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Testing Charts: viewer's perceptual accuracy in surveys

Kiegan Rice*[1], Heike Hofmann†[2], Nola du Toit‡[1], Edward Mulrow§[1], and [2]

[1]*National Opinion Research Center (NORC)*

[2]*Department of Statistics, Iowa State University*

Abstract

The use of visuals is a key component in scientific communication, and decisions about the design of a data visualization should be informed by what design elements best support the audience's ability to perceive and understand the components of the data visualization. We build on the foundations of Cleveland and McGill's work in graphical perception, employing a large, nationally-representative, probability-based panel of survey respondents to test perception in statistical charts. Our findings provide actionable guidance for data visualization practitioners to employ in their work.

Introduction

Should the abstract match – or be close to – our SDSS short abstract?

Outline for introduction:

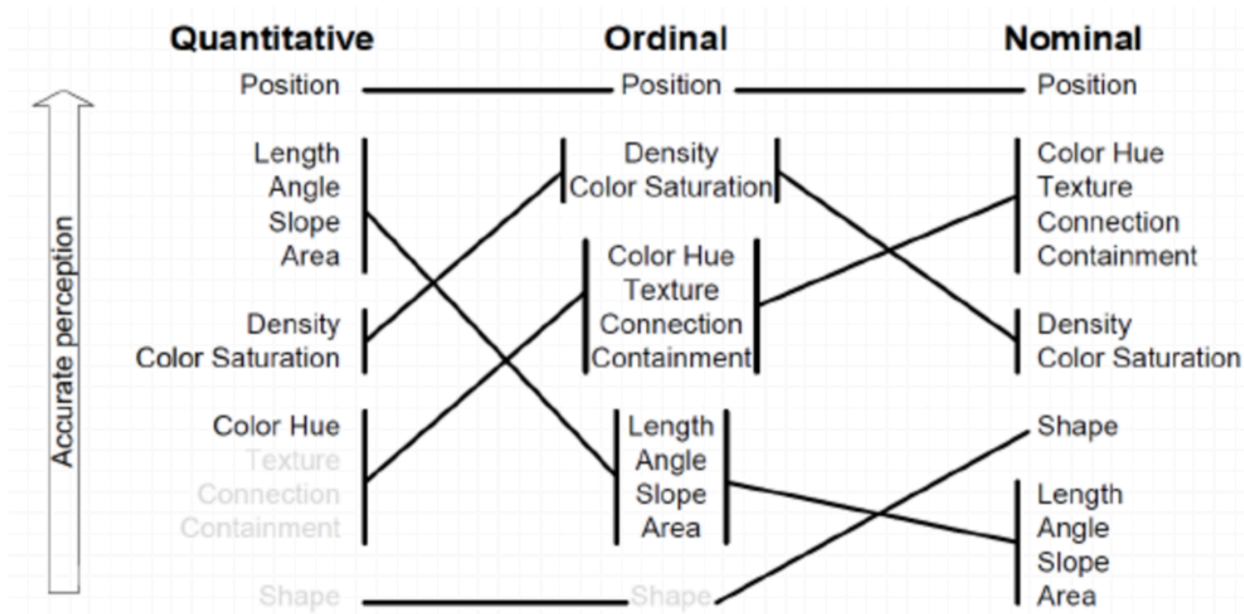
- What do viewers see when we show them a data chart?
- Visuals allow us to make comparisons between values
- Design of a data visualization impacts viewer ability to make those comparisons
    - And more broadly, impacts how viewers interact with a chart

*Corresponding author. Email: rice-kiegan@norc.org
†Email: hofmann@iastate.edu
‡Email: dutoit-nola@norc.org
§Email: mulrow-edward@norc.org

- There is prior work studying this topic
  - Cleveland and McGill laid the foundations
  - Mackinlay expanded to theoretical scales
  - Heer/Bostock expanded to larger study population
- However, prior work has utilized specific populations of study respondents. These populations are not representative of the general population, a common target audience for data visualization and scientific communication work
- Our work focuses on the following:
  - Utilizing a survey panel as a mechanism to test perception in data visualizations
  - Testing whether prior results from convenience samples hold with a nationally representative sample
  - Studying variations in data visualization design and their impact on respondent behavior and accuracy of participants' responses.
- This paper presents a series of tests completed and the resulting findings.
  - We consider structural (and aesthetic?) variations on bar charts and pie charts
  - Our tests are centered around the following central research questions:
    * How do structural design choices in a data visualization impact viewers' ability to identify the larger of two elements?
    * How is viewer behavior (zooming, time spent on question, certainty of response) impacted by structural and aesthetic design choices in a data visualization?
- The remainder of the paper is organized as follows:
  - we first describe the stimulus design
  - then we describe the study population (and survey design?)
  - subsequently, we share analyses of resulting survey responses across a series of stimuli
  - finally, we discuss implications of this study and next steps.

What do viewers see, when we show them a data chart? A crucial step in the process of 'understanding' a chart, is that a visual allows us to make comparisons between its parts.

Cleveland and McGill (1984) defined for the purpose of their seminal study the better visual as the one that allows viewers to make more accurate comparisons. Based on mappings of quantitative variables to different graphical elements, Cleveland and McGill's study resulted in a ranking of perceptual tasks from most accurate to least accurate. Mackinlay (1986) took this approach and expanded the tasks and their order to ordinal and nominal scales, as shown in Figure 1.



The Mackinlay ranking of perceptual task.

Figure 1: Ranking of perceptual tasks, as given by Mackinlay (1986). The ranking of tasks on the quantitative scale are empirically verified by Cleveland and McGill (1984).

What we need to remember, is that Mackinlay's work is purely theoretical. Cleveland and McGill's rankings based on a study. However, this study is a small convenience sample, consisting of only a few individuals recruited from among the authors' coworkers and their spouses. Heer and Bostock (2010) have reproduced Cleveland and McGill's rankings using a crowd sourcing platform. A total of XXX amazon turkers were involved.

Crowd workers are known to be biased towards male, young and relatively higher education: Borgo et al. (2017)

Here, we seek to – first – answer the question whether it is possible to use a survey to reproduce (some of) the rankings.

(a) **Unaligned bars** (b) **Aligned bars**

Figure 2: The only difference between the two pairs of rectangles A, B and C, D is their alignment, i.e. A and C are of identical size, as are B and D. When participants are asked to compare the size of these tiles in barcharts, the predominant response for the unaligned pair on the left is 'they are of the same size'. In contrast, more than half of the viewers respond with 'D is bigger' to the aligned pair of bars on the right.

Study design – stimulus

Outline for study design - stimulus

- Use of Just-Noticeable Difference
  - Differences between cognitive lab and survey
  - Understanding how design impacts the most difficult comparisons
- Stimuli within context of data viz
  - Title, legend, axes, etc.
- Structural variations
  - Alignment – across all tests
  - Stacked bar chart – vertical, horizontal, and horizontal wide
    - Vertical and horizontal bars are the same exact visual stimuli but rotated/presented differently
  - Facetted bar chart
  - Facetted pie chart – 4 colors, one color framed, one color floating
- Results are organized as follows:

   - …. Haven't decided yet.

Asking perceptual questions in a survey is different from the controlled environment of a cognitive lab, where these kind of questions would usually be addressed. This means, that instructions to participants have to be delivered in a very short and easily understandable, because questions arising from the task can not be answered. Similarly, rather than asking the same (or similar) type of question with varied signals multiple hundred times, in a survey we can ask only a few questions. In order to observe any effect, we need to ask questions that are perceptually hard, which means that we need to ask questions about stimuli that are close to our perceptual threshold. The **Just-Noticeable Difference** (JND) is defined as the smallest difference that will be detected 50% of the time. We are using results from studies on barcharts and pie charts (Lu et al. 2022) to inform the differences in charts shown to survey panelists.

- How do structural design choices in a data visualization impact viewers' ability to identify the larger of two elements?
- How do aesthetic design choices in a data visualization impact viewers' ability to identify the larger of two elements?
- How is viewer behavior (zooming, time spent on question, certainty of response) impacted by structural and aesthetic design choices in a data visualization?

Structural design choices

Mapping, Stacked bar, Vertical, Horizontal, Horizontal wide

Facetted bar

Only have a split sample for this

Pie, Alignment

We have this for all above mappings, but the setup is a little different for facetted bar

Aesthetic design choices (structural choices seems stronger/there could be a lot to talk about there... should we skip aesthetic on this one?)

Colors

Use of gridlines

Outcomes/responses for modeling:

Binary accuracy (correct/incorrect – 'they are the same' is incorrect here)

Ordinal response (a/b/they are the same)

Zooming behavior (zoomed/did not zoom)

Time spent on question (continuous, in seconds)

Certainty

I've noted this below, but: how to model? Ordinal response? Binary (certain or very certain vs everybody else)?

Study design - survey population

Participants were recruited as part of NORC's AmeriSpeak panel, which utilizes a probability-based sampling methodology and samples U.S. households from NORC's National Sample Frame that provides coverage of over 97% of U.S. households. The current panel size is 54,001 panel members aged 13 and over residing in over 43,000 households **CITE DENNIS 2022**. Each test was conducted using the AmeriSpeak Omnibus survey, which runs biweekly and samples around 1,000 U.S.adults to answer questions on a variety of topics. The advantage of using a probability-based approach is two-fold. First, we have access to a large sample of survey participants and thus have greater power in making inference about graphical perceptional abilities. Second, the sample is representative of the general adult public in the U.S., which is an important target audience for scientific communication.

XXX I think what you are trying to say is that we do not know, if participants have seen the stimuli multiple times, but if they did, there was at least a month in between?

Given the nature of pulling a sample from the panel for each Omnibus round, there is a possibility that some participants may have been included in multiple rounds; however, our collected data is not a longitudinal or panel study, so we do not have repeated responses from the same participants across each of our tests. Each of the tests was run at least a month apart, so if respondents participated in multiple rounds, there was at least a one month gap between viewing each visual stimulus.

Survey setup - Stimulus description

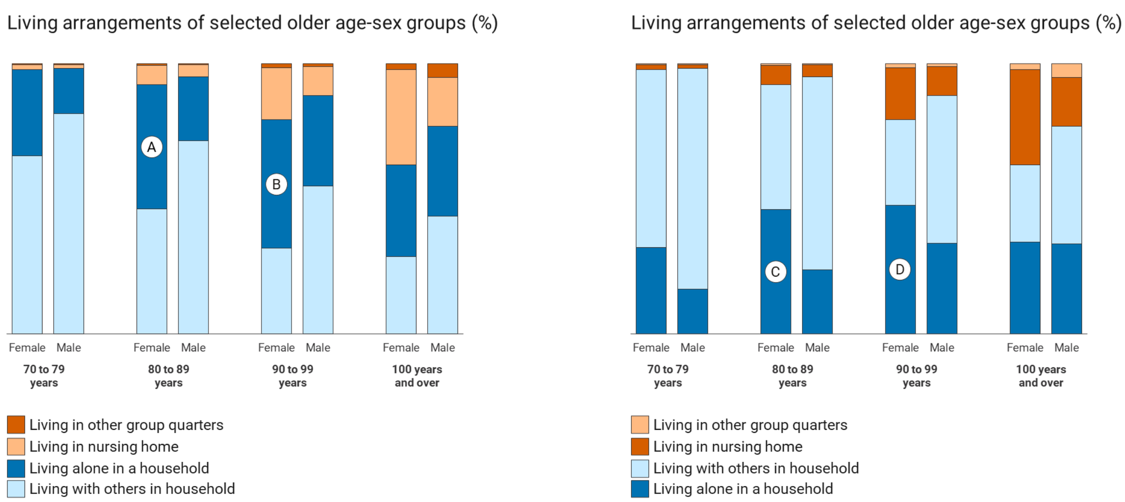
Figure 3 shows the two stacked barcharts shown to participants in the survey. The marked tiles in each plot are 155 pixels apart. Based on Lu et al. (2022)'s model, a difference of 155 pixels leads to a just noticeable difference of 3.5 pixels. The heights of the bars are 205 (left) and 213 pixels (right), respectively, corresponding to about twice the JND. This difference should lead to a relatively high accuracy rate for participants and simultaneously limit the amount of frustration resulting from a task that is perceived as 'too hard'.

Both charts in Figure 3 show the same data with slight modifications to the order of the levels – the first and second level in each of the bars are reversed between the left and the right chart. Participants were asked to compare the relative sizes of the tiles marked A and B (C and D, respectively) and select the correct response out of the possible choices:

1. A is bigger
2. B is bigger

3. They are the same

Answer 2 is the correct answer for both charts. Both charts are shown at the same size, i.e. in both cases the difference in size between the bars is exactly the same, the vertical distance between the bars is the exact same amount. This leaves the vertical positioning of the bars as the only difference between the charts. Any differences in observed accuracy can therefore be attributed to this difference in presentation.



(a) **Unaligned bars** (b) **Aligned bars**

Figure 3: Two stacked (vertical) barcharts. In each barchart, two tiles are marked. In both instances, the tile on the right is (very slightly) larger.

DATA THAT MAY BE INCLUDED IN ANALYSIS:

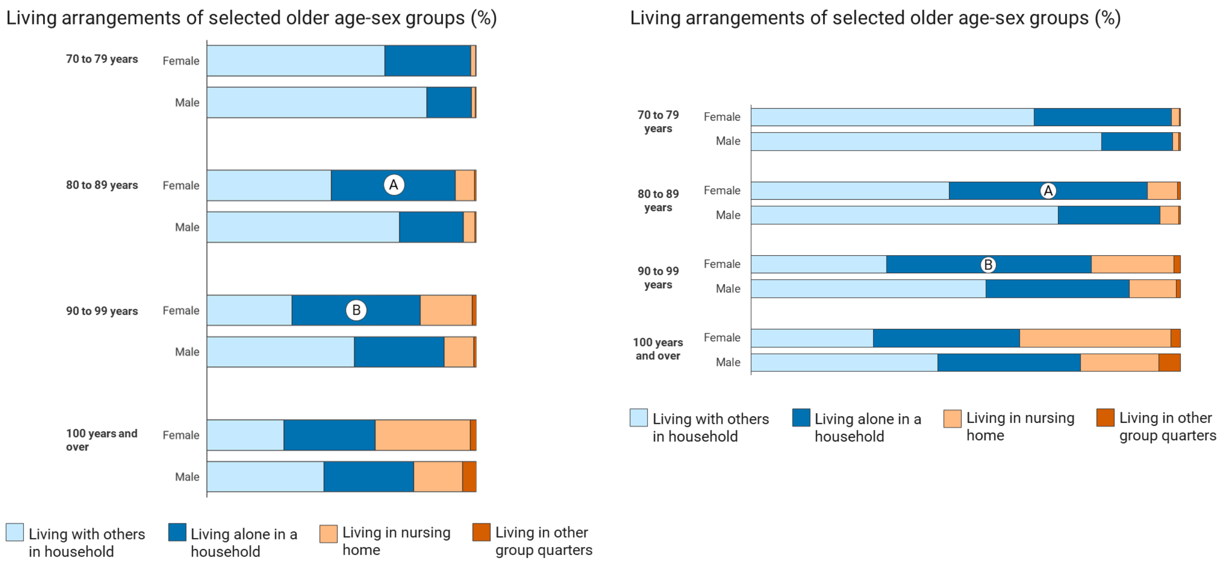
ROUNDS 1-2: Color variations on vertical stacked bar, aligned and unaligned

ROUND 3: Horizontal and horizontal wide, aligned and unaligned

ROUND 5: Horizontal wide gridlines (only dark grid split sample)

ROUND 6: Facetted bar (split sample w/o forcing choice)

ROUND 7: Aligned vs unaligned pie (full sample)



(a) **Tall horizontal bars**, unaligned (b) **Wide horizontal bars**, unaligned

Figure 4: Changes to to the vertical design are made in two steps. First, the original chart is rotated. The areas of all tiles are kept the same. In a second step, the aspect ratio of tiles is changed while keeping the areas of tiles the same.

Results

Respondents

Description of respondents

- # of respondents in each round
- broad overview of demo characteristics(?)
- raw sample size and effective sample size

Paragraph on combining samples across rounds

- Pull from analysis doc
- When combining responses from multiple rounds, we make weighting adjustments to ensure that weights in each sample are properly calibrated, to the population total across both rounds. **NEED ED REVIEW OF THIS LANGUAGE.** This adjustment is completed as follows: [insert Heike text from analysis doc here].

Test 1

- Alignment in stacked bars
  - Accuracy and responses
  -

Test 2

- Structure of stacked bars

Test 3

- Facetted bars and pies

How should we group results?

- By stimulus/structural variation?
- By response (binary, ordinal, certainty, time spent, etc.)
- By accuracy vs by behavior (zooming, time spent, etc.)

Results to discuss:

- Differences in accuracy between aligned and unaligned bar
- Differences in accuracy between framed, floating, and general pie
- Differences in timing and zooming behavior across all designs

COMBINING SAMPLES AND WEIGHTING NOTES:

We can combine responses across samples into one combined dataset, but we need to adjust weights accordingly so that each sample is weighted equally in the model (O'Muircheartaigh and Pedlow 2002).

All calculations in this paper are done in R (R Core Team 2022) using the `survey` package

(Lumley 2004) version 4.0 (Lumley 2020) based on Lumley (2010).

The data used for assessing the accuracy of comparisons in **??** is collected in two rounds of the NORC Omnibus survey. Rounds 1 and 2 are combined by adjusting the weights with $\lambda = 0.495$ for an effective sample size of 1004. Figure 5(a) shows that more than twice the number of responses is accurate, when the tiles are aligned along the same axis. Because each participant was shown both versions of the chart, we can use a paired t-test to compare mean accuracy between the two charts. The resulting t-statistic is highly significant (t statistic: 16.1, df: 1656, p-value: $<$ 2.2e-16).

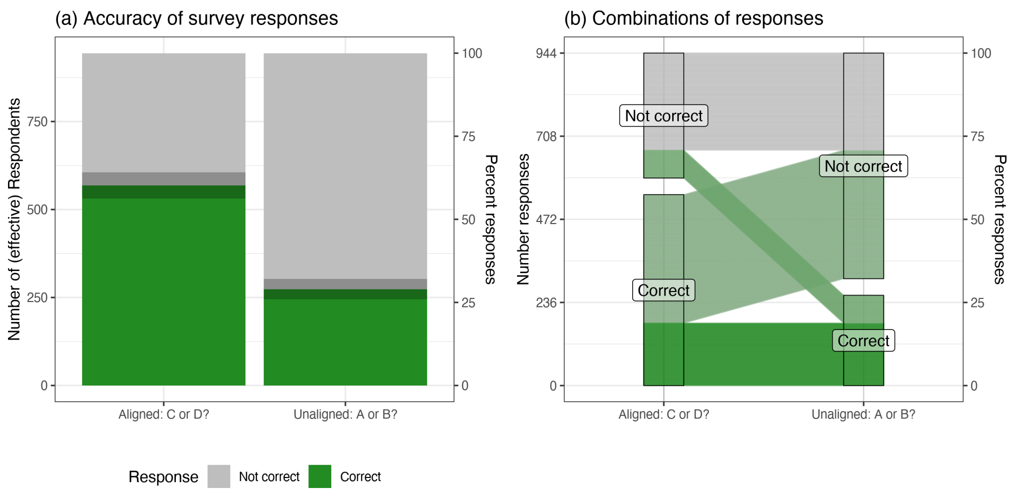


Figure 5: On the left (a), a stacked barchart shows the number of respondents with correct (green) and incorrect (grey) responses to the two comparison questions. When tiles are aligned along the same axis, more than twice the number of responses is accurate. The shaded area along the top of the green tiles corresponds to 95% confidence intervals around (marginal) correct responses. On the right (b), a parallel coordinate plot shows all combinations of responses. There's a huge asymmetry in the number of responses, where participants answered only one of the questions correctly. A lot more responses are correct when comparing aligned tiles than unaligned tiles.

ANALYSIS PLAN:

Models below structured as:

Response

Covariates to use in each model

STRUCTURAL VARIATION – START HERE

Binary accuracy across structural choices

Model 1:

Alignment only, just vertical stacked bar

Using the AmeriSpeak survey tool, a total of 1902 participants were exposed to two barcharts each, as shown in **??**.

Model 2:

Alignment

Bar vs pie (comparable question for pie is A vs B)

Model 3:

Alignment

Vertical x horizontal x horizontal wide

Model 4:

Alignment

Every structure (vertical bar, horizontal bar, horizontal wide bar, facet bar, pie)

Visuals:

% yes across each different structural condition

Facet by aligned/unaligned?

Model estimates + CIs

Ordinal response

Model 1:

Alignment only, just vertical stacked bar

Model 2:

Alignment

Bar vs pie (comparable question for pie is A vs B)

Model 3:

Alignment

Vertical x horizontal x horizontal wide

Model 4:

Alignment

Every structure (vertical bar, horizontal bar, horizontal wide bar, facet bar, pie)

Visuals:

All responses across each different structural condition

Facet by aligned/unaligned?

Model estimates + CIs

Zooming behavior (zoomed/did not zoom)

Model 1:

Device type

Alignment

Vertical x horizontal x horizontal wide

Visuals:

% zoomed by device + alignment (already have this chart)

Model estimates + CIs

Time spent on question (in seconds)

Model 1:

Device type

Zoom

Alignment

Vertical x horizontal x horizontal wide

Model 2 (this may not be feasible for comparison depending on what level the 'TOTALTIME' is captured at):

Device type

Zoom

Alignment

Every structure (vertical bar, horizontal bar, horizontal wide bar, facet bar, pie)

Visuals:

Distribution of time spent variable

Facet by device type, zoom, structural condition, alignment? Play around with it

Average time spent by each of the conditions

Certainty?

Same models as above, but I'm not sure how we want to do the response. Ordinal response? Binary (certain or very certain vs everybody else)?

AESTHETIC VARIATION – ONLY IF TIME

Binary accuracy (correct/incorrect – 'they are the same' is incorrect here) across structural choices

Model 1:

Dark grid vs no grid (only have for horizontal wide)

Response choice (ordinal response)

Model 1:

Dark grid vs no grid (only have for horizontal wide)

Zooming behavior (zoomed/did not zoom)

Model 1:

Device type

Dark grid vs no grid

Time spent on question (in seconds)

Model 1:

Device type

Zoom

Dark grid vs no grid

Certainty?

Same models as above, but I'm not sure how we want to do the response. Ordinal response? Binary (certain or very certain vs everybody else)?

Conclusion

Key findings to discuss:

- Surveys can be used to ask these types of questions – in the midst of other topics and with a limited number of questions, we are able to ask perception questions and produce results consistent with prior studies
- Reproduced (some) prior convenience sample results using a large, nationally-representative survey population:
  - Cleveland: position (aligned) versus unaligned
  - unaligned tiles within stacked bar are a hybrid between framed bar and floats
  - Talbot: pie charts - individual wedges vs piecharts
- Design choices impact viewer accuracy:
  - new finding: pie charts accuracy in work better when framed (wedges)
- Other important measures beyond accuracy: time to completion (automatic on web), certainty in response (asked).
- Studying how viewers interact with charts can be done in a survey, and more expansive

work on this topic should be completed to understand how the general public interacts with and understands charts.

  - Design choices impact viewer behavior: zooming

- (some) Demographics matter: age and gender does not seem to matter for perception economic background and education does matter for perception: we need to know, we do not want to create a hurdle in communication

Supplementary Material

- **Participant Data (Linear):** Link to csv file with the data.
- **Data Analysis Code:** Link to an html document with annotated code chunks.

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