

# Where's my Data? Visualizing Missing Values in Times Series Data

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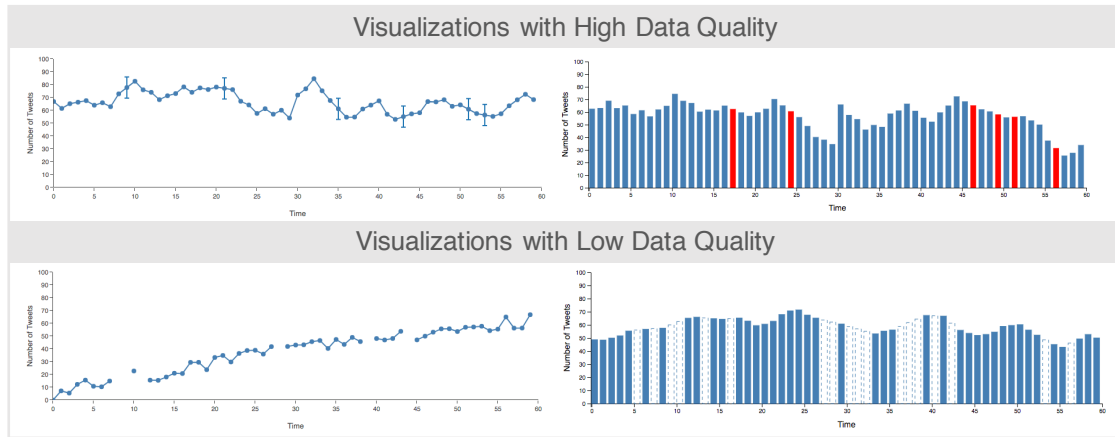


Fig. 1. We measured factors influencing response accuracy, data quality, and confidence in interpretation for time series data with missing values. Our studies found that visualizations associated with uncertainty that preserve visual continuity lead to high perceived data quality, while representations that break continuity decrease these perceptions and can bias interpretation. These effects are mediated by the methods used to impute missing data.

**Abstract**—Many real-world datasets are incomplete due to factors such as data collection failures or misalignments between fused datasets. Visualizations of incomplete datasets should allow analysts to draw conclusions from their data while effectively reasoning about the quality of the data and resulting conclusions. We conducted a pair of crowdsourced studies to measure how the methods used to impute and visualize missing data may influence analysts' perceptions of data quality and their confidence in their conclusions. Our experiments used different design choices for line graphs and bar charts to estimate averages and trends in incomplete time series datasets. Our results provide preliminary guidance for visualization designers to consider when working with incomplete data in different domains and scenarios.

**Index Terms**—Information Visualization, Graphical Perception, Time Series Data, Data Wrangling, Imputation

## 1 INTRODUCTION

Visualizations allow people to analyze and interpret data to understand current phenomena and help guide informed decisions. However, analysts often must make decisions using imperfect datasets. These datasets may be missing datapoints due to factors such as failures in the data collection pipeline, fusing data at different granularities, or censored data due to information privacy. As part of the data wrangling process, visualizations have several choices for dealing with missing data, including not encoding missing elements or *imputing* new data (calculating substitute values) based on existing data. Prior studies show that the ways we represent data influence how accurately people interpret and change their confidence in their data and results [16, 19, 35, 45]. We hypothesize that the ways we impute and visualize missing data may also bias analysts' perceptions of that data. Our intention in this study is to form a deeper empirical understanding of visualization for missing data. While we do not assert that this categorization is exhaustive, we instead use this categorization as a scaffold for exploring a subset of techniques used in existing visualization systems.

We measure how imputation and visualization techniques influence perceived confidence and data quality for visualizing incomplete datasets. We explore how four different categories of visualization designs employed in prior systems might manipulate perceived data quality: upweighting imputed data (e.g., making data more salient as in highlighting), downweighting imputed data (e.g., making the data less salient, as in alpha blending), annotation imputed values (e.g., adding additional information about the imputation outcomes, such as adding uncertainty through error bars), and visually removing information (c.f., Fig. 2). We measure the existing techniques corresponding to these four categories of these visual attributes on perceived data quality, result confidence, and response accuracy in two common visualizations: line graphs and bar charts.

We also explore how methods of imputing missing values might additionally shift perceptions of data quality and bias responses. Systems use imputation to compute values that approximate missing datapoints to support analysis. As missing data is itself a type of data (it is information that no values are available for some unspecified reason), imputation allows systems to indicate where data is unexpectedly absent and provide principled approximations to avoid potential misinterpretation of absent data values [7]. Imputing values also allows systems to indicate potential threats to data quality by providing visual anchors the analysts can readily enumerate and contextualize quality errors [5, 46]. We focus on three common imputation methods encountered in current visualization systems: ad-hoc zero-filling, local linear interpolation, and marginal means (Fig. 3).

We compare imputation and visualization methods in four crowdsourced studies measuring the effects of these factors on analysts' ac-

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curacy with and without imputed data, confidence in their conclusions, credibility, and perceived data quality. Our results indicate significant trade-offs between different approaches for managing missing data. We found that upweighting and annotating imputed values lead to higher perceived data quality and more accurate interpretation. Using downweighting imputed visualization or removing information associated with missing values significantly degraded perceived quality. Our findings suggest ways visualizations might leverage imputation and visualization to appropriately manipulate perceived data quality in different scenarios.

## 2 RELATED WORK

Missing data is typically a challenge associated with “dirty data”—datasets containing missing data, incorrect data, misalignments, and other such anomalies that may lead to erroneous conclusions [36]. Missing data can occur throughout the data lifecycle and has significant implications for analyst trust in data [43]. These implications can be especially problematic for data visualizations as little empirical understanding exists to guide how visualizations can balance between indicating the presence of dirty data and not distracting from or biasing of the rest of the data [33]. Our research builds such knowledge by measuring the influence of various designs for visualizing missing data.

### 2.1 Methods for Analyzing Incomplete Data

Missing data can arise at all points in the data lifecycle, including during data capture, storage, updates, transmission, access, deletions, and purges [36]. A scraping process might fail due to an interrupted script, packet loss, or memory errors. Subsets of data may be withheld due to privacy considerations [20]. Part of the process of data wrangling [23, 33] is locating missing data and deciding how to manage it. In many cases, systems choose to *impute*—estimate a substitute value for—missing data to address potential anomalies affecting the quality of dataset coverage [40].

A broad variety of methods exist for data imputation (see Little and Rubin [38] and Lajeunesse [37] for surveys). For example, hot-deck imputation samples substitute values from the current signal while cold-deck imputation estimates values using other sources, such as related datasets [25] or domain heuristics [29]. Interpolation methods use weighted combinations of available data to statistically infer missing values using methods like linear interpolation, regression, and adaptive interpolation [24]. More complex imputation methods can integrate information about the processes used to generate the dataset [44] or use machine learning and related techniques to holistically estimate missing values [2].

While an exhaustive survey of imputation methods is beyond the scope of this paper, understanding the relationship between different imputation choices and perceived data quality is critical for visualizing missing data. As Babad and Hoffer note, even if data values can be inferred with reasonable accuracy, it is important for analysts to understand when and where missing data occurs [7]. Missing data can have a significant impact on inference and decision making and can lend context to analyses. Most significantly for our work, missing data is a key component of *data quality*, a measure of the trust and suitability of data for addressing a given problem [42].

Time series data has specific considerations for data quality (see Gschwandtner et al. for a survey [28]). For example, non-uniform sampling may force interpolations. Joining data across two temporal sources with different granularities can lead to misalignment [6]. Measures taken at the same time may conflict with another. Since data is typically continuous, violations to trends may be especially salient. Due to these factors, we elect to use time series data as the basis as it is commonly used in both real-world analysis and empirical studies for visualization and these factors make it an important special case for understanding the implications of missing data for temporal analysis.

### 2.2 Visualizing Incomplete Data

Wong and Varga refer to missing data as *black holes* in a visualization—“a dark area of the cognitive workspace that by the absence of data

indicates that one should take care [51].” They argue that it is unclear when and how visualizations should replace missing data to support sensemaking, yet it is clear that people should be able to detect and reason about missing data. Many visualization systems support data quality analysis, including quality change over time [11], data preprocessing [8], and highlighting missing, incorrect, or imputed values [9, 10, 21]. For example, Visplause [5] supports data quality inspection for time series data in order to assist analysts in inferring potential causes of missing data. Wrangler [34] uses statistical methods to help analysts impute missing values. xGobi [46], MANET [50], and VIM [47] offer visualization suites that allow analysts to understand the amount of missing data and compare different imputation methods.

Many visualization systems oriented towards specific domains or datatypes automatically process missing data. Some visualizations provide little to no visual indication of imputed data. For example, Turkay et al. [48] substitute missing values with the feature mean. Systems in meteorology [18] and psychology [29] interpolate missing data based on domain heuristics. Other systems leverage visual saliency to manipulate whether analyst attention is drawn to imputed values. For example, TimeSearcher uses brightly colored marks to indicate locations of missing values [14]. Restorer uses grayscale to reduce the salience of missing spatial data, and luminance to interpolate imputed values [49]. However, the influence of imputation and the corresponding visualization methods used in these systems is not well understood. We ground our exploration of imputation in the practices currently used in missing data visualization.

### 2.3 Graphical Perception

Prior studies in graphical perception show how the methods used to visualize data change our interpretation of that data. For example, studies show that visualization design changes our abilities to estimate and compare statistical values [3, 15, 22, 30] and shift our confidence in those estimations [1]. As imputed values represent uncertain information, we draw on prior findings in uncertainty visualization to inform our study. Specific visual attributes, such as luminance, blurriness, and sketchiness, can indicate uncertainty in data and shift people’s confidence in their conclusions [13, 16, 27, 35, 39]. Presenting data as “sketchy” additionally increases engagement with and willingness to critique data [52], which may have interesting ramifications for perceived data quality. Individual values can shift statistical perceptions of data [17], indicating imputed points introducing variation may potentially bias analyses. As many imputation methods provide no quantifiable measure of uncertainty, we evaluate encodings that both present either the level or the existence of uncertain information.

A handful of prior studies have explicitly evaluated the influence of visualization methods on perceptions of data quality. Xie et al. [53] measure how to communicate data quality in high dimensional data using size, brightness, and hue, and found hue and size to be strong channels for encoding quality information. Eaton et al. [20] compared how different methods for visualizing missing data in line graphs influenced accuracy and confidence in response for point-comparison and trend estimation recall tasks. They substituted missing values with zero, rendered no marks for missing data (*data absent*), and used gapped circles to indicate missing data. They found that people interpreted confidently even when critical data was missing, but found no significant differences between methods. Participants expressed an overall preference for visualizations that explicitly indicated missing data. Andreasson and Riveiro [4] conducted a similar study comparing the effects of absent data, fuzziness, and annotated absent data on analyst confidence in a decision making task. Their results showed that people had a strong preference for conditions with annotated absent data and a strong dislike for fuzziness.

Our work looks to significantly extend these findings by separating effects of imputation methods such as the zero-filling in [20] from visualization methods, considering variable numbers of missing values, and leveraging a wider variety of visualization methods. We also evaluate bar charts in addition to line graphs, where not drawing missing data is indistinguishable from zero values. Prior studies indicate that the kinds of information people synthesize across bars and lines can

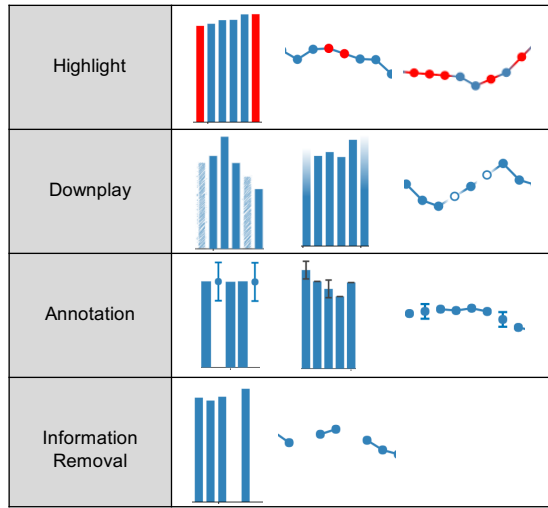


Fig. 2. Our studies looked at three distinct categories of visualizations that could encode imputed values: **visual highlight** encodings that draw attention to imputed values, **visual downplay** encodings, **annotation** encodings that provide additional information, and encodings that use **visual information removal**.

vary [54], and these differences may significantly impact perceptions of missing data.

### 3 MOTIVATION & HYPOTHESES

Data quality concerns how suitable a given dataset is to solve a problem or make a decision. Dimensions of data quality include several factors related to a data source (e.g., accessibility, volume, and relevance) and others that relate to perceptions of the dataset (e.g., completeness, credibility, and reliability) [42]. While analysts must consider factors of a data source when choosing a dataset, the visualizations used to analyze data directly influence perceptions of the data. In this study, we measure how imputation and visualization choices impact response bias and perceptions when data is incomplete. We focus on completeness, credibility, reliability, and confidence in analysis as key indicators of data quality.

Our inspiration for this study comes from collaborations with public health analysts. These analysts fuse data from sources of both low (e.g., social media) and high (e.g., CDC and WHO reports) quality data sources to develop deeper insights into data. Data collection errors and temporal misalignments after fusing these sources frequently lead to incomplete data. While our collaborators care about large scale patterns in this data, their imputation methods and whether or not they need to include imputed data in assessing these patterns is less well defined: analysts want to assess patterns in light of missing data, but can often generate reasonable approximations about that data or want to know when and where data is missing to temper their decision making processes. As a result, we opt to evaluate missing data using similar methods to Jensen & Hornbæk where we allow participants to naturally integrate imputed values without explicit instructions as to how to consider those values in their estimates [32].

We tested four categories of visualization type for communicating missing data that we encountered in the systems discussed in §Related Work. The first category focused on making missing data **upweight** by leveraging bright colors to attract participant attention to missing data points (e.g., [10, 14]). The second category emphasized that missing data was **downweight** by using encodings that reduce the salience of imputed values relative to the rest of the data (e.g., [4, 9]). The third category used the encodings to showing additional statistical information such as error bars drawing confidence from the imputation estimate (e.g., variance statistics for cold- or hot-deck methods, pooled confidence intervals for multiple imputation) [9]. The fourth category used encodings corresponding to **information removal** for missing data as

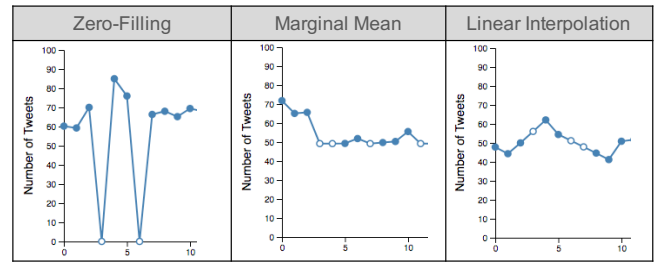


Fig. 3. We measured effects of three different imputation methods on data interpretation: zero-filling (substituting missing values with zeros), marginal means (substituting with the mean of the available data), and local interpolation (linear interpolating between adjacent available data-points).

some portion of their visual representation is missing (e.g., [4, 20]). As these semantically related to incompleteness, we anticipate that these encodings will also degrade data quality perceptions. Some tested manipulations were hybrids of these categories that examine dependencies across conditions. To mirror prior studies, we included a condition where missing data was entirely absent as a baseline.

We draw our tested imputation methods from three methods we observed in existing visualization systems. **Zero-filling** substituted a single value (0) for all missing data points, as in many commercial systems. **Local interpolation** linearly interpolated between adjacent available items, as in [29, 49]. **Marginal means** replaced each missing data value with the mean of all available signals, as in [21, 48]. For our data, zero-filling introduced the highest deviation from the original dataset, marginal means the second, and local interpolation the lowest. While we experimented with more complex interpolation methods, we found no significant differences in our results between those methods and the three selected. Figure 3 provides examples of the tested imputation and visualization categories.

Based on these conditions, we hypothesized that:

**H1**–Perceived data quality and response accuracy will both degrade as the amount of missing data increased.

**H2**–Highlighting visualization methods will generate higher perceived data quality than downweight visualization and information removal methods.

**H3**–Linear interpolation will lead to higher perceived confidence and data quality than marginal means or zero-filling as takes into account current trends in dataset.

**H4**–Imputed values will lead to higher perceived data quality than removed values.

**H1** stems from the idea that completeness is a key indicator of data quality and provides a quality check for our experiment. **H2** arises from certainty and completeness as aspects of data quality. As upweight visualizations provide no visual indications associated with either completeness (as with information removal) or with reduced visual weight (as in downweighting), we anticipate it will lead to higher perceived quality. This corresponds with observations from Andreassen and Riveiro [4] who found evidence that “fuzzy” visualizations, correlated with downweighting [13], were not well-liked for decision making with missing data. We predict **H3** on the basis of potential biases introduced by zero-filled and mean values and that local interpolation will create plausible variation in imputed values. This aligns with Correll and Heer’s findings that values outside of a distribution can bias statistical perceptions in data [17]. **H4** stems directly from Eaton et al. [20], who showed a preference for visualizations using explicit visual indications of missing data compared to absent values.

## 4 METHODS

We ran two  $7$  (visualization type)  $\times 3$  (imputation method)  $\times 4$  (percentage of missing data) full factorial within-participants studies to measure how visualization and imputation influence time series analysis, focusing on two conventional visualizations: line and bar graphs. Each study followed the same general procedure. Specific differences between the two studies are discussed in their respective sections. For each study, we had three independent variables—visualization type, imputation method, and percentage of missing data—and five dependent variables—accuracy, confidence in response, data credibility, data reliability, and data completeness.

### 4.1 Stimuli & Tasks

We generated each graph as a  $1000 \times 400$  pixel graph using D3 [12] and Plot.ly [31]. Figure 1 shows examples of these graphs. Each graph visualizes 60 values representing the frequency of Tweets collected per minute over an hour. This context provided a concrete problem scenario where we often find missing data in the real-world due to failures in data collection. We simulated missing data completely at random (MCAR) by randomly removing a subset of values in each graph (0%, 10%, 20%, or 30%). We replaced these values with an imputed value computed using one of the three imputation methods described in Conditions & Hypotheses (zero-filling, local interpolation, or marginal mean). The 0% removed condition provided a baseline for measuring changes to our dependent variables due to data removal. The imputed values were then rendered using one of the seven candidate visualization methods per graph type (c.f., Figures 4 and 6).

Above each graph, we provided a brief sentence contextualizing the data, a statement encouraging participants to complete the questions as quickly and accurately as possible, and a counter indicating current progress through the study. Below each graph, we enumerated five questions, answered using radio buttons:

We evaluated two tasks each for line graphs and bar charts: average and trend comparison. Each task required participants to answer five questions for each stimuli with task language determined in piloting.

1. Were there more Tweets on average in the first or second half-hour? (*Averaging*)  
Is the overall rate of change larger in the first or second half-hour? (*Trend Detection*)
2. How confident are you in your response?  
1–Extremely Unconfident, 7–Extremely Confident
3. How credible is this data?  
1–Extremely Uncredible, 7–Extremely Credible
4. How complete is this data?  
1–Extremely Incomplete, 7–Extremely Complete
5. How reliable is this data?  
1–Extremely Unreliable, 7–Extremely Reliable

We chose to use averaging and trend comparison tasks in our evaluation as they forced participants to consider information from all points in the dataset and mitigated changes to the correct response and task difficulty introduced by randomly removing values. Prior studies in missing data visualization have relied on trend detection tasks (e.g., [20]), while our public health collaborators noted the importance of averaging for comparing relative frequencies across disparate datasets. Questions 2 through 5 provide different perspectives on the perceived quality of the data and conclusions.

#### 4.1.1 Data Generation

**Average Data:** Both noise and task difficulty may influence perceptions in our study: noisier signals may change the effects of different imputation methods and confidence in a conclusion may correlate with difficulty. To control for these concerns, we used synthetic datasets to provide control over noise and difficulty. Each graph contained 60 y-values ranging from  $y = 0$  to  $y = 100$ . X-values corresponded to each value's order within the dataset (i.e.,  $x = 0$  to  $x = 59$ ). We computed the y-values by first generating a signal from structured random noise [41]. We generated signals using five different noise levels and considered

noise as a random effect in our analyses. We then used a constraint-based optimization to adjust the mean difference between the first and last thirty points while minimizing deviation from the original random signal to control difficulty. We separated the means of the first and last half hour by 2.0, 4.0, and 6.0, randomly selecting which half hour was highest. We used this difference threshold as it achieved desirable response accuracy in prior studies [3].

For the average task, each graph visualized a randomly selected dataset from 110 total datasets generated using this method. To assist with reproducing our results, the datasets and experimental infrastructures are available online at `removed.for.review`.

**Trend Data** Like average data generation, both noise and task difficulty may influence perceptions in our study: noisier signals may change the effects of different imputation methods and confidence in a conclusion may correlate with difficulty. To control for these concerns, we used synthetic datasets to provide control over noise and difficulty. Each graph contained 60 y-values ranging from  $y = 0$  to  $y = 100$ . X-values corresponded to each value's order within the dataset (i.e.,  $x = 0$  to  $x = 59$ ). We computed the y-values by first generating a signal from structured random noise [41]. We generated signals using four different noise levels and considered noise as a random effect in our analyses. We separated the difference in the slopes of the first and last half hour by 0.5, 0.7, and 1.0, randomly selecting which half hour larger overall rate of change. We used this difference threshold as it achieved desirable response accuracy in prior studies [3].

For the trend task, each graph visualized a randomly selected dataset from 96 total datasets generated using this method. To assist with reproducing our results, the datasets and experimental infrastructures are available online at `removed.for.review`.

### 4.2 Procedure

Our study consisted of five phases: (1) consent, (2) screening, (3) instructional tutorial, (4) formal study, and (5) demographic questionnaire. Each participant first provided informed consent to participate in the study in accordance with our IRB protocol. We then screened participants for color vision deficiencies using a set of four Ishihara plates. Participants then received instructions about the study and were serially shown examples of each of the seven visualization conditions with one missing value. Each stimuli in the tutorial explained that some data was missing and that we had “guessed” at the values and described how we visualized “guessed” values. They had to correctly identify the half-hour with the highest average value for each condition before beginning the formal study.

The formal study consisted of 87 trials presented serially (84 from our factorial design and 3 engagement checks). To mitigate effects from changing the visualization paradigm, we blocked stimuli by visualization method and randomized the order of blocks. Within each block, participants saw all twelve combinations of missing data (0%, 10%, 20%, and 30%) and imputation method (zero-filling, local interpolation, and marginal mean) presented in random order. Each stimuli visualized a random dataset, with each dataset occurring at most once per participant. The format is the same for both average task and trend task but for average task we constructed three engagement checks with 0% missing data where the average between halves of the dataset differed by 20.0. For trend task we constructed three engagement checks with 0% missing data where the difference in slopes between halves of the dataset differed by 1.0. For These engagement checks were added to blocks 2, 4, and 6.

After completing the formal study, participants completed a demographic questionnaire, which included an opportunity for open-ended comments, and were compensated for their participation.

### 4.3 Measures & Analysis

We used three primary measures to analyze participant responses: perceived confidence in their answer (Question 2), perceived credibility (Question 3), and a two-item scale describing perceived quality (Questions 4–5). Accuracy both with and without imputed values was also evaluated as a secondary metric to detect performance biases introduced by the tested methods. Unless otherwise specified, our main



Fig. 4. We tested seven different visualization methods that manipulated point and line encoding for missing data. These stimuli show examples of all seven conditions at our lowest noise level.

analysis used a repeated measures analysis of covariance (ANCOVA) to test for main and interaction effects with question order and noise treated as random effects and the actual (difference in when data points are removed) and imputed difference between means as covariates to mitigate effects of task difficulty. In both experiments, our response data was normally distributed. To control for Type I errors in planned comparisons across conditions, we used Tukey’s Honest Significant Difference test with  $\alpha = .05$  for post-hoc analyses. We elected not to use response time as a measure for this study. While understanding the effects of missing data on analysis speed is an interesting question, the inclusion of our subjective measures and use of crowdsourcing make it less reliable given our experimental apparatus.

Our four questions relating to perceived data and analysis quality were framed as 7-item Likert scales. We constructed a three-item scale from responses about perceived data reliability, credibility, and completeness to investigate perceptions of data quality. We used this new scale as a dependent measure in-place of the component questions.

#### 4.4 Participants

We collected data from 303 U.S. participants on Amazon’s Mechanical Turk ( $\mu_{age} = 36.3$ ,  $\sigma_{age} = 12.7$ , 150 female, 153 male, 3 DNR). All participants reported normal or corrected to normal vision. To ensure honest participation and task understanding, we excluded any participants who answered more than two of the three engagement check stimuli incorrectly. Individual participant demographics and exclusions are reported in the respective Results sections.

### 5 EXPERIMENT ONE: LINE GRAPHS

Prior studies in missing data visualization focused on line graphs, one of the most common and ubiquitous methods for visualizing data. We tested three factors we hypothesized may effect missing data interpretation in line graphs: visualization type, percentage of missing data, and imputation method. Line graphs visualize data both through point marks and lines connecting those marks. As a result, we tested seven different visualization approaches that manipulated some combination of the point marks and lines themselves. We anticipated that since the connection between values in a line chart is salient, manipulating the lines may have different effects from manipulating the points alone.

Figure 4 shows the seven tested visualization designs: (a) Data Absent (baseline) [20], (b) Color Points [14], (c) Color Points with Line Gradients (where the imputed value and its connections are both colored red) [14], (d) Connected Error Bars, with error corresponding to the standard deviation of the present values [4], (e) Disconnected Error Bars (where the line does not pass through imputed points) [4], (f) Unfilled Points [20], and (g) Unfilled Points with Line Gradients (where the line passing through imputed data is alpha-blended) [49]. Drawing on our four target visualization categories, the color conditions highlighted imputed values, unfilled points downplayed imputed values, error bars annotate data with additional statistical information, and data absent falls into information removal (Fig. 4). We conducted a 7 (visualization type)  $\times$  3 (imputation method)  $\times$  4 (percentage of missing data) within participants study to evaluate the effects of visualization and imputation on analyzing incomplete datasets using the procedure outlined in §4.

### 5.1 Results

We found a strong correlation between perceived completeness and reliability (Cronbach’s  $\alpha > 0.70$ ) for both average results and trend results. We constructed a two-item scale using these factors to describe data quality. We analyzed this scale as well as task performance using a three-factor full factorial rmANCOVA with question order and difficulty as random covariates. Figure 5 summarizes our results for perceived data quality and accuracy. Complete data is available on the project page (removed.for.review).

#### 5.1.1 Averaging Results

**Participants:** We collected data from 66 U.S. participants on Amazon’s Mechanical Turk ( $\mu_{age} = 37.2$ ,  $\sigma_{age} = 13.22$ , 36 female, 30 male, 2 DNR). All participants reported normal or corrected to normal vision. Two participants were excluded for failing two or more of the large difference engagement check stimuli, resulting in 5,742 total trials.

#### Subjective Results

**Data Quality:** We found significant main effects on data quality due to percentage of missing data ( $F(1,62) = 1519.38$ ,  $p < .0001$ ) and visualization method ( $F(6,57) = 22.92$ ,  $p < .0001$ ). As expected, the 0% missing data baseline had significantly higher overall perceived quality than any other conditions. Connected error bars led to higher perceived data quality, whereas the data absent condition used in prior studies led to lower perceived data quality ( $\mu_{error} = 4.53 \pm .12$ , 95%CI vs.  $\mu_{absent} = 3.60 \pm .11$ ). Also, color points with line gradients had significantly higher perceived data quality than disconnected error bars led to lower perceived data quality, ( $\mu_{color} = 4.3 \pm .12$ , 95%CI vs.  $\mu_{disconnectederror} = 3.85 \pm .12$ ). We also found main effects of imputation method ( $F(2,61) = 61.77$ ,  $p < .0001$ ). Local interpolation had higher perceived quality than marginal means ( $\mu_{local} 4.43 \pm .07$  to  $\mu_{means} = 4.24 \pm .07$ ), and both methods had higher perceived quality than zero-filling ( $\mu_{zero} = 3.77 \pm .08$ ).

We found three significant interaction effects on data quality: visualization type and missing amount ( $F(6,56) = 6.86$ ,  $p < .0001$ ), visualization type and imputation method ( $F(12,51) = 3.047$ ,  $p < .0002$ ), and imputation method and missing amount ( $F(5,409) = 17.04$ ,  $p < .0001$ ). Color points with local interpolation had the highest perceived quality overall ( $\mu_{colorpoint,local} = 4.75 \pm .19$ ), while disconnected error bars with zero-filling had the lowest ( $\mu_{disconnectederror,zero} = 3.50 \pm .23$ ). Connected error bars and zero-filling ( $\mu_{error,zero} = 4.09 \pm .20$ ) had significantly higher perceived quality than all other zero-filling conditions.

**Data Credibility & Analyst Confidence:** Our general observations regarding data quality were mirrored in perceived data credibility and analyst confidence. Connected error bars led to high perceived credibility ( $\mu_{connectederror} = 4.59 \pm .12$ ) and led to more confidence in results ( $\mu_{connectederror} = 4.63 \pm .12$ ), whereas the data absent condition used in prior studies was seen as less credibility ( $\mu_{absent} = 4.08 \pm .12$ ) and generating lower confidence ( $\mu_{absent} = 4.29 \pm .12$ ). However, data visualized using color points was seen as more credible ( $\mu_{colorpoint} = 4.61 \pm .11$ ) and led to higher confidence ( $\mu_{colorpoint} = 4.66 \pm .11$ ) than all other visualization types. We found the same preference ranking for different imputation methods across both confidence and credibility: local interpolation being highest ( $\mu_{credibility} 4.88 \pm .07$ ,  $\mu_{confidence} 4.67 \pm .07$ ), followed by marginal



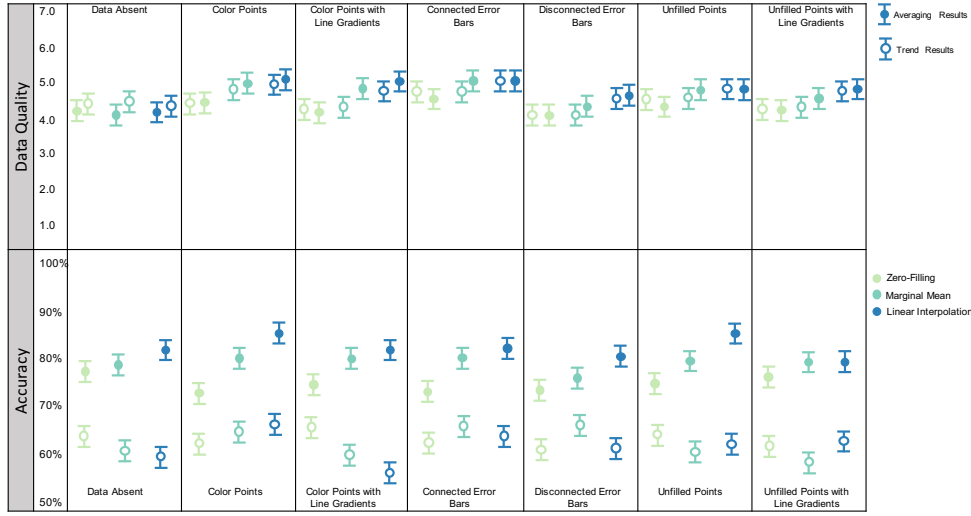


Fig. 5. Our results indicate that the imputation method and design techniques used to visualize missing data directly influence perceived data quality and can bias data interpretation in line graphs.

means ( $\mu_{credibility} = 4.76 \pm .07$ ,  $\mu_{confidence} = 4.48 \pm .08$ ), and zero-filling ( $\mu_{credibility} = 4.45 \pm .08$ ,  $\mu_{confidence} = 4.35 \pm .08$ ).

### Objective Results

**Without Imputed Values:** Overall, participants correctly identified the half-hour with the higher mean in 78.8% of trials. First, we found a significant main effects of percentage of missing data on accuracy without imputed values ( $F(1,63) = 23.81, p < .0001$ ). Second, we found a significant main effects of imputation methods on accuracy ( $F(2,61) = 8.76, p < .0002$ ). Linear interpolation and marginal means ( $\mu_{local} = .80 \pm .02$  to  $\mu_{means} = .76 \pm .02$ ) both led to higher accuracy than ( $\mu_{zero} = .72 \pm .02$ ), providing preliminary evidence that missing imputed values can complicate task performance. Third, we found a significant interaction effect of accuracy on imputation method and missing amount ( $F(2,61) = 6.14, p < .002$ ).

**With Imputed Values:** Overall, participants correctly identified the half-hour with the higher mean in 78.3% of trials. First, we found a significant main effects of percentage of missing data on accuracy with imputed values ( $F(1,63) = 26.79, p < .0001$ ). Second, we found a significant main effects of imputation methods on accuracy ( $F(2,61) = 15.65, p < .0002$ ). Linear interpolation and marginal means ( $\mu_{local} = .80 \pm .02$  to  $\mu_{means} = .75 \pm .02$ ) both led to higher accuracy than ( $\mu_{zero} = .69 \pm .02$ ). Third, we found a significant interaction effect of accuracy on imputation method and missing amount ( $F(2,61) = 8.69, p < .0002$ ).

#### 5.1.2 Trend Detection Results

**Participants:** We collected data from 80 U.S. participants on Amazon's Mechanical Turk ( $\mu_{age} = 36.05, \sigma_{age} = 11.75$ , 38 female, 42 male, 2 DNR). We did not excluded anyone as all participants correctly answered two or more of the engagement checks, resulting in 7,134 trials.

### Subjective Results

**Data Quality:** First, we found significant main effects on data quality due to percentage of missing data ( $F(1,64) = 1185.901, p < .0001$ ) and visualization method ( $F(6,59) = 17.56, p < .0001$ ). As expected, the 0% missing data baseline had significantly higher overall perceived quality than any other conditions. Connected error bars led to higher perceived data quality than all other visualization types, whereas the disconnected error bars led to lower perceived data quality than all other types ( $\mu_{error} = 4.85 \pm .12$  vs.  $\mu_{disconnectederror} = 4.06 \pm .13$ ). Also, color points with line gradients led to higher perceived data quality whereas the data absent from prior studies led to lower perceived

data quality, ( $\mu_{color} = 4.76 \pm .17$  vs.  $\mu_{absent} = 4.19 \pm .11$ ). We also found main effects in imputation method ( $F(2,63) = 24.63, p < .0001$ ). Local interpolation had higher perceived quality than marginal means ( $\mu_{local} = 4.72 \pm .08$  to  $\mu_{means} = 4.46 \pm .08$ ), and both methods had higher perceived quality than zero-filling ( $\mu_{zero} = 4.30 \pm .08$ ). We found a significant interaction effect between imputation method and missing amount ( $F(2,63) = 5.81, p < .003$ ).

**Data Credibility & Analyst Confidence:** Main effects of visualization type on data quality were again mirrored in our confidence and credibility metrics. Connected error bars ( $\mu_{credibility} = 4.90 \pm .12$ ,  $\mu_{confidence} = 5.42 \pm .12$ ) and color points ( $\mu_{credibility} = 4.86 \pm .11$ ,  $\mu_{confidence} = 5.48 \pm .11$ ) led to high perceived data credibility and confidence in trend detection, whereas disconnected error bars ( $\mu_{credibility} = 4.27 \pm .12$ ,  $\mu_{confidence} = 5.07 \pm .12$ ) and information removal ( $\mu_{credibility} = 4.51 \pm .10$ ,  $\mu_{confidence} = 5.27 \pm .11$ ) led to lower overall perceptions of confidence and credibility. Of note, connected error bars and zero-filling also had significantly higher perceived credibility than all other zero-filling conditions ( $\mu_{error,zero} = 4.83 \pm .20$ ). We again found a consistent preference ranking across these factors for imputation method: local interpolation being highest ( $\mu_{credibility} = 4.90 \pm .07$ ,  $\mu_{confidence} = 5.55 \pm .06$ ), followed by marginal means ( $\mu_{credibility} = 4.62 \pm .07$ ,  $\mu_{confidence} = 5.40 \pm .07$ ), and zero-filling ( $\mu_{credibility} = 4.49 \pm .06$ ,  $\mu_{confidence} = 5.42 \pm .07$ ).

### Objective Results

**Without Imputed Values:** Overall, participants correctly identified the half-hour with the larger overall rate of change or slope in 62.8% of trials. We did not find any significant effects of our independent variables on trend detection accuracy.

**With Imputed Values:** Overall, participants correctly identified the half-hour with the larger overall rate of change or slope in 63.2% of trials. We did not find any significant effects of our independent variables on trend detection accuracy.

## 5.2 Line Graphs–Synthesis of Results

Our results provide preliminary support for all of our hypotheses:

**H1:** As the percentage of missing data increased, perceived quality, credibility, and confidence in analysis decreased.

**H2:(partial)** We found that encodings highlight missing values (e.g., our color points and color points and lines conditions) led to significantly higher perceived quality than visualizations that removed data. We failed to find evidence supporting the same comparison with down-playing techniques.

**H3:** Linear interpolation led to the highest perceived data quality

**H4:** The data absent condition led to significantly lower perceived data quality, credibility, and confidence than all other visualization conditions.

We found limited evidence of accuracy bias from imputation methods, consistent with Eaton et al. [20].

Our results showed that the participants regarded color with line gradients as of higher quality overall while removing missing data-points from the graph caused analysts to see the data as having lower quality and led to lower reported confidence in their task performance. While most methods within a given design category performed comparably, we also saw an interesting contrast between our two annotation conditions (connected versus disconnected error bars). Participants perceived the connected error bars as having higher data quality, being more credible, and leading to higher confidence in interpretation. On the other hand, when the error bars were disconnected they reported significantly lower scores on these subjective measures. This conclusion offers an interesting consideration when juxtaposed with results from Andreasson and Riveiro [4] who found that fuzziness, another correlate for uncertainty, led to the lowest overall preference for decision making tasks. This discrepancy suggests that adding additional information is insufficient to increase perceived data quality: the underlying structure of the visualization and integration of imputed values into the visual structure of a dataset may also play a role. Additionally, the robustness demonstrated by connected error bars as the amount of missing data increased suggests that connected error bars may preserve perceived quality even as actual quality decreases, which could bias decision making. As this assumption is grounded in descriptive statistics and a lack of an effect, further testing is needed to determine the validity of this observation.

## 6 EXPERIMENT TWO: BAR CHARTS

We extended our line graph study to more deeply explore the influence of missing data imputation and visualization. While prior studies in missing data visualization focus on line graphs, bar charts provide an interesting case for visualizing missing data as they use bar height to encode data rather than position and connection. This change in encoding may shift the data patterns people observe [54]. Many techniques for bar charts also visualize absent data, zero-filling, and  $y = 0$  the same way, which may change biases and quality perceptions compared to line graphs.

As in the lines study, we evaluated seven visualization designs. Several of our designs mirrored those used in the line graph conditions; however, we extended our techniques to include sketching [52] and dashed outlines [13] to prioritize encodings correlated to downplaying imputed values. Figure 6 seven shows the seven tested visualization designs: (a) Data Absent [20], (b) Color Bars [14], (c) Sketched Bars [52], (d) Bars with Error Bars [4], (e) Points with Error Bars [4], (f) Unfilled Bars with Dashed Outlines [13], and (g) Alpha-blended Gradient Bars [49]. Error bars again approximated a standard deviation error of the data used in the imputation, and gradients used this amount to define the blend radius. Color bars highlighted imputed values; error bar and points with error bars annotated imputed values; sketchiness, gradient bars, and dashed outlines downplayed imputed values; and not showing the values exemplified information removal.

### 6.1 Bar Graph Results

We again found a strong correlation between perceived completeness and reliability (Cronbach's  $\alpha > 0.70$ ) for both averaging and trend detection. We constructed a two-item scale using these factors to describe data quality. We analyzed this scale as well as task performance using a three-factor (visualization technique, imputation method, and amount of missing data) full factorial rmANCOVA with question order and difficulty as random covariates. Complete data is available on the project page ([removed for review](#)).

#### 6.1.1 Averaging Results

**Participants:** We collected data from 80 U.S. participants on Mechanical Turk ( $\mu_{age} = 37.1, \sigma_{age} = 11.4$ , 38 female, 42 male). All participants answered at least two of the engagement check stimuli correctly, resulting in 6,960 trials. Figure 7 summarizes our results.

##### Subjective Results

**Data Quality:** We found significant main effects on data quality due to percentage of missing data ( $F(1, 78) = 2927.716, p < .0001$ ) and visualization method ( $F(6, 73) = 24.15, p < .0001$ ). As expected, the 0% missing data baseline had significantly higher overall perceived quality than any other conditions. Bars with error bars led to higher perceived data quality whereas the point with error bars led to lower perceived data quality ( $\mu_{barerror} = 4.82 \pm .11$  vs.  $\mu_{pointerror} = 4.26 \pm .09$ ). Color bars ( $\mu_{color} = 4.71 \pm .07$ ) and gradient bars ( $\mu_{gradient} = 4.71 \pm .08$ ) led to higher data quality while other downplaying techniques—sketched bars ( $\mu_{sketch} = 4.41 \pm .07$ ) and dashed outlines ( $\mu_{dash} = 4.32 \pm .08$ ) and information removal ( $\mu_{absent} = 4.36 \pm .08$ ) led to lower perceived data quality. We also found main effects in imputation method ( $F(2, 77) = 52.76, p < .0001$ ). Both local interpolation and marginal mean had higher perceived quality ( $\mu_{local} = 4.67 \pm .07$ ,  $\mu_{means} = 4.60 \pm .07$ ) than zero-filling ( $\mu_{zero} = 4.26 \pm .07$ ).

We found four significant interaction effects on data quality: 1) visualization type and missing data ( $F(6, 73) = 10.73, p < .0001$ ), 2) visualization type and imputation ( $F(12, 67) = 7.97, p < .0001$ ), 3) amount of missing data and imputation method ( $F(2, 77) = 21.35, p < .0001$ ), 4) visualization type, amount of missing data, and imputation method ( $F(12, 67) = 3.11, p < .0002$ ). Bars with error bars and local interpolation had the highest perceived data quality overall ( $\mu_{barerror, local} = 5.14 \pm .19$ ), while points with error bars and zero-filling led to lower data quality ( $\mu_{pointerror, global} = 4.19 \pm .23$ ). Gradient bars and color bars with local interpolation ( $\mu_{gradient, local} = 5.01 \pm .21$  to  $\mu_{color, local} = 4.99 \pm .22$ ) led to higher perceived data quality.

**Data Credibility & Analyst Confidence:** Self-reported perceptions of data credibility and analyst confidence in the data generally mirrored data quality measures. Color bars led to the highest overall perceived confidence ( $\mu_{color} = 4.75 \pm .10$ ); however, color bars, bars with error bars, and gradient bars generated higher perceived credibility scores ( $\mu_{color} = 4.85 \pm .07$ ,  $\mu_{barerror} = 4.90 \pm .11$ , and  $\mu_{gradient} = 4.86 \pm .08$ ). Points with error bars led to consistently lower credibility ( $\mu_{pointerror} = 4.52 \pm .09$ ) and confidence ( $\mu_{pointerror} = 4.64 \pm .10$ ). Sketched and outlined bars also led to low reported confidence ( $\mu_{sketch} = 4.57 \pm .07$ ,  $\mu_{outline} = 4.56 \pm .08$ ) as did the data absent condition ( $\mu_{absent} = 4.60 \pm .07$ ).

We mirrored results from data quality again finding that both local interpolation and marginal means led to higher perceived credibility ( $\mu_{local} = 4.81 \pm .07$ ,  $\mu_{means} = 4.75 \pm .06$ , and  $\mu_{zero} = 4.52 \pm .07$ ) and confidence ( $\mu_{local} = 4.71 \pm .07$ ,  $\mu_{means} = 4.64 \pm .06$ , and  $\mu_{zero} = 4.47 \pm .07$ ). Unlike with lines, we found no evidence of significant differences between local interpolation and marginal means for bars.

##### Objective Results

**Without Imputed Values:** Overall, participants correctly identified the half-hour with the higher average in 80.76% of trials. First, we found a significant main effects of percentage of missing data ( $F(1, 78) = 32.98, p < .0001$ ) and different visualization techniques ( $F(6, 71) = 3.76, p < .0009$ ) on accuracy without imputed values. Accuracy directly correlated to the amount of missing data. Bars with error bars led to higher accuracy, whereas the dash outline bars led to lower accuracy ( $\mu_{barerror} = 83.98 \pm .01$  vs.  $\mu_{dashoutline} = 77.95 \pm .02$ ). Also, color bars led to higher accuracy ( $\mu_{color} = 83.4 \pm .02$ ). We found no significant main effects of imputation methods on accuracy.

**With Imputed Values:** Participants correctly identified the half-hour with the higher overall average in 80.73% of trials. We found a significant main effects of percentage of missing data and different visualization encodings on accuracy with imputed values ( $F(1, 78) = 47.71, p < .0001$ ) and ( $F(6, 71) = 3.30, p < .003$ ). Accuracy again correlated to the amount of missing data. Color bars and bars with error bars led to the highest overall accuracy, whereas the disconnected error bars led to lower accuracy than all other types ( $\mu_{color} = 83.98 \pm .01$  and  $\mu_{barerror} = 83.33 \pm .02$  versus  $\mu_{pointerror} = 77.95 \pm .02$ ). We

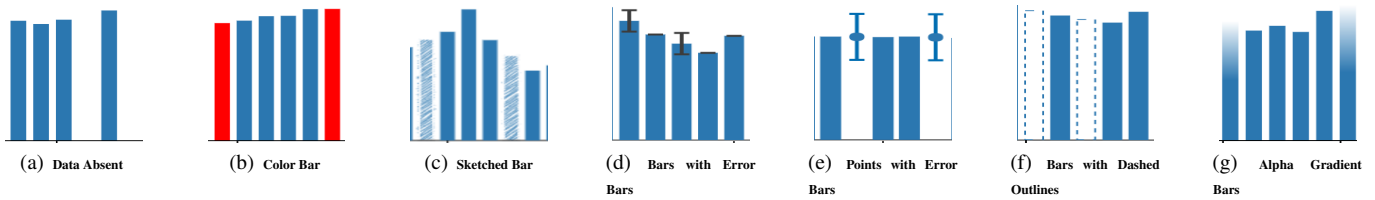


Fig. 6. We tested seven different visualization methods that manipulated bar encoding for missing data. These stimuli show examples of all seven conditions at our lowest noise level.

found a significant main effect of imputation methods on accuracy ( $F(2, 77) = 4.96, p < .0070$ ). Linear interpolation and marginal means ( $\mu_{local} = .81 \pm .02$  to  $\mu_{means} = .81 \pm .03$ ) both led to higher accuracy than ( $\mu_{zero} = .78 \pm .02$ ).

We found a significant interaction effects of imputation method and missing amount on accuracy ( $F(2, 78) = 8.48, p < .0002$ ) and interaction effects of visualization, amount of missing data, and imputation method ( $F(12, 67) = 1.95, p < .0240$ ). Notably, bars with error bars using local linear interpolation led to significantly higher overall accuracy than linearly interpolated points with error bars ( $\mu_{barerror, linear} = 88.3 \pm .03$  versus  $\mu_{disconnectederror, local} = 76.60 \pm .05$ ).

### 6.1.2 Trend Detection Results

**Participants:** We collected data from 77 U.S. participants on Mechanical Turk ( $\mu_{age} = 34.9, \sigma_{age} = 11.9$ , 38 female, 39 male). We excluded 3 participants who failed to answer at least two of the engagement check stimuli correctly. We analyzed data from the remaining 74 participants, resulting in 6,483 trials. We found a strong correlation between perceived data completeness and reliability ( $\alpha = .70$ ). We constructed a two-factor scale describing data quality using these measures.

#### Subjective Results

**Data Quality:** We found significant main effects on data quality due to amount of missing data ( $F(1, 72) = 1803.289, p < .0001$ ) and visualization method ( $F(6, 67) = 22.80, p < .0001$ ). Perceived quality varied directly with the different types of visualization. Bar error ( $\mu_{barerror} = 4.81 \pm .10$ ) led to significantly higher perceived data quality than data absent ( $\mu_{absent} = 4.18 \pm .11$ ), dashed outline bars ( $\mu_{dash} = 4.10 \pm .08$ ), and points with error bars ( $\mu_{pointerror} = 4.03 \pm .07$ ).

We found a significant main effect of imputation method on perceived quality ( $F(2, 71) = 127.61, p < .0001$ ). Participants found local linear interpolation as resulting in the higher data quality ( $\mu_{local} = 4.58 \pm .04$ ), followed by marginal means ( $\mu_{global} = 4.39 \pm .04$ ), and data absent ( $\mu_{absent} = 4.14 \pm .04$ ).

We found four significant main interaction effects on data quality: 1) visualization and amount of missing data, ( $F(6, 67) = 7.64, p < .0001$ ) 2) visualization method and imputation ( $F(12, 61) = 5.73, p < .0001$ ), 3) amount of missing data and imputation ( $F(2, 67) = 9.34, p < .0001$ ), and 4) missing data and imputation ( $F(12, 61) = 2.54, p < .0024$ ).

**Data Credibility & Analyst Confidence:** Gradient bars led to higher perceived credibility and confidence ( $\mu_{credibility} = 5.18 \pm .05$ ,  $\mu_{confidence} = 5.45 \pm .11$ ) than dashed outline bars ( $\mu_{credibility} = 4.85 \pm .10$ ,  $\mu_{confidence} = 5.17 \pm .11$ ) and points with error bars ( $\mu_{credibility} = 4.80 \pm .11$ ,  $\mu_{confidence} = 5.13 \pm .12$ ).

Linear local interpolation ( $\mu_{credibility} = 4.84 \pm .11$ ,  $\mu_{confidence} = 5.26 \pm .04$ ) led to higher perceived confidence than marginal mean ( $\mu_{credibility} = 4.65 \pm .12$ ,  $\mu_{confidence} = 5.02 \pm .04$ ) and zero-filling ( $\mu_{credibility} = 4.55 \pm .12$ ,  $\mu_{confidence} = 5.10 \pm .05$ ).

#### Objective Results

**Without Imputed Values:** Overall, participants correctly identified 60.6% of trials the half-hour with the larger overall rate of change or slope in. We found no significant effects of our independent variables on accuracy.

**With Imputed Values:** Overall, participants correctly identified 61.4% of trials the half-hour with the larger overall rate of change or slope in. We found significant main effects on accuracy depending on imputation method ( $F(2, 71) = 5.66, p < .0035$ ). We found that zero-filling

( $\mu_{absent} = .63 \pm .02$ ) led to higher accuracy than linear interpolation ( $\mu_{local} = .57 \pm .02$ ) and marginal mean ( $\mu_{global} = .58 \pm .02$ ).

## 6.2 Bar Graphs—Synthesis of Results

Our results provide support for each of our four hypotheses:

**H1:** As the amount of missing data increased, accuracy, confidence in result, and perceived data quality decreased.

**H2:** (*partial*) Our data absent condition and two downplaying techniques (sketching and dashed outlines) led to consistently low perceived data quality, whereas color bars led to high quality perceptions. However, gradient bars, which also downplay imputed values, led to consistently high perceived data quality.

**H3:** (*partial*) Local interpolation outperformed zero-filling and led to higher quality perceptions and confidence, and credibility through different visualization types tested. However, local interpolation only led to higher subjective impressions for our trend detection task.

**H4:** (*partial*) The data absent condition again led to low overall perceived quality, confidence, and credibility; however, other techniques performed comparably poorly on this metric.

Across both tasks, we found that bars with error bars, gradient bars, and color bars led to consistently high perceived confidence and overall accuracy. However, our other annotation condition—points with error bars—and downplay conditions—sketched bars and dashed outline bars—led to lower perceived confidence, credibility, data quality, and task accuracy. Combined with our results from Experiment One and findings from Andreasson & Riveiro [4], these findings suggest that visual encodings that break the continuous visual structure of a graph reduce perceptions of data quality and may actually inhibit analysis.

We hypothesize the observed subjective and objective bias for encodings that break continuity may be due to attentional selection. The process used to visually average information may be impacted by the point condition's use of height and position encodings. Our lowest performing conditions—data absent, points, dashed outlines, sketching, and zero filling—reduce or remove the lightness of imputed bars. Based on known mechanisms of visual attention (see Gleicher et al. [26] for a discussion), these reductions may cause participants to group consecutive sets of imputed and real data values prior to estimating aggregate statistics, complicating visual aggregation tasks. Gradient bars would not exhibit these effects as the majority of the bar appears consistent with the rest of the bars in the sequence. Future testing is needed to verify this hypothesis.

## 7 DISCUSSION

We measured the effect of missing data on interpretation response confidence, credibility, and data quality in time series data across 14 visualization methods and three imputation types. Our results show:

- Perceived data quality and analysis confidence generally degrade as the amount of missing data increases.
- Visualizations associated with highlight tend to support higher perceptions of data quality than down weight or information removal encodings.
- Information removal can significantly degrade perceptions of data quality, confidence, and even lead to incorrect responses if they break the visual continuity of a visualization.



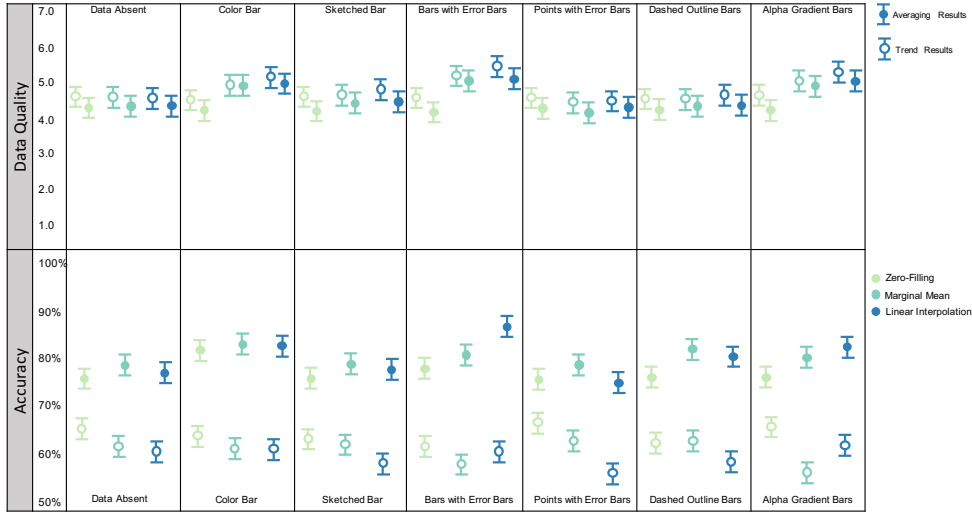


Fig. 7. Our results for data quality and accuracy (replaced with imputed values) in bar charts across visualization type, and imputation type. Overall, bars with error bars and colored bars led to higher perceived data quality than absent data and points with error bars.

- Local interpolations lead to higher perceptions of quality and confidence in the analysis.

While avoiding bias is a critical element of effective visualization, we find that the ways systems impute and visualize missing data can manipulate perceived data quality and confidence in results. Whether ideal perceptions of quality are high or low is likely dependent on parameters of the data, problem, and domain.

We found preliminary evidence that high confidence, credibility, and perceived quality in interpreting incomplete datasets depend on multiple factors. Our studies show that visualizing imputed datapoints using highlight encodings and annotation while preserving the continuity of available data lead to the highest perceived data quality and confidence in result. We see this in color bars, gradient bars, and bars with error bars in bar graphs and with connected error bars and unfilled points with line gradient in line graphs. This conclusion runs somewhat contrary to prior work on preference in decision support [4]; however, it is inline with research on visual selection [26] and uncertainty and trust (see Sacha et al [45] for a discussion). Specifically, visual explanations of errors, such as those indicated by error bars, may increase trust in a system [19]. This trust may manifest in increased confidence and perceived data quality. Examining further design components associated with uncertainty visualization could offer further insight into this phenomena (e.g., alternative designs [35] and cognitive biases [16]). However, we found that error bars that do not preserve continuity, disconnected error bar in line graph and point errors lead to low perceived confidence, credibility, and data quality.

Linear interpolation consistently produced the highest confidence and perceived data quality, while zero-filling led to the lowest. Given both marginal means and zero-filling both used a fixed-value interpolation method, our results indicate that fixed-value methods should favor approaches where data values are selected based on parameters of the data distribution. The increased quality perceptions associated with linear interpolation indicate that sophisticated imputation methods may be worth added complexity to avoid response bias in scenarios requiring high analyst confidence and perceived quality. We offer first steps towards a systematic understanding of the role of imputation in visualization; however, our studies focused on a simple domain, single statistical task, and relatively smooth signals. Further evaluation is needed to more deeply understand the effects of imputation in visualization.

While our results enumerate how design choices for visualizing incomplete datasets might modulate perceived quality, a number of factors may inform the desirable level of perceived quality, including:

**Decision Risk:** Accuracy is often paramount in high risk situations. Missing values may jeopardize that accuracy. Visualization systems can encourage caution in interpreting flawed datasets by using representations that avoid bias and appropriately decrease perceived data quality and decision confidence.

**Data Fusion:** Combining data from multiple sources may mean that the overall anticipated data quality varies between those sources. In these scenarios, systems can leverage domain knowledge to guide analysts to visualizations that modulate confidence and apparent quality appropriately for each source.

**Confidence in Imputation:** Individual imputation methods may differ in how faithfully they represent the original data. In scenarios like cold-deck imputation, analysts may know how well the imputed data mirrors the original data. Visualizations can leverage this knowledge to choose methods that adapt perceived quality proportionally to the imputation quality.

**Intent to Persuade:** Persuasive visualizations typically require the audience to trust in the argument illustrated by the data. Such visualizations should optimize perceived data quality and interpretation confidence to achieve this goal.

## 7.1 Limitations & Future Work

Our study significantly extends prior work on visualizing missing data, exploring new visualization methods, effects of imputation, and using different chart types. However, we made several simplifying assumptions in our experiment. For example, the smooth characteristics of our signals meant there were few outliers in the datasets. Our narrative scenario used a familiar but simple and low-risk task. While these choices allowed us strong control over our tested conditions to encourage general understanding, future testing should extend our work to real-world datasets and scenarios to better understand the impact of these choices.

Further, we tested a small set of possible imputation and visualization methods, drawing inspiration from visualization tools that actively manage missing data. However, we found few tools explicitly discuss missing data management. Future work should extend to a broader set of visualization and imputation methods, such as multiple imputation and machine learning-based approaches (e.g., expectation maximization) to understand their broader utility for data in different domains.

## 8 CONCLUSION

Data is often incomplete due to factors like deletions, misalignments, or collection failures. Missing data elements can complicate data

interpretation and comparisons. We used time series data with missing values to measure how missing data influences factors of perceived data quality. We found that the design choices and interpolation methods used to represent data significantly influence analysts' perceptions of data. We found that upweighting imputed values and local linear interpolation led to higher perceived confidence, credibility, and data quality. Downweighting visual encodings, zero-filling, and electing not to draw data can lead to lower subjective perceived measurements. Our results enumerate design trade-offs for designers to consider when crafting behaviors for handling missing data in visualization.

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