To this end, we will incorporate experiential learning into the introductory statistics courses at UNL by introducing a semester-long project. Students will participate in a statistical graphics experiment, and will think critically about how that experience connects to the material being taught in class at the time through guided written reflections. At the end of the course, students will read a 2-page extended abstract submitted as a conference publication and will watch a 15-minute conference presentation recording, encouraging them to compare and reflect upon how the results of research are presented in different venues and for different audiences. This component will reinforce concepts learned in class [78–80], but it will also introduce students to research in statistical graphics and introduce the idea that not all graphs or charts are equally useful for communicating results.

In the first year, we will examine different aspects of 2D and 3D charts; the addition of 3D printed charts means that we cannot conduct this research as easily online, but it also has pedagogical benefits: students must attend office hours at least once at the beginning of the semester, reducing barriers to subsequent attendance [81]. Subsequent semesters will involve different graphics experiments but we will prioritize hands-on studies that require in-person participation where possible. A tentative plan is shown in Figure 7, but experiments will primarily be drawn from those proposed as part of research objective 3, because these experiments are interesting, relatively high level, and connect graphical design to statistical data in a way that will hopefully be clear to participants in the experiments. The PI and graduate student funded on the project will work together to coordinate and implement this objective; a pilot of the full experiential learning semester project is underway in Summer 2023.

Expected Outcomes and Significance: Student written reflections will draw connections between concepts learned in class and the experience of participating in the experiment. Students will also have to critically assess the claims made in the written report and presentation, leveraging their statistical training to question the presented study results and identify limitations of the methodology. We expect to publish data generated

from the evaluation process (as well as curricula and course materials) in a statistics education journal to contribute the discipline's understanding of the effect of experiential learning activities in undergraduate statistics education.

Evaluation: Success will be evaluated through the addition of questions on to the end of course evaluations, as well as through feedback solicited from course instructors. We will also systematically examine student reflections, identifying connections between course concepts and experiential participation as well as critical assessments of scientific claims.

5.3 Education Objective 2: Create graduate course modules for educators that connect ongoing graphics research to hands-on STEM classroom activities.

Audience and Motivation: The second objective has both a primary and a secondary audience: the primary audience is teachers taking continuing education credits through the Nebraska Math and Science Summer Institutes (NMSSI), and the secondary audience is their students. The goal of the Nebraska Math and Science Summer Institutes is to offer teachers of math and science intellectually rich graduate coursework that will enhance their ability to offer their students challenging courses and curricula[82] (see letter). Graphics are a promising topic for graduate courses in NMSSI because they provide a unique window into complex statistical topics as well as a way to gently introduce statistics and data science to students. Topics such as regression can be enriched with discussions of visual statistical procedures and how results compare to computational procedures [55, 58]; the addition of these hands-on activities provide opportunities for teachers to make STEM subjects less intimidating. While courses are open to K-12 teachers, we expect that the courses and modules developed as part of this project will be primarily of interest to middle and high school educators.

Course Modules: I will develop two modules for an existing 'special topics' courses; the first will introduce probabilistic concepts through statistical shoe print forensics; the CSI theme tends to get students interested, but the problem they solve is one with much broader societal impact that touches on questions with not-yet-implemented statistical solutions. The second module will discuss data visualization design choices through the lens of perception and science communication; this module will be updated each summer to incorporate new results from this project as well as new developments in the field.

Short Course: In the final two years of the proposal period, I will develop a short two-week course which focuses on the mathematical and statistical concepts underlying generative data art: that is, the use of programming and mathematical theory to generate art from data. This course will include discussions of more traditional data visualization, but ultimately it is designed to target a secondary audience of students who are not interested in or are actively intimidated by STEM, but are interested in artistic expression. By motivating the learning process through the desire to create art, we can introduce scientific programming, the collection and use of data, randomization, and mathematical functions[83]; we can connect color theory to perception and discuss the implications for scientific data visualization, and we can emphasize the beauty present in even the messiest data. These courses will be included in the NMSSI summer offerings and will be taught with the assistance of a graduate student; we will both benefit from a greater understanding of the challenges in K-12 education and through the interaction with K-12 educators [84].

Expected Outcomes and Significance: These courses will introduce new mathematical and scientific concepts to middle and high school educators, who will take the material learned in these courses and modules and apply it within their classrooms to enrich students' education. Courses and modules will be structured to encourage discussion among participants, providing the PI and team with additional insights into the needs and constraints of STEM educators. This interaction may seed additional collaborations during and beyond the CAREER grant period and may suggest potential research questions for future work. We expect that

these courses will produce better collaborations across the K-12/university boundary, increase student engagement, and help teachers reach students who are averse to STEM topics through alternative engagement activities such as generative data art.

Evaluation: NMSSI will evaluate the short courses and modules; curricula will be updated to incorporate this feedback for subsequent years.

5.4 Education Objective 3: Improve the dissemination of visualization research by incorporating summaries of empirical research into resources used by data scientists, industry analysts, and researchers.

The third education objective also has two audiences: the primary audience is individuals who use the From Data to Viz site [85] and the associated R or Python graph gallery sites [86, 87] hosted by Yan Holtz. The secondary audience is statistics and data science undergraduate students who will be recruited as research assistants. These students will systematically catalog and evaluate empirical studies of statistical graphics, enumerating the design space of each study and assessing its conclusions based on the collected data. In addition, students will also track how previous studies are cited and described in the literature, assessing the tendency to broaden the conclusions of a study in the interests of describing it more concisely. Ultimately, this research will be used to create short summaries of relevant empirical research about each chart topic; students will then contribute these summaries to the website using pull requests. This objective will improve connections between the empirical research and people doing data visualization and analysis, but it will also expose undergraduate statistics and data science students to systematic research, help them develop better scientific communication skills, and emphasize the importance of using good visualization practice. These skills will be valuable whether students take jobs in industry or pursue graduate school in STEM fields.

Expected Outcomes and Significance: This education objective will result in greater contact between practitioners (individuals creating data visualizations in industry or academia) and empirical graphics research; in theory, this should help those practitioners produce better graphics which communicate more clearly with the public. Approximately In addition, undergraduate statistics and data science students will gain an appreciation for principles of good statistical graphics, empirical testing and data analysis, and the complexity of collecting your own data; this is often left out of statistics classes and represents an important gap between statistics and the practice of data science.

Evaluation: The impact of this educational objective will be assessed through web analytics which will allow us to track how often a page is viewed and how often viewers engage with links to empirical studies. The undergraduate researchers will assess their development each semester by completing a short research skills inventory and identifying areas for growth over the next semester. These records will be used to measure the effectiveness of the undergraduate research skills development component of this objective.

5.5 Connection to Research

Experiential learning activities proposed in educational objective 1 will provide data for experiments proposed in research objective 3; as a result, introductory students will learn about guidelines for designing charts and graphs as part of introductory statistics courses. Conversations with middle and high school educators about statistics, data visualization, and pedagogical approaches will provide additional experiential information about accessibility and graphics, with the potential to inspire additional research or modifications to the proposed research in response to educator observations.

Educational objective 3 connects tightly to research objectives 2 and 3: the systematic literature reviews generated during the academic year by undergraduate researchers will be used to identify potential topics for summer research projects relating to measurement methods. Results from summer research projects

will then inform summaries which incorporate historical results, providing contextual information that will mediate conflicting experimental results. In addition, the systematic literature review will inform design guideline experiments by examining not only the experimental results, but how those experiments were interpreted in later studies. This will allow us to trace the evolution of design guidelines from very specific experiment interpretations to much stronger, more general statements such as “pie charts should never be used”, providing better context for the best way(s) to test a specific set of design guidelines.

6 Intellectual Merit

This work will expand our understanding of graphical perception and communication by empirically and systematically examining chart design through comprehensive, task-based testing. The proposed studies will be used to generate a framework relating evaluation methods to user engagement with graphics, establish the impact of different experimental design decisions on results, and promote integration of multiple evaluation methods to provide a holistic assessment of visualization effectiveness. Additionally, this project will prioritize inclusion of individuals with cognitive differences, ensuring that design guidelines account for accessibility concerns. The results of the systematic examination of different experimental design and testing methods will not only ground design guidelines in empirical results, but if successful, the experiments will also help reconcile the results from historical studies with conflicting results. While there are task-based taxonomies for selection of chart types, a systematic framework for selecting testing methods based on levels of engagement and critical tasks is innovative; we expect that this framework will facilitate well-rounded experiments that examine chart design and use from multiple perspectives, providing nuanced results focused on audience use of graphics. An additional impact is the methodological and measurement groundwork laid to support the development of empirical guidelines: these tools and evaluations will be made available to other researchers in the form of an R or python package that will make it easier to design and implement graphical user studies. The education activities are closely tied to the research objectives, providing avenues for dissemination of research results as well as inclusion of audiences in graphics research. As a result, education and research activities will combine to support new pedagogical research in experiential learning for statistics. This new research will examine the use of statistical graphics as an entry-point to quantitative subjects for individuals who are not traditionally interested in pursuing STEM careers. Previous collaborative research projects have established new and re-imagined old methods for testing statistical graphics; when combined with training and experience in statistics at the intersection of computer science, psychology, and communication, I am well equipped to complete this project.

7 Broader Impacts

Data visualization is an essential part of science communication; as a result, there are broader impacts woven through every thread of this project’s tapestry. The broadest impact is the development of empirically driven guidelines for chart creation that are robust, nuanced, and are designed with accessibility in mind: these guidelines will help scientists, journalists, and data analysts communicate more clearly so that all people can make better data-driven decisions.

The educational objectives will result in empirical graphics research being presented to K-12 students, undergraduates, graduate students, and professionals. In addition, this project will bring in high schoolers interested in STEM, undergraduate students (both in statistics and data science, and those interested in STEM more generally), and graduate students, introducing these students to research in the communication of statistical information and the perception of charts and graphs as well as reinforcing principles of scientific reasoning and statistical thinking. Through contact with this diverse set of students, many of whom may eventually go on to careers in other STEM fields, this project will help to emphasize the importance of carefully creating data visualizations for science communication. Both educational objectives 1 and 2 are

also designed to reach students who are not interested in STEM, leveraging statistical graphics to engage with STEM-focused questions such as how to collect, use, display, and make decisions based on data. By incorporating groups who have been historically excluded from graphics research as well as groups who are less motivated to pursue STEM topics, this project uses graphics as a bridge to promote greater inclusion in science.

8 Timeline

	Summer	Fall	Spring	Summer	Fall	Spring	Summer	Fall	Spring	Summer	Fall	Spring	Summer	Fall	Spring
Multi-method Measurement Validation	A3	A1 A2 A3	A1 A2 A3	A6 A4 A5 A6	A7 A5 A6	A7 A8 A9	A7 A8 A9	A10	A10				Toolkit Dev	Pilot Testing	Data Collection
Input Experiments	B1			B2			B3			B4			B5		
Design Guidelines	C1			C2			C3	C4		C5	C6		C7		
Experiential Learning Reflections	3D printed graphs			Chartjunk			Overplotting			Categorical Charts			Polar Coords		
NMSSI Courses and Modules	Hands-on, Shoes off Statistics			Analyzing Data Visually			Analyzing Data Visually			Data Art			Data Art		
Design Guideline Evaluation	numeric vars			categorical vars			categorical-numeric combinations			spatiotemporal			networks		

Figure 7: Timeline of planned activities and experiments.

9 Results from Prior NSF Support

Susan Vanderplas is currently serving as a co-investigator on NSF-SES #1952007 (October 1, 2020 - September 30, 2024): SCC-IRG Track 2: Overcoming the Rural Data Deficit to Improve Quality of Life and Community Services in Smart & Connected Small Communities led by PI Kimberly Zarecor, Iowa State University; \$1,532,000.00 has been awarded to date. **Broader Impact:** Research on rural communities is underrepresented in the research literature. We are working with rural communities in Iowa who are serving as sites to test innovative data science tools. **Intellectual Merit:** The project falls contextually within the research areas of rural demography and quality of life, smart shrinkage, and secondary data utilization. We explore how data science provides new insights into the relationships between subjective and objective measures of quality of life and test new ways to collect, analyze, and visualize community-level data. **Results:** Three papers have been published [88–90], and two more papers are currently submitted. Data compiled for the data visualization component of the project is publicly available [91]. The project has funded four graduate students and seven REU students.

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