A Four-Stage Framework of Visual Complexity and Trust as Mediated by Effort

Kylie Lin, Hui Guan, David Rapp, Cindy Xiong Bearfield

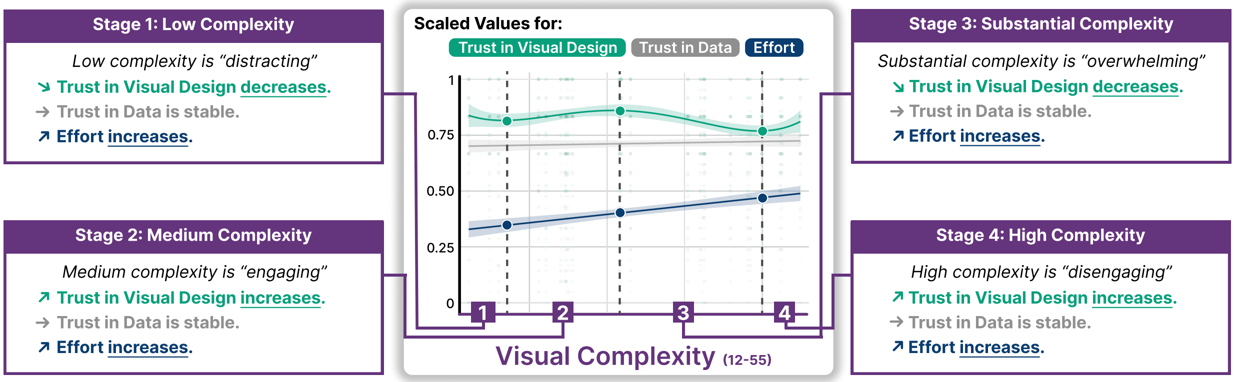

Fig. 1: We visualize data from the results of a human-subjects experiment in the above figure, showcasing relationships between visual complexity, effort, and a person's level of trust in the visual design and underlying data of a visualization in four stages.

Abstract—Visual complexity plays a crucial role in shaping how readers trust data visualizations. While recent empirical studies suggest that increased complexity can reduce trust, we propose a more nuanced relationship: one that is nonlinear and mediated by effort. In our investigation, we conducted an experimental study (N=759) where participants viewed visualizations of varying designed complexity and rated their trust in the visual design and underlying data. Participants also reported the effort they expended reading the visualization and completed a comprehension assessment of the presented information. With regards to trust in the data, we found no significant relationship with visual complexity. However, we found that the relationship between visual complexity and trust in a visualization's visual design unfolds in four stages, with effort playing a distinct mediation role. At a low level of visual complexity, viewers are *distracted* as the effort needed to process the visualization is low; at the same time, trust decreases. At a medium level of visual complexity, more effort is required to process the visualization, leading viewers to *engage* with a visualization while reporting higher trust ratings. At a higher, substantial level of complexity, even higher levels of effort necessary to process a visualization result in *overwhelmed* viewers, and we observed a decrease in trust. At the highest level of complexity captured in this work, even more effort needed to process the visualizations leads overwhelmed viewers to *disengage*, while trust in the visual design increases. We present these results as a framework showing how cognitive factors interact during visualization interpretation, revealing a nuanced relationship between visual complexity and trust.

Index Terms—Visual complexity, Trust, Effort, Static Visualization.

1 Introduction

Well-designed data visualizations leverage our perceptual and cognitive mechanisms to enhance information acquisition during visual data communication [21, 26], striking a careful balance in designed visual complexity [38, 61, 68]. Overly simplistic designs risk misrepresenting data and discouraging critical user engagement [68]. On the other hand, when a visualization is overly cluttered with visual elements, it can obscure important patterns and increase the risk of miscommunication between a designer and their audience [1, 63].

Navigating this delicate balance between visual complexity and information clarity is critical because complexity and clarity can directly impact a viewer's *trust* in a visualization [18]. Visualization scholars have defined trust as "a user's implicit or explicit tendency to rely on a visualization and build upon the information it presents" [43]. Trust in visualizations has also been recognized as a multi-faceted concept; it can be affective or cognitive and may relate to either the visual design of a visualization or its underlying data [18]. Visualization researchers have begun to explore the relationship between the perceived complexity of a visualization and trust [55, 69, 70], consistently identifying a linear, negative relationship [18, 46] and suggesting that reducing complexity may enhance perceived trustworthiness [70]. These findings support a more minimalist design philosophy, dovetailing with a number of visualization studies identifying design strategies to reduce the amount of effort required to extract key insights from data [1, 13, 21].

However, insights from cognitive science research problematize such an approach to the complexity-trust relationship by suggesting that reducing the complexity of a task is not universally beneficial. For example, a certain level of task complexity can promote long-term learning outcomes [5, 6]. In the context of visualization design, researchers have proposed the concept of 'visual difficulties,' which are purposeful complexities intended to foster deeper engagement and more thoughtful interpretation of data through an increased cognitive load [30]. Other researchers have further theorized that such involved cognitive *effort*

- *Kylie Lin, Sean Ru, and Cindy Xiong Bearfield are with Georgia Institute of Technology. E-mails: klin368@gatech.edu, sru3@gatech.edu, cxiong@gatech.edu.*
- *David Rapp is with Northwestern University E-mail: rapp@northwestern.edu.*
- *Hui Guan is with University of Massachussetts Amherst. Email: huiguan@cs.umass.edu.*

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during visualization interpretation contributes to *calibrated trust*, a balanced trust that encourages viewers to critically evaluate the information they encounter, rather than blindly accepting or rejecting it [36]. Thus, in the context of visual data communication, a well-calibrated level of visual complexity may foster trustworthiness in a visualization and empower viewers to think critically about presented data, rather than passively consuming or dismissing it [17].

We aim to reconcile the two perspectives on the complexity-trust relationship presented thus far—one suggesting that increased complexity reduces trust by reducing information clarity and another proposing that complexity may enhance trust by fostering deeper engagement. While the first perspective articulates a linear relationship between visual complexity and trust established through empirical studies, the second perspective proposes a more nuanced relationship where trust may not consistently decrease as visual complexity increases. We expect that the relationship between visual complexity and trust is not strictly linear. Instead, there may be optimal levels of complexity that encourage effort without overwhelming the viewer to promote trust in visualizations.

We construct two testable propositions as the main hypotheses for this work. We evaluate each through a human-subjects experiment examining how visual complexity relates to trust, while considering the role of effort as a potential mediator:

H1: The relationship between visual complexity and trust in a visualization is not strictly linear.

H2: Their relationship is mediated by the effort viewers invest while reading the visualization.

Prior to our main investigation, we first operationalize visual complexity and trust. We adopt a widely cited high-level definition of visual complexity from perceptual psychology: the "amount of detail or intricacy" in an image [60]. Using this definition, we asked participants in an online crowdsourcing study to rate a series of visualizations for visual complexity, thus leveraging *human perceived visual complexity* as our measure of visual complexity.

For measuring trust in a visualization, we drew on Vistrust [18], a multidimensional framework that characterizes trust as pertaining either to trust in the visual design (with antecedents of visualization clarity, accuracy, and usability) or trust in the underlying data (with antecedents data accuracy, currency, coverage, and clarity). To capture these constructs, we used a validated questionnaire from Wang et al. [64], which includes two diagnostic items each for assessing trust in the visual design of a visualization and trust in the underlying data.

In our experiments, we manipulated visualization complexity by adding or removing design elements while holding the underlying data constant. This approach allowed us to focus specifically on how changes in visual design complexity influence trust in design, while also examining whether such design changes indirectly affect trust in data when the data itself remains unchanged. This focus enables a clearer understanding of how design choices influence users' trust in visual information, which is essential for cultivating calibrated trust in visualization systems where the data remain fixed across conditions.

Based on our experimental results, we developed a cognitive process framework that links visual complexity, perceived effort, and trust in the visual design of a visualization, as shown in Fig. 1. We found that the relationship between complexity and trust is a nonlinear relationship comprised of four stages (see Section 4.8). Moreover, the effort a reader invests in interpreting a visualization mediates the relationship between visual complexity and trust in the visualization and its underlying data uniquely across each stage. In sum, we contribute a cognitive process framework of the relationship between visual complexity, effort, and trust in a visualization, derived from a human-subjects study involving ratings of visual complexity and trust.

2 Related Work

In the evaluation of Vistrust, Elhamdadi et al. found a significant effect of three levels of complexity (simple, moderate, complex) on trust in a visualization and that the relationship was driven by enhanced clarity of the simpler visualizations [18]. In another investigation, Xiong et al. found that people prioritize clarity and thoroughness when deciding between simple or complex map-based visualizations in a crisis scenario; however, neither construct significantly predicted a person's trust in the visualization [70]. The inconsistency between these works highlights a shortcoming in extant research on the complexity-trust relationship: each work focuses on antecedents of trust in visual data communication while operationalizations of visual complexity are less established. What does it mean for a visualization to be of low, moderate, or high complexity as opposed to simple vs. complex?

In this section, we outline existing conceptions of visual complexity and its role in effective visualization design as related to the effort needed to process a visualization. We then discuss connecting visual complexity to trust in visual data communication.

2.1 Conceptions of Visual Complexity

Scholars across domains have varied approaches to operationalizing visual complexity. In human vision science, researchers have developed computational visual clutter metrics—including feature congestion (local variability in key features), subband entropy (the number of bits required for subband image coding), and edge density (the percentage of edge pixels) [54]—which have been used as proxies of visual complexity in the study of maps [56]. Work in human-computer interaction has operationalized visual complexity for webpages as the number of elements (e.g., text and images) present [53], and complexity in the visual design of icons has been characterized by the number of lines, open and closed figures, and letters in a given icon [22].

However, 'visual complexity' as it refers to data visualizations benefits from a unique operationalization informed by the visualization design space. The visual design of a visualization is but one aspect that contributes to its complexity; the topic being conveyed and the complexity of the underlying data have upstream effects on the extent to which a visualization is perceived as complex [68]. Moreover, previous work has demonstrated that reading visualizations is more similar to reading a paragraph than an image [28, 35], as components in a visualization can be interpreted in multiple ways like sentences in a paragraph [4, 58]. In addition, visual saliency maps trained on natural images tend to underperform when predicting where people might look in a visualization [41]. These findings suggest that the visual processes a viewer engages in when making sense of a visualization fundamentally differ from those required to interpret images more generally.

There is also diversity in how researchers study visual complexity within the visualization community. Meyer et al. [45] have considered the complexity of displayed data via three factors—the number of points in the display, the configuration of the display, and the regularity of the displayed data. Shah et al. [59] defined visual complexity as the extent to which data are organized to emphasize relevant relationships and reduce the cognitive processes needed to intake information, where less organization implies heightened complexity. In the study of map complexity, Schnur et al. [56] used the number of object types as well as feature congestion and subband entropy measures from Rosenholtz et al. [54], finding clutter to be an effective predictor of complexity. More recently, researchers have begun to model human perceived visual complexity by considering qualities of the visualization as an image [11] and aspects of the visualization's design and underlying data [38] as predictive features.

Another consideration for conceptualizing complexity is that visualizations provide subjective experiences to individual viewers [39, 50]. Thus, understanding how design decisions come together to impact this subjective experience requires an understanding of the *perceived* complexity of a visualization. Data humanists such as Giorgia Lupi have proposed 'embracing complexity' in a visualization by presenting an abundant amount of information to allow viewers to explore data at a personal level [39]. We draw on this perspective for our work, considering visual complexity in a human-centric way.

2.2 Visual Complexity & Effort

An open question in regard to effective visualization design is whether there exists an 'optimal' level of visual complexity that designers can

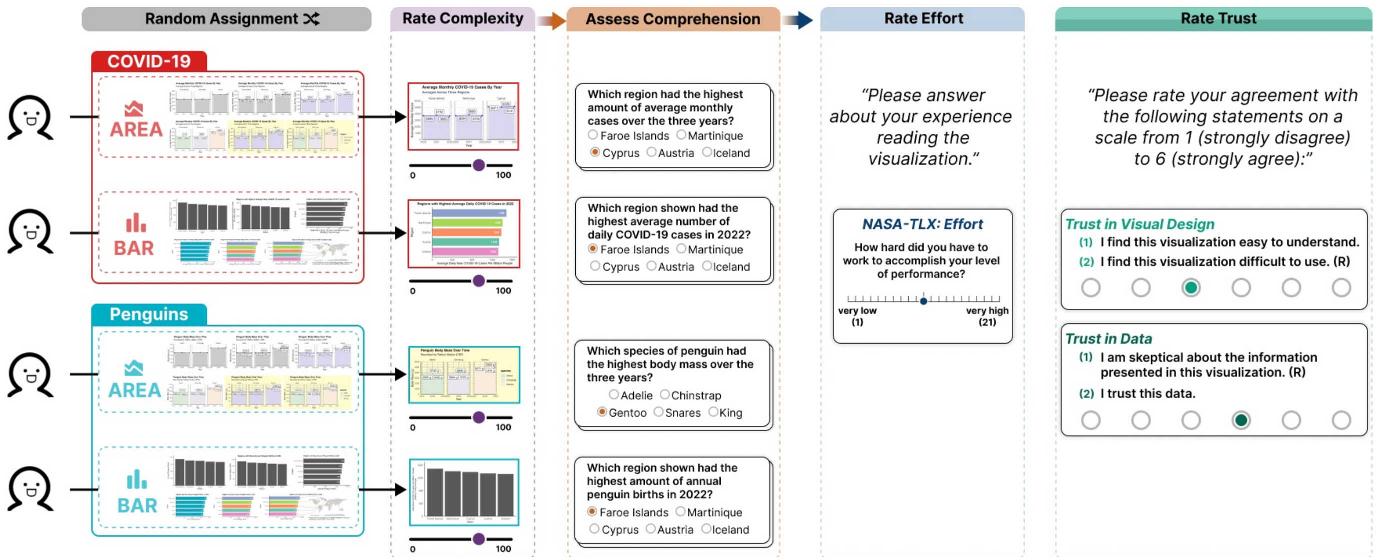

Fig. 2: The flow of our study design. Participants viewed one randomly assigned visualization and rate it for complexity. Then, they answer questions on comprehension, effort, and trust.

strive for—one that balances efficient information intake and deep reflections on data [23, 30]. Literature from cognitive psychology has established that expending a certain degree of cognitive effort is essential to understanding this balance. For example, static displays can be more effective at communicating dynamic processes than animated displays because the static displays encourage learners to construct mental representations in a more active learning process [27]. These findings are part of a larger body of work on 'desirable difficulties,' which are challenges during learning that can enhance information acquisition and long-term retention [5, 6]. In the visualization research space, Hullman et al. [30] have leveraged the concept of desirable difficulties to support the claim that certain 'visual difficulties' can lead readers to reflect more deeply on presented data. Subsequently, a body of visualization research work has emerged considering a balance between overly minimal and overly cluttered designs [1, 2, 23, 61]. In the current work, we leverage the notion of desirable difficulties to theorize about the relationship between visual complexity and trust as potentially mediated by effort. If we find that the relationship between visual complexity and trust is non-linear and mediated by effort, then certain moderate amounts of visual complexity may serve as visual difficulties that enhance reflections on data.

2.3 Visual Complexity & Trust

In visual data communication, theoretical conceptions of trust abound. Mayr et al. have decomposed trust into two constructs: trustworthiness as qualities of a visualization that contribute to trust and trust perception as people's subjective interpretations of trust [43]. In addition, Pandey et al. have identified credibility, clarity, reliability, familiarity, and confidence as key factors influencing trust [48]. Elhamdadi et al.'s Vistrust framework, in addition to decomposing trust into trust in a visualization's design and its underlying data, also conceptualizes trust as either affective or cognitive [18]. In the current work, we draw primarily on the Vistrust framework to operationalize trust for our experimental study. We consider trust in a visualization's data and visual design as separate constructs and leverage a validated and compact inventory of questions from Wang et al. [64] that assess trust in a visualization based on two factors: trust in information, mapping intuitively to trust in data from Elhamdadi et al., and clarity, usability, and likeability, which map to trust in a visualization's visual design [64]. In addition, recent work by McKinley et al. has considered trust more concertedly from the perspective of the viewer of a visualization. They categorized qualitative responses to visualizations and identified a series of design factors that influence trust: readability, integrity & transparency, quality & design, familiarity, and personal factors [44]. Subcomponents of the readability factor were 'simple' and 'complex,' providing further support for the notion that visual complexity is key to understanding people's trust in visualizations.

Relating to visual complexity, existing work has suggested that the volume and detail of presented information influence trust and perceived transparency in a visualization [32–34]. Findings suggest that too much information can overwhelm a reader and distract from primary takeaways, leading to a visualization that is overall less interpretable [51] and less trustworthy [32–34]. Beyond visual data communication, researchers have also found a positive association between processing fluency and trust [57]; for example, people are more likely to trust investors with easier-to-pronounce names in trust game scenarios [71]. Similarly, perceptual fluency has been found to influence truth judgments; statements presented in highly visible colors are more likely to be judged as true compared to those in moderately visible colors [52]. Seeing as prior research has found that increased complexity can inhibit the clarity of a visualization [18, 46, 70], the current work focusing on visual complexity also contributes to the literature on trust and perceptual fluency in visual data communication.

3 Study Overview

In this work, we develop a framework characterizing the relationship between the perceived visual complexity of a visualization and a readers' trust in the visualization based on an experimental study.

We investigated the relationship between visual complexity and trust in a visualization's visual design and underlying data, with effort as a potential mediating variable. We conducted a survey study where participants (1) viewed the visualizations of varying visual complexity generated based on our preliminary study, (2) rated the visual complexity of visualizations, (3) completed a comprehension assessment on the presented data, (4) rated the effort they felt they had expended reading the visualization, and then (5) provided ratings of trust in the visualization's visual design and underlying data (see Fig. 2). We found partial support for our **H1** hypothesis of a nonlinear relationship between visual complexity and trust and then characterized the relationship via a four-stage framework. We also conducted a mediation analysis to provide support for our **H2** hypothesis that effort mediates the relationship between visual complexity and trust.

4 Study: Visual Complexity, Effort, and Trust

As discussed in Sec. 2, prior work has identified a negative linear relationship between visual complexity and trust in a visualization [18, 46, 70]. However, others [30] have proposed that introducing visual difficulties to a visualization's design may increase the amount of effort needed to process a visualization and therefore prompt deeper reflections on data [6]. To reconcile these perspectives, we explore the complexity-trust relationship via two hypotheses:

H1: *The relationship between visual complexity and trust in a visualization is not strictly linear.*

H2: *Their relationship is mediated by the effort viewers invest while reading the visualization.*

4.1 Experimental Stimuli

Datasets: We designed our experimental visualization stimuli using two datasets, following the approach of VisTrust [18], aiming to cover diverse topics while balancing real-world relevance with the potential to bias participants by evoking pre-existing beliefs [37]. The first dataset depicts the highest Coronavirus (COVID-19) case counts in 2022 based on global rolling seven-day averages from the publicly available source OurWorldinData [40], which can be more belief-triggering. Therefore, to contrast the first dataset, we used the `penguins` dataset as our second dataset from the `palmerpenguins` package in R [29], depicting the change in body mass across Gentoo, Adelie, and Chinstrap penguin species at the Palmer Station in Antarctica from 2007 to 2009.

Visualizations: Examples of our experimental stimuli are shown in Fig. 3. To systematically manipulate the visual complexity of our visualization stimuli, we drew on the visual complexity model developed by Lin et al. [38], which predicts perceived complexity based on a combination of design, color, text, and data features in static visualizations. Their model, which is a support vector regression (SVR) model trained on an augmented version of the MASSVIS dataset [8] containing 5,800 annotated visualizations, identifies the number of panels, chart types, color usage, and textual annotations as the strongest predictors of perceived complexity.

Building on these findings, we used the feature importance weights from Lin et al.'s model to guide our design manipulations along a continuum from low to high complexity. We selected two baseline visualization types: bar charts and area charts, which allowed controlled variation in key design features associated with perceived complexity. We started from a minimalist design that Lin et al.'s model predicted to have the lowest complexity, which is a black-and-white chart with minimal text. Then, we incrementally added features predicted by their model to increase complexity, such as color encodings, textual annotations, and additional panels of map elements. For example, one of the high-complexity bar chart designs incorporated a linked world map alongside bar elements to increase chart multiplicity and layout intricacy, see Fig. 5. We then manually labeled each visualization with the features needed to run Lin et al.'s model and derive predicted complexity scores. Since Lin et al. derived feature importance using the permutation importance technique [3], there was no explicit formula for how design changes directly would affect predicted visual complexity. For replicability purposes of this work, we provide the feature labels and scripts necessary to derive the predicted complexity of our experimental stimuli in the supplemental materials.

To control for potential topic effects, each visualization was relabeled to depict either COVID-19 or penguin data while maintaining identical visual design and underlying data structure. This procedure yielded twelve bar charts and twelve area charts with systematically varied levels of visual complexity. Half of the visualizations were labeled as COVID-19 charts and half as penguin charts, counterbalanced across conditions. The underlying data values remained the same for charts despite the new labeling

4.2 Study Design and Measures

We conducted a between-subjects study where participants viewed one of the 24 visualizations, randomly assigned. This design was selected over a within-subjects design as we aimed to mitigate participant fatigue that can arise from completing overly long surveys [31] and as well as to minimize the possibility of anchoring effects, where prior judgments influence future ones [10]. They were then asked to (1) provide a *rating of visual complexity* of the visualization (independent variable), (2) answer six *comprehension* questions about the information in the visualization (manipulation check), (3) provide a rating of *effort* applied when reading the visualization (covariate), and finally (4) rate their *trust* in the visualization (dependent variable) via a four-item Likert scale survey. Detailed descriptions of each task are provided below.

Visual Complexity (0-100). We asked participants to rate the visual complexity of a visualization on a scale from 0 (not at all complex) to 100 (extremely complex) using a continuous slider widget. At the beginning of the survey, we defined visual complexity as "the amount of detail or intricacy in an image," drawing from the perceptual psychology literature [60], to provide a better sense of the task. We further emphasized that there was no correct answer, so participants should follow their intuition. This subjective measure of visual complexity, rather than the model-predicted complexity scores used to develop the visualizations, is the measure that we analyze in the following results sections.

Comprehension (0-1). For each of the two datasets in our study (penguins & COVID-19), we created six-item multiple-choice assessments to assess participants' comprehension of the information in a presented chart (resulting in a total of twelve comprehension questions across the two sets). Participants also rated their confidence in their answer on a scale from 0-100. Questions were created in batches of two, intended to be of easy, moderate, and high levels of difficulty. Examples of questions can be seen in Fig. 2. These questions served as a manipulation check that participants were engaged with the visualizations in the study. To analyze responses to comprehension questions, we calculated a normalized comprehension score ranging from 0 to 1 for each participant, computed as the proportion of correct responses across the six multiple-choice questions. The full list of questions can be found in the supplemental materials.

Effort (1-21). We presented participants with the NASA Task Load Index (NASA-TLX) [24], which measures perceived workload for a task. For our analysis of effort, we analyzed only responses to the *'Effort'* subscale, as recent work has advised against aggregating the six subscales and found evidence suggesting that *Effort* may lie on a distinct scale as compared to the other constructs [7].

Trust (1-6). Elhamdadi et al. [18] identified trust in visualizations as comprised of two constructs: *trust in the visual design* and *trust in the underlying data*. Follow-up work comparing a set of survey items has found that *trust in the visual design* shares the same factor loadings as measures of visualization clarity [65], which is often described as the 'perceived level of comprehensibility of information' [70]. Specifically, two Likert scale items—*'I find this visualization easy to understand'* and *'I find this visualization difficult to use' (reverse-coded)*— predict the same dimension of trust in visual design as the five-item measure used by Elhamdadi et al. [18] while having empirically evaluated content and criterion validity, as demonstrated in the trust inventory developed by Wang et al. [65]. Furthermore, the inclusion of one inverse item enhances the experimental reliability of these measures. Therefore, to assess **trust in the visual design**, we adopted these two Likert items on a 6-point scale, following [64]. For measuring **trust in data**, we adopt the following two questions from the same work: *'I am skeptical about the information presented in this visualization' (reverse-coded)* and *'I trust this data.'* We anticipate minimal variations in trust in data across designs since we used the same two datasets across visualizations.

4.3 Study Procedure

Upon consenting to participate in the study, participants were asked to keep their browser in full-screen for the duration of the survey to ensure sustained attention. We then showed participants one of our 24 visualizations and instructed them to take as long as they liked to understand it as best as possible, as they would later be asked questions about it. After viewing the visualization, participants rated its visual complexity. They then completed the comprehension assessment (with-

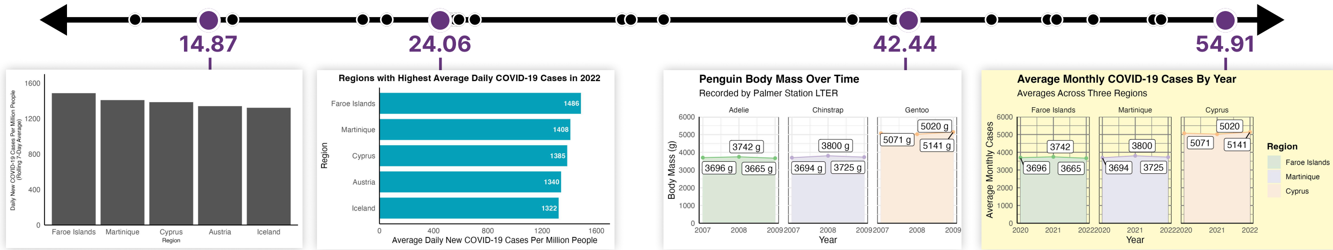

Fig. 3: Examples of our stimuli, organized by increasing mean human perceived visual complexity (left: lowest; right: highest).

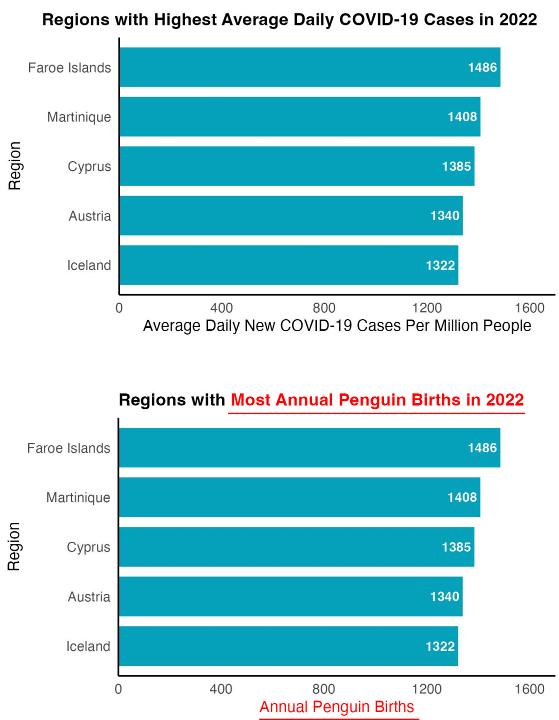

Fig. 4: Example relabeled stimuli. The original chart (top) describes COVID-19 cases. The relabeled chart (bottom) describes penguin births. Changes are highlighted in red.

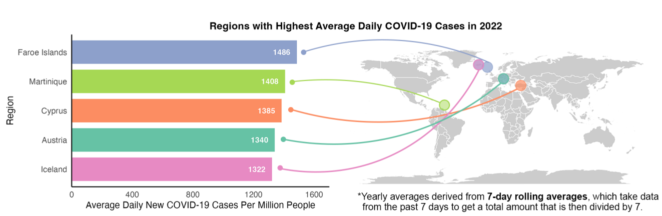

Fig. 5: The linked world map that increases complexity through chart multiplicity and layout intricacy.

out viewing the original visualization) as well as the NASA-TLX, with clear instructions to answer based on their experience reading the chart, not on answering the comprehension questions. Lastly, participants provided ratings of their trust in the visual design and in the underlying data of the visualization. The study finished with demographics questions. They were compensated at a rate of 12 dollars per hour. The flow of our study can be seen in Fig. 2.

4.4 Participants

We recruited 800 participants from Prolific [47]. Participants had to be based in the United States, have normal-to-corrected vision, and have normal color vision to participate in the study. Participants were required to maintain full-screen mode on their browser to ensure sustained attention; they also had the option at the end of the survey to self-report if they used AI or left the computer at any time during the survey. After excluding responses that failed attention checks or contained low-quality data (e.g., self-reported to using AI/leaving the computer, exited full screen), the final sample size was 759 participants ($mean_{age}$ = 40.72, 429 women, 311 men, 15 non-binary, 4 preferred not to disclose). Based on a power analysis of pilot data using G*Power [20], this sample size provided approximately 90% power at an alpha level of 0.05.

4.5 Results: Overview

Participants spent an average of 52.12 seconds viewing individual visualizations, although times across participants varied ($SD = 54.07$). From conducting a Pearson correlation analysis, viewing time seemed to be weakly positively correlated with visual complexity ($corr = 0.11$, $p = 0.0029$). We calculated the mean value of all visual complexity ratings for each experimental stimulus, resulting in 24 visual complexity values. These mean ratings ranged from 12.19 to 54.91, with an average of 34.62. We present a more in-depth manipulation check of these measures in Sec. 4.9.

Response distributions of the other collected metrics, including comprehension scores ($M = 58\%$), effort ratings ($M = 5.64$), and trust ratings ($M_{design} = 4.91$, $M_{data} = 4.28$), can be seen in Fig. 6.

4.6 Results H1: Relationship between Complexity & Trust

To test our hypothesis regarding the relationship between complexity and trust, we conducted a two-step analysis. First, *we examined the pair-wise linear relationships between visual complexity and metrics of effort and trust* to determine the *overall* directionality of the relationships. Next, we explored whether any of the relationships may be better understood as a nonlinear, higher-degree polynomial. This approach involved formally characterizing the relationship between visual complexity and effort/trust metrics by analyzing the variance explained in a series of polynomial regression models with degrees from one to ten. As the polynomial degree increases, the model captures more variance and becomes more complex.

This means we had to balance model fit and complexity to select the best model. We did this by first identifying the elbow points where the R^2 and Akaike information criterion (AIC) of the model showed minimal improvement with additional degrees, see Fig. 7. We then ran hypothesis tests (as Analysis of Variance (ANOVA) tests using the `anova()` function in R) to determine whether the fit of a more complex polynomial model identified from examining the elbow points significantly reduced the residuals relative to the linear model of the data. If the result was significant, we concluded that there was strong evidence for the selection of the n^{th}-degree polynomial model over the linear model.

This procedure, which combines information-theoretic model selection criteria such as AIC with nested-model comparisons via ANOVA, is a standard and widely accepted practice in statistical modeling and

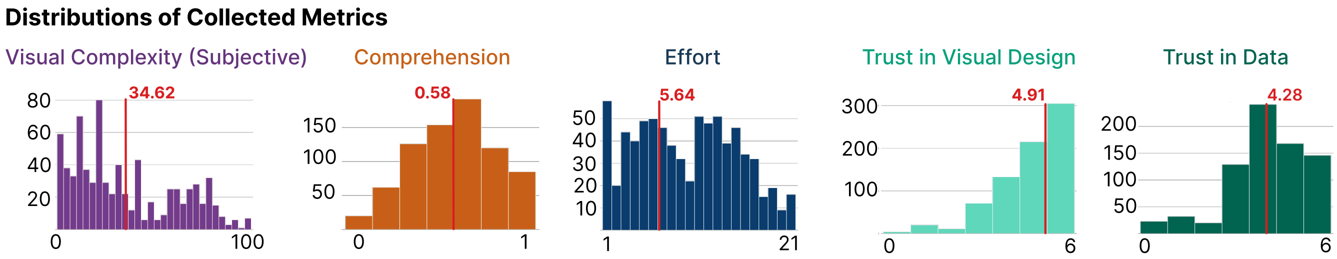

Fig. 6: Distributions of collected measures of visual complexity, comprehension, effort, and trust.

regression analysis (e.g., see [9]). It provides a principled balance between model parsimony and explanatory power while guarding against overfitting. We distill the following conclusion from this analysis:

> We found partial support for **H1**, such that the relationship between visual complexity and trust in visual design is best described a **fourth-degree polynomial**.

4.6.1 Visual Complexity and Trust in Visual Design

Aligning with findings from Elhamdadi et al. [17], a linear regression model predicting trust in the visual design with visual complexity revealed an overall weak, negative relationship ($R^2_{adj} = 0.013$, $F(757) = 11.30$, $p < 0.001$). This suggests that as the visual complexity of our stimuli increased, trust in the visual design decreased.

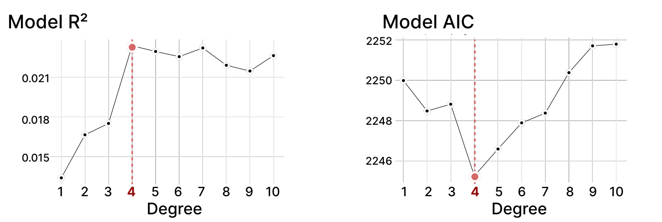

Fig. 7: Model R^2 and AIC for visual complexity and trust in visual design.

We then constructed a series of polynomial regression models with degrees of freedom ranging from one to ten. From comparing all the models' adjusted R^2 and AIC values (see Fig. 7), we determined that the model that best fit the data while abiding by the principle of parsimony was a fourth-degree polynomial regression ($R^2_{adj} = 0.02$, $F(757) = 5.53$, $p < 0.001$). For this fourth-degree polynomial model, the second ($p < 0.05$), third ($p < 0.05$), and fourth ($p < 0.05$) degree terms all offered a statistically meaningful contribution to explain additional variances in trust in visual design. A model comparison between the fourth-degree polynomial and the linear model further revealed significant differences ($F = 3.6$, $p < 0.05$). Thus, we conclude that:

> The fourth-degree polynomial regression model is preferred over a linear model for characterizing the relationship between visual complexity and trust in the visualization's visual design.

4.6.2 Visual Complexity and Trust in Data

We did not find a significant relationship between visual complexity and trust in data ($R^2_{adj} < 0.001$, $F(757) = 0.963$, $p = 0.327$). While this contrasts with the findings of Elhamdadi et al. [18], this outcome aligns with our study design, as we intentionally did not manipulate the underlying data. Our goal was to isolate and examine trust in design, rather than trust in data; accordingly, we did not expect participants' trust in the data itself to vary across visualizations.

Although our study was designed to isolate trust in design, we also examined trust in data to verify that visualization design changes did not inadvertently influence perceptions of the underlying data. To explore the possibility of a nonlinear relationship between visual complexity and trust in data, we constructed a series of polynomial regression models ranging from first to tenth degree. Increasing the number of polynomial terms marginally improved R^2 and reduced AIC values; however, ANOVA tests comparing the linear model to higher-degree polynomials indicated that additional terms did not significantly improve model fit ($F = 1.642$, $p = 0.109$). Thus, we conclude that:

> There was no relationship between the visual complexity and a person's trust in the visualization's underlying data in our study.

4.7 Results H2: Effect of Effort

To test our second hypothesis that the relationship between visual complexity and trust is mediated by effort, we first conduct an analysis to determine the relationship between visual complexity and effort. Then, we conduct a mediation analysis to understand whether effort acted as a mediating variable in the relationship between visual complexity and trust.

4.7.1 Visual Complexity and Effort

We found a weak positive linear relationship between visual complexity and a participant's self-reported effort expended processing the visualization ($R^2_{adj} = 0.034$, $F(757) = 27.56$, $p < 0.001$), suggesting that overall as the visual complexity increased, effort required for processing increased. Examining R^2 and AIC across polynomial regressions of the relationship with degrees ranging from one to ten, we observed that while R^2 scores improved with increasing degrees, AIC scores consistently worsened. A hypothesis test between the linear regression model and the more complex third-degree and six-degree polynomials, which had resulted in the most notable R^2 score improvements, revealed no significant improvement in model fit ($p_3 = 0.570$; $p_4 = 0.695$). Thus, we conclude that:

> The relationship between the visual complexity and effort was best characterized as a linear relationship.

4.7.2 Mediating Analysis: Effort as a Pathway between Complexity and Trust in Design

We conducted a mediation analysis to better characterize the relationship between the visual complexity of our experimental stimuli, effort, and trust in the visual design of a visualization. We omitted trust in underlying data in our model, since the data was held constant in our experiments.

To examine whether perceived effort explains part of the relationship between visual complexity and trust in visual design, we tested a mediation model in which **visual complexity** served as the independent variable (X), perceived **effort** as the mediator (M), and **trust** in visual design as the dependent variable (Y). The model follows the causal structure proposed in Fig. 8 but is operationalized here as a set of linear regressions with additive terms, estimated using the `Process` macro for R [25]. We used 10,000 bootstrap resamples to correct for biases in our confidence intervals for the indirect effects, since some study metrics were non-normally distributed.

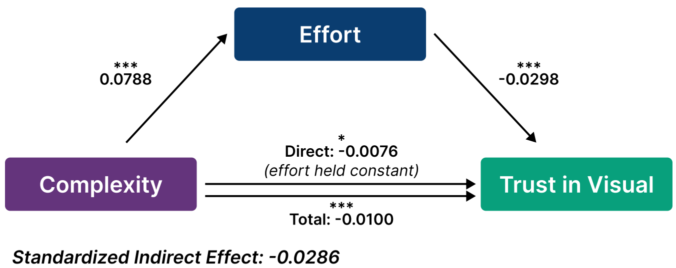

Fig. 8: Diagram of the mediation model ran to assess effort as a mediator.

This mediation model represents a theoretically motivated yet empirically testable assumption. It examines whether the portion of variance in trust associated with visual complexity is *statistically* transmitted through perceived effort, assuming that any unobserved common causes are minimal. Other causal explanations, such as unobserved factors that influence both effort and trust, could produce similar statistical associations but would imply different underlying mechanisms. We therefore view these findings as suggestive rather than definitive evidence of mediation.

As shown in Fig. 8, the *direct effect* of visual complexity on trust, controlling for effort, was small but significant and negative ($\beta = -0.008,\ p < 0.05$). The standardized *indirect effect* through effort was also negative and statistically significant ($VAF = 4.35\%$, $\beta = -0.002$, $SE = 0.009$, $95\%\ CI = [-0.049, -0.015]$). The total effect of visual complexity on trust (capturing both direct and indirect influences through effort) was also significant and negative ($\beta = -0.010$, $p < 0.001$). Together, these results suggest a weak but reliable tendency for higher visual complexity to reduce trust *partially* via increased perceived effort. We interpret this mediation effect as modest in magnitude but consistent with the proposed theoretical pathway.

> These results provide partial support for **H2**: greater visual complexity is associated with reduced trust in a visualization's design, and this relationship is modestly mediated by perceived effort.

4.8 A Four-Stage Complexity-Trust Relationship

Drawing on these relationships and mediation analyses involving effort (Sec. 4.7), we propose a four-stage framework of the complexity-trust relationship as shown in Fig. 1. Examples of visualizations for our study stimuli set that fall into each stage of the framework can be seen in Fig. 9.

We normalized all of the outcome variables (trust and effort) to be on a scale from 0 to 1 so that the data and the best-fit models could be plotted and compared on the same axes, as seen in Fig. 1. The best-fit model describing the relationship between trust in visual design and visual complexity follows a fourth-degree polynomial. We identified its four local extrema that defined the four stages of this relationship. Below, we describe each stage and theorize how effort and comprehension interact with complexity to shape changes in trust.

4.8.1 Stage 1: Low Complexity

When mean ratings of human perceived visual complexity are low (in the range with complexity ratings between 12.2 and 17.1 in our experiment), we observe that increasing visual complexity leads to a decrease in trust in the visual design, consistent with findings by Elhamdadi et al. that simple designs are more trustworthy than complex ones [18]. In this stage, although effort increases slightly, we theorize that it likely remains below a threshold needed to trigger deep reflection or engagement with the presented data. That is, complexity in this stage is not great enough to introduce any desirable difficulty [6] where effort dampens the negative relationship between complexity and trust.

We therefore characterize the role of increasing visual complexity in this stage as *"distracting"* the reader.

4.8.2 Stage 2: Medium Complexity

At medium levels of visual complexity (complexity rating 17.1–31.7), we observe a positive relationship between visual complexity and trust in a visualization's visual design, contrasting with prior work suggesting that increased visual complexity decreases trust [18]. We theorize that this occurs because the increased visual complexity of the stimuli in this range acts as a form of desirable difficulty [6]. In our case, the visualizations' visual complexity may be high enough to evoke meaningful effort, but not so high as to overwhelm the viewer. This encouraged critical reflection, in turn, increases trust.

In addition, we posit that the relationship between visual complexity and trust in this range can be understood in relation to the concept of *interpretive complexity*, defined by Windhager et al. as the "relative ease or difficulty with which a viewer interprets a visualization" [68]. We conceptualize interpretive complexity as comprising two components: perceptual and cognitive complexity. *Perceptual complexity* refers to the ease of visually processing information (which we manipulated directly by varying the visual complexity in our experimental stimuli) while *cognitive complexity* refers to the ease or difficulty involved with reasoning about or make sense of the visualization (which we to evoked to varying degrees as a result of our visual complexity manipulations).

Considering this framing, in this stage we reason that increased perceptual complexity leads participants to invest even more effort into interpreting the visualizations than in Stage 1. In turn, the increased effort spent processing the visualization on a perceptual level reduces the cognitive complexity of the visualization. Combining this relationship with our findings from Sec. 4.7 that effort mediates the relationship between visual complexity and trust, we propose that, in this range, participants exert enough effort to reduce the difficulty involved with interpreting the visualization, offsetting the potential negative effect of complexity on trust in the visual design of a vsiualization to result in a slightly positive relationship.

Ultimately, we characterize the role of increasing visual complexity in this stage as *"engaging"* the reader.

4.8.3 Stage 3: Substantial Complexity

The positive effect of complexity in Stage 2 holds only up to a point. In the next stage of visual complexity (complexity rating 31.7–50.0), we observe that trust in visual design begins to decline again, even as effort continues to rise. We interpret this reversal as evidence that the level of visual complexity has surpassed a threshold, no longer acting as a desirable difficulty to enhance reflection on the data.

In this stage, additional effort no longer yields cognitive benefits such as reduced cognitive complexity or deeper reasoning. Instead, the increasing effort leads to cognitive overload or fatigue. As a result, interpretive complexity remains high as cognitive complexity is no longer reduced, and the visualization becomes more difficult to interpret. This increased difficulty likely contributes to a decline in trust, as viewers struggle to extract meaning from the display. The inverse relationship between effort and comprehension further supports this observation.

We characterize the role of increasing visual complexity in this stage as *"overwhelming"* the reader.

4.8.4 Stage 4: High Complexity

Finally, at high levels of visual complexity (50.0-54.9), we observed another reversal: trust in the visualization begins to increase again. We theorize that this may reflect a 'zone of overtrust,' where visual complexity reaches such a high level that viewers default to assuming the visualization is credible, perceiving it as authoritative or sophisticated [49]. In this stage, viewers may even begin to doubt their own ability to understand the content, attributing the difficulty to personal incompetence rather than to potential flaws in the visualization design. This shift in attribution may reinforce trust, not because the visualization is clearer or more effective, but because its complexity evokes a sense of legitimacy or expertise [62, 67]. In this stage, trust may no longer be based on whether the visualization is interpretable, but rather on perceived legitimacy or expertise implied by the complexity itself.

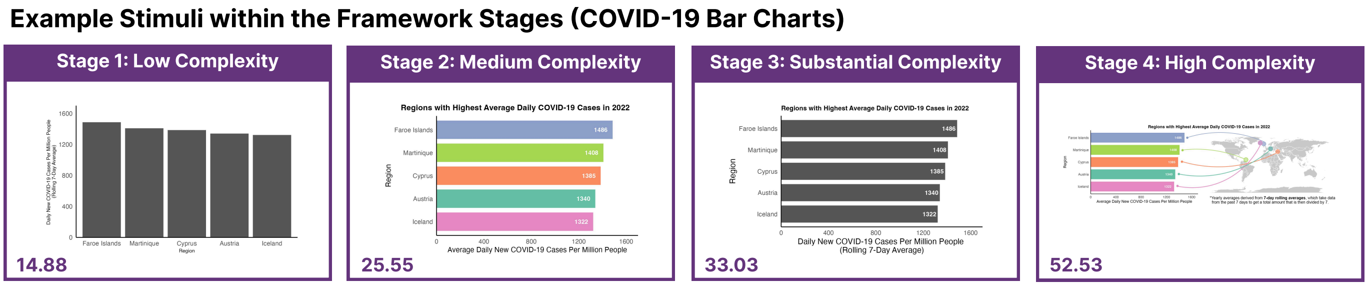

Fig. 9: Examples of visualizations that fall across the four stages of our proposed framework.

We characterize the role of increasing visual complexity in this stage as *"disengaging"* the reader.

4.9 Manipulation Checks

Finally, to assess our measure of visual complexity for this work, we conducted two manipulation checks using model-predicted visual complexity scores as well as the administered comprehension assessment.

Model-Predicted Visual Complexity: First, we examine the relationship between model-predicted complexity scores and the subjective ratings collected in our study. We conducted a Pearson correlation analysis of predicted complexity scores and the mean human complexity ratings for a given experimental stimulus. We found a strong positive correlation ($r(22) = 0.83$, $p < 0.001$), suggesting that the complexity model predicted the mean perceived visual complexity of a visualization with reasonable accuracy. We note that Lin et al.'s model was trained on and built to predict *mean* visual complexity ratings across a set of individual ratings. Thus, when model output is compared to any individual rating of complexity, the predictive power was low. To illustrate, we conducted a Pearson correlation analysis of predicted visual complexity and all participant ratings of visual complexity, unaggregated, and found a much weaker correlation ($r(22) = 0.40$, $p < 0.001$).

Comprehension: We further validated our visual complexity manipulation in the experimental study by analyzing the mean ratings of visual complexity against participants' comprehension scores on the visualization stimuli. A linear regression revealed a small but significant negative relationship between visual complexity and comprehension ($R^2_{adj} = 0.029$, $F(757) = 23.52$, $p < 0.001$), indicating that as complexity increased, performance decreased. This result suggests that our complexity manipulation was effective and had a measurable effect on participants' ability to interpret the visualized data.

5 Discussion

We have examined the relationship between the visual complexity of a visualization and a person's trust in its visual design and underlying data, identifying effort as a partial mediator. In this section, we discuss the implications of the four-stage cognitive process framework in relation to existing research and how it can inform the design of appropriately complex visualizations to support well-calibrated trust.

5.1 The Four-Stage Framework

At the outset of this work, we introduced two perspectives that inform how the visual complexity of a visualization influences trust. The first perspective comes from an emerging body of empirical work that has identified a negative relationship where people find simple visualizations more trustworthy than complex ones [17,70]. The second perspective emerges from the learning sciences [5, 6] as extended to the visualization space. Researchers have theorized that certain types of visual complexity may act as desirable difficulties that increase the effort needed to process a visualization [30], prompting deeper reflections on data and fostering calibrated trust [36].

The four-stage framework we derived reconciles these perspectives for the construct of *trust in a visualization's visual design*. Overall, we found that as the visual complexity of our experimental stimuli increased, participants' trust in the visual design decreased. But this relationship is not strictly linear. As shown in Fig. 1, there are actually two stages in which, as the visual complexity of a visualization increases, trust in the visual design also increases. We have proposed two theoretical explanations for this. The first is framed through the lens of desirable difficulties—the visual complexity of the visualizations in Stage 2 is *just enough* to act as a desirable difficulty that prompts greater reflections on the presented data. The second explanation builds on the concept of interpretive complexity from Windhager et al. [68], suggesting that the effort involved in processing the visualization may actually reduce *cognitive* complexity (distinct from perceptual complexity). This might have made it easier for people to reason about the underlying data, potentially leading to greater trust.

What about Trust in Data? We only found partial support for **H1** as we found no clear relationship (neither linear or nonlinear) between visual complexity and participants' trust in the underlying data presented. This result is not entirely surprising, given that the data content across all of our experimental stimuli depicted the same COVID-19 and penguins datasets. Prior work by Elhamdadi et al. [18] and Wang et al. [66] has shown that trust in visual design and trust in data are orthogonal constructs. Our findings align with this distinction, suggesting that manipulating visual design alone may not significantly influence trust in the data itself (a non-visual construct).

5.2 Implications for Visualization Design

From our framework, we identify an 'optimal' level of visual complexity for promoting trust, which is located at the intersection of Stage 2 and Stage 3, where trust peaks alongside substantial cognitive effort, suggesting a form of effort-calibrated trust. Examples of experimental stimuli near this optimal point are shown in Fig. 10. These visualizations are moderately complex, with complexity ratings of 31.59 and 31.84. However, we do not suggest interpreting the visual complexity scores in this work as universal thresholds of optimal complexity, or treating our specific designs as universally optimal for promoting trust.

Rather, our findings in this work highlight a *process for exploring and identifying designs that promote calibrated trust*. Designs can be tailored to specific contexts and audiences, and visualization designers should consider the complexity of the visual design in terms of the cognitive demands placed on viewers when aiming to foster thoughtful engagement with data.

6 Limitations and Future Work

Our study and framework provide a way for visualization researchers to articulate how visual complexity facilitates or inhibits trust in a visualization. However, much work remains to fully capture the relationship between visual complexity and trust. We detail limitations of our investigation that lay the foundation for future research.

6.1 Extending the Framework

The vast design space of visualizations presents an ongoing challenge in efficiently capturing the qualities of diverse designs in experimental work. Currently, our framework is based on an evaluation of only 24 bar and area charts derived from two datasets. Additionally, we

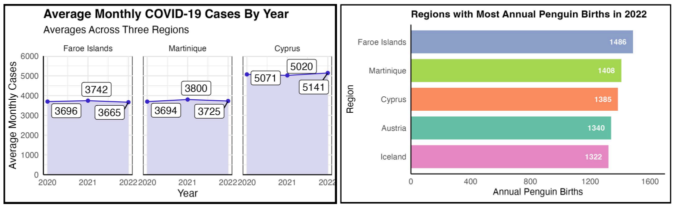

Fig. 10: Visualizations that lie close to the transition between Stage 2 and 3 of our framework, where participants expend substantive effort interpreting the visualization and trust is high, but visual complexity is not yet overwhelming.

only examine static visualizations in this work, leaving factors such as animation and interaction unexplored. Future work is needed to validate the extent to which our framework applies to the broader landscape of visualization designs. Such investigations can examine complexity changes for additional common chart types (e.g., scatterplot, pie charts), data types (e.g., time series data, hierarchical data), and use cases (e.g., high-stakes decision-making).

Additionally, our experimental procedure involved removing the presented visualization when participants were answering comprehension questions. Thus, it is possible that factors not considered in our current study such as short-term memory play a role in moderating or mediating the relationship between visual complexity and effort. Future research can investigate the role of additional cognitive factors in influence the relationship between visual complexity, effort, and trust.

6.2 Consider Greater Ranges of Complexity

The experimental stimuli we presented elicited mean visual complexity ratings ranging from 12.2 to 54.91. Therefore, Stage 1 and Stage 4 of our framework were derived based on narrow ranges of visual complexity (Stage 1 range: 4.9; Stage 4 range: 4.5) as compared to Stage 2 (14.6) and Stage 3 (18.4). Future work can explore broader levels of visual complexity to uncover boundary conditions in the complexity–trust relationship.

6.3 Consider Diverse Sources of Complexity

We have taken a broad-brush approach to studying visual complexity, effort, and trust in visual data communication by operationalizing visual complexity as a quantitative measure ranging from 0-100, derived from human perceptions. However, across the desirable and visual difficulties literature there is a common thread on the relationship between complexity and effort stating that *certain types* of visual and task complexities can promote deeper reflections on data [6, 23, 30]. Our investigation does not consider these types of complexity but rather explores complexity as a single-dimensional, continuous spectrum. Future work can move toward more fine-grained models of visual complexity that account for diverse sources of complexity to better capture their unique influence on cognitive effort and trust.

6.4 Potential Authority Bias

In Sec. 4.8.4, we theorized that at high levels of visual complexity, trust in a visualization's visual design may increase because the overly complex design evokes a sense of legitimacy or scientific authority, rather than prompting critical reflection on the data itself. If this is true, this phenomenon would be an instance of *authority bias*, where people have a tendency to be more influenced by information from authoritative sources [12]. For example, just the presence of a neuroscientific image of a brain scan can hinder people's ability to critically reason about presented information [67]. While this bias has been established as relevant to data visualizations [15], there have been inconsistent results from experimental studies attempting to demonstrate that charts can evoke a form of authority bias [16, 62]. Future empirical visualization research ought to examine whether visual complexity plays a role in exacerbating the effect of authority bias to increase poorly-calibrated trust without meaningful data engagement.

6.5 Considering Individual Differences

Finally, a critical goal for visualization designers involves generating visualizations for specific audiences who can differ by visual literacy and a host of demographic factors such as education, vocation, and age. As discussed in Sec. 4.9, our approach to measuring visual complexity aggregates ratings from multiple study participants. Thus, our framework does not well capture the influence of individual differences. Future work can consider alternative metrics of complexity that explicitly account for characteristics such as an individual's trust propensity, defined as "a dispositional willingness to rely on others" [14, 42]. This effort may involve conducting experiments to test whether perceptions of visual complexity for particular visualizations differ across demographic delineations and personalities [19]. Continuing this line of work will advance the visualization community's understanding of visual complexity and trust by addressing *for whom* and *why* perceptions of complexity might emerge during visualization experiences.

7 Conclusion

In this paper, we have presented an empirically-backed framework depicting the relationship between a visualization's visual complexity and reader trust in the visualization's visual design and underlying data, aiming to reconcile disparate perspectives in extant visualization research on how complexity relates to trust. We designed stimuli of varying visual complexity and conducted a human-subjects experiment, capturing measures of visual complexity, effort, and trust in a visualization from participants. Overall, we found that effort partially mediates the relationship between visual complexity and trust, paving the way for future research to explore effective strategies for designing trustworthy visualizations.

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