

Escaping Flatland: Graphics, Dimensionality, and Human Perception

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Abstract. Almost 40 years ago, Cleveland and McGill published the first of 3 papers detailing experiments assessing the accuracy of numerical perception using different types of charts. This study is often cited as a reason to avoid the use of extraneous dimensions in data visualization: 2D bar charts produced more accurate estimates than 3D bar charts; in addition, lines (length) produced more accurate estimates than circles (area). Graphics have changed fairly significantly in the last 40 years: where we once had fixed 3D perspective charts, we now can rotate 3D renderings in digital space and even 3D print our charts to examine physically. Many optical illusions result from perceptual mismatches of 3D visual heuristics and 2D, planar, data representations; more realistic renderings available with modern tools might change the outcome of Cleveland and McGill's experimental comparison of 2D vs. 3D accuracy. In this paper, we present several experiments which replicate the bar chart portion of Cleveland and McGill's original study, comparing 2D, 3D fixed perspective, 3D rendered, and 3D printed charts. We discuss the findings and the importance of replicating classic experiments using modern technology, as well as the benefits of incorporating hands-on research in introductory classes as experiential learning activities.

Keywords: teaching · graphics · user-study · perception · accuracy

Almost 40 years ago, Cleveland & McGill published the first of 3 papers detailing experiments assessing the accuracy of numerical perception using different types of charts. This study is often used to justify aesthetic advice [18, 20, 11, 10, 21] to avoid extraneous dimensions in data visualization, though it never reports experimental results for 3D comparisons. Cleveland and McGill [6] create a hierarchy of elementary perceptual tasks, claiming that 2D bars should be more accurately perceived than 3D bars; in addition, lines (length) produced more accurate estimates than circles (area). To support these claims, they ran a series of experiments described over multiple papers [6, 4, 5] assessing the accuracy of participant estimations when making comparisons between elements of different types of charts. While estimation precision is not (and should not be) the only goal in statistical graphics [1], the advice to avoid 3D charts persists, even

though the charts tested in Cleveland and McGill [6] are an extremely limited version of the different types of 3D charts which we can generate today.

Technological Innovation

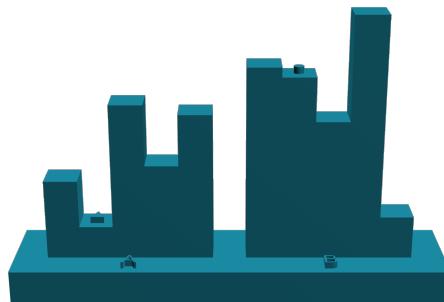
While 3D computer graphics have existed since Sketchpad was created in 1963 [17], and home computer software has existed since 1978 [13], there were significant developments in 3D software in the 1980s (AutoCAD) [23]. In the 1990s, 3D charts were introduced in MS Excel 3.0 [22], and though this might not be considered an overall improvement, it certainly represented an innovation in the graphical rendering features available to the average user. What is undeniable, however, is that since the 1990s, the pace of 3D graphics rendering software (and the hardware to support ever-increasing detail) has only accelerated. Two important (and related) software innovations worth mentioning for statistical graphics are the development of OpenGL [2], which is still used in packages such as `rgl` [15] and `modernrgl` [8] and WebGL, which made these graphics available for publication in web browsers [16, 7].

While Cleveland & McGill did directly examine volume comparisons in any of their experiments [6, 4, 5], it seems reasonable to conclude that the capabilities to create and interact with rendered 3D graphics have moved well beyond the simple image shown in Figure 1a; even the full realism of modern interactive 3D representations is not possible to show in PDF form; a screenshot of one such chart is shown in Figure 1b.



Figure 10. Volume chart

(a) Volume chart recreated from Cleveland and McGill [6]. Stimuli used in the experiment were printed and provided to participants on paper.



(b) Screenshot of a WebGL rendered 3D bar chart. The WebGL context allows this chart to be manipulated by the user; rendered shadows, lighting, and other effects contribute to the realism of the 3D effect.

Figure 1: A comparison of 3D data renderings from 1984 and 2024.

Moreover, we now have the capability to easily create physical objects from digital renderings using 3D printers. While 3D printing is typically not fast enough

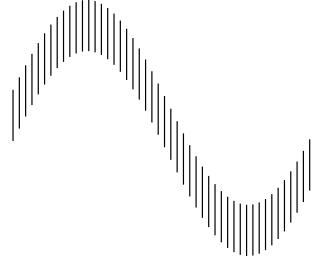
to be used for exploratory data analysis (the chart in Figure 1b takes 5 hours to print even at relatively low quality), it does provide a few advantages over digital renderings: tactile experience, accessibility for those with visual impairments, and (for the moment) novelty. More importantly, if we are interested in comparing realistic 3D renderings to the 3D renderings in Cleveland and McGill [6] (or 3D perspective charts more generally), it is useful to assess both the physical objects and the digitally rendered images when comparing to the fixed perspectives used in Figure 1a.

Perception of Graphics

Because the visual context of 3D graphical renderings has changed so significantly in the past 40 years, it is important to reassess the common guidance to avoid using the third dimension in data visualization in light of new technological capabilities. It is common for artists to intentionally leverage our 3D visual system to create illusions in two dimensions that give a three-dimensional effect, as in Figure 2a; unfortunately, similar misperceptions can be unintentionally triggered by common charts: stream graphs, candlestick charts, and even confidence interval bands.



(a) Sidewalk art by Zebit in Liverpool which leverages visual heuristics to provide the illusion of depth. Image by [Bill Hunt](#).



(b) An illustration of the sine illusion [19], also known as the line-width illusion. All vertical lines are the same length, but the lines in the middle of the curve appear to be much shorter.

Figure 2: Two dimensional situations which create the illusion of three dimensions, either intentionally (a) or unintentionally (b).

A simple example of this phenomenon is shown in Figure 2b; evenly spaced line segments are shown following a sine curve; even though each line segment is the same length, it appears that the segments along the inflection point are much shorter than the segments at the minimum and maximum of the curve. This illusion results from misapplied depth perception; the perceived length of the lines corresponds instead to the width of the line tangent to the sine curve - that

is, the entire series of lines is instead perceived as a single object that exists in 3 dimensions, and the heuristics which would normally determine depth are applied to the stimuli, providing an erroneous estimate of the length of the line. Providing visual stimuli which are rendered using 3D shading and perspective alleviates the effects of the sine illusion and allows viewers to estimate line length properly [19, Fig 3].

It stands to reason, then, that more realistic renderings of three-dimensional chart objects may alleviate the decreased precision of quantitative estimates found in Cleveland and McGill [6].

Motivation

In this paper, we present the results from several experiments designed to mimic Cleveland and McGill [6]’s exploration of different types of grouped bar charts, with the goal of exploring perception of 2D and 3D charts. We describe the process used to recreate the stimuli from the original experiment, using 2D, 3D fixed perspective, 3D rendered, and 3D printed charts to assess estimation accuracy in a population of undergraduate statistics students. Finally, we discuss the results of our experiment and the importance of replicating classic experiments using modern technology. We also describe the benefits of incorporating hands-on research in introductory classes as experiential learning activities.

Methodology

Participant Recruitment and Experimental Context

Participants were recruited from online and in-person sections of introductory (non-calculus based) statistics courses taught at University of Nebraska Lincoln during the Summer and Fall of 2023; overall, students from sections led by 3 different instructors took part in the experiment. The experiment was integrated into the course as an experiential learning activity accompanied by several written reflections. The stages of the experiential learning activity were as follows:

1. Informed consent - on the LMS during the first 2 weeks of the semester.
2. Pre-study reflection - on the LMS prior to experiment participation. Asks participants to write 3-5 sentences about how scientific investigations happen.
3. Experiment participation - code from experiment entered into the LMS
4. Post experiment reflection - on the LMS after experiment participation. Asks participants to guess at the purpose of the experiment, what the hypothesis under investigation might have been, potential sources of error, what variables were examined, and whether they thought there were elements of randomization or experimental control.
5. Abstract - Students read a 2-page extended abstract written for a scientific conference and reflect on how the information presented differed from their experience of participating in the experiment.

6. Presentation - Students watch a 15-minute conference presentation about the experiment and results and reflect on how the information presented differed from the information in the abstract.

During step 3, experiment participation, students were provided with an additional informed consent for the perceptual experiment. Students were able to opt-out, which prevented their data from being saved, but were required to at least participate in the process of the experiment to receive course credit, which ensured that they would be able to reflect on that experience during the later stages of the experiential learning activity.

Replicating Cleveland & McGill

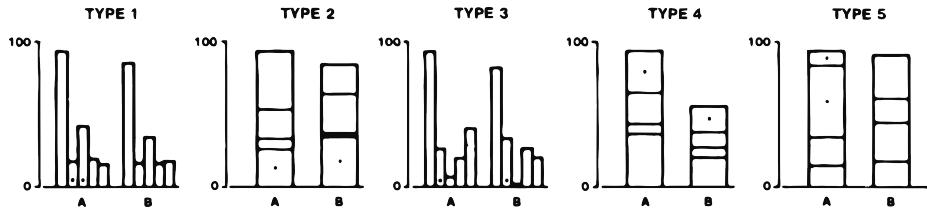


Figure 3: Types of judgments used in Cleveland and McGill [6].

We decided to only examine the Type 1 and Type 3 comparisons (e.g. those corresponding to grouped bar charts) because multi-color 3D printing was not supported by equipment we had available, and it was easier to mark the bars used for comparison if we did not attempt to segment bars vertically.

Cleveland & McGill asked participants in the position-length experiment (described in [6]) to evaluate marked bars, first indicating which bar was smaller, and then estimating “what percent the smaller is of the larger”. The values involved in the judgments were $s_i = 10 \times 10^{(i-1)/12}$, $i = 1, \dots, 10$, that is, $s_i = \{10, 12.12, 14.68, 17.78, 21.54, 26.1, 31.62, 38.31, 46.42, 56.23\}$. Participants judged “10 pairs of values with ratios ranging from 0.18 to 0.83”. There are 9 ratios available, as available bar lengths are equally spaced on the log scale; of these, the study examined 7, replicating 3 ratios twice, presumably to provide some estimate of within-participant error. Examining the graphical results in Cleveland and McGill [6], it seems that the values used were 17.8, 26.1, 38.3, 46.4 (twice), 56.2, 68.1 (twice), and 82.5 (twice). The exact bar lengths corresponding to these ratios were not disclosed, but we added the additional constraint that no bar length was used more than twice in the creation of the data sets which would be rendered in 4 different chart types. Bar heights which were not to be compared were chosen “at random, but subject to certain constraints”; these constraints applied to the stacked bar charts, but not the grouped bar charts. To mimic this, we used a scaled Beta(2, 2) distribution to define the size of the other 8 bars not used for comparison.

Experiment Design

We created 7 sets of data containing 10 bars lengths, one for each selected ratio used in Cleveland and McGill [6]. These data sets were assigned colors within chart type (so red in a 3D fixed bar chart represents a different ratio than red in a 3D printed bar chart), primarily to facilitate visually checking that combinations of 3D printed charts in a kit were all of different ratios. Each data set was rendered in 4 different chart types, with two different bar arrangements corresponding to Type 1 and Type 3 comparisons. Thus, the experiment involves $7 \times 2 \times 4 = 42$ different charts.

Each participant evaluated either 15 or 20 different charts, with a charts of each display type shown for each of 5 ratios, allocated according to Figure 4. Whether participants were shown adjacent (Type 1) or separated (Type 2) comparisons was randomly determined. Participants recruited from online sections of introductory statistics were shown 2D, 3D fixed, and 3D rendered charts; participants recruited from in-person sections were shown 2D, 3D rendered, and 3D printed charts. Due to an application configuration error, some in-person participants were initially shown 2D, 3D fixed, 3D rendered, and 3D printed charts, for a total of 20 trials. This error was fixed after the first 2023 summer session. Figure 9 provides example stimuli from each different display type. The order of trials for each participant was randomly determined by the data collection app, and in the case of 3D printed chart trials, by the participant themselves.

In order to facilitate the data collection process, we 3D printed sufficient charts to create 21 different kits of 5 physical charts each. Participants in the in-person condition participated in the experiment during office hours: each participant selected a kit from a bin of available options and participated in the experiment via the online app in a quiet study carrel before returning the kit to the bin. The app asked for a kit ID from in-person participants; this ID was used to select digital charts which had the same ratios as those in the kit of 3D printed charts. Each day, an instructor would shuffle the kits within the bin to ensure that each kit had a reasonably equal selection probability.

Stimulus Creation

This experiment uses 4 different presentations of grouped bar charts, shown in Figure 9.

It is relatively simple to create an all-digital experiment and keep track of the different stimuli (or render them during the experiment based on the parameters used to create them). With physical stimuli, this experiment was slightly more complicated, and as a result, we used slightly different methods to create the 3D files used for both prints and digital renderings. In particular, we wanted to ensure that each chart had a label which could not easily fall off or be removed in order to ensure the ability to audit kit composition reliably. This meant that the direct plot-to-STL pipeline provided by `rgl` [15] and `rayshader` [14] was not

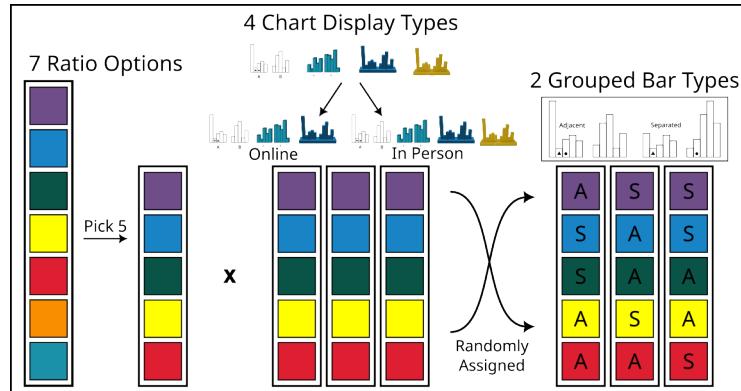


Figure 4: Schematic showing how trials were determined for each participant.

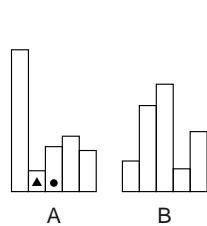


Figure 5: 2D

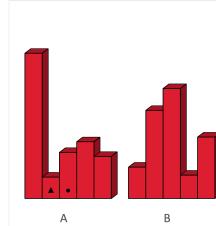


Figure 6: 3D fixed rendered

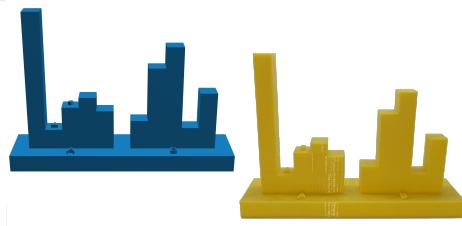


Figure 7: 3D ren-

dered



Figure 8: 3D printed

Figure 9: Rendering types used in this experiment. All charts show the same data.

sufficient. Instead, we inscribed an ID code (“data/pilot/Set85/id-xx/Typexx-Rep01”) on the bottom of the base of the charts by creating an OpenSCAD [12] template for a grouped bar chart in OpenSCAD and populated the template with values for each chart using an R script. The ID code was designed to be informative for the experimenters but not the participants, as numerical IDs were randomly assigned to ratio; the use of comparison type in the ID did not provide any information that would not also be available looking at the top of the chart.

2D bar charts were created using `ggplot2` [24] with an extremely minimalist theme. 3D fixed bar charts were created using Microsoft Excel in order to most accurately represent the angle used in these sorts of charts ‘in the wild’. While we could have created these using some sort of snapshot of the RGL rendering from a fixed angle, we felt using the same tool used in industry would increase external validity.

App Design

Data were collected using a Shiny app [3]. The app first asked participants for informed consent and basic demographic information: age range, gender identity, and highest education level, along with an identifier (“what is your favorite zoo animal”) used as an additional way to distinguish participants using the applet at the same time. Participants then were given three practice problems with 2D charts; these were designed to get participants comfortable with the online interface and the questions which would be asked, similar to the way Cleveland and McGill [6] provided practice problems (Figure 10) of each type of comparison in their two experiments.

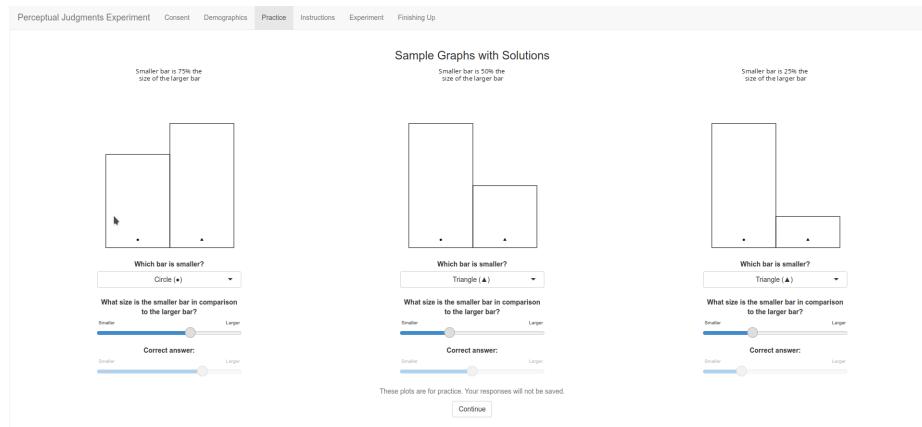


Figure 10: Practice screen providing participants with guidelines for how to use the sliders and identify the smaller bar.

Just before the experiment started, participants were provided with the basic trial instructions and asked for a Kit ID (one option was ‘online’). Participants who were online were randomly assigned a kit ID that was used throughout the remainder of the study. During each trial, participants were asked to evaluate a chart which was either displayed on the screen or randomly chosen from the kit of physical charts by the participant (in this case, they were asked to select the chart ID from a list, as shown in Figure 11).

 A screenshot of a mobile application titled 'Perceptual Judgments Experiment'. The top navigation bar includes tabs for 'Consent', 'Demographics', 'Practice', 'Instructions', 'Experiment' (which is highlighted in blue), and 'Finishing Up'. The main content area contains several input fields and controls. At the top left is a dropdown menu labeled 'What is the identifier on the bottom of the graph?' with the value 'data:piezSet60:id-C3Type1-Rep01'. Below it is another dropdown labeled 'Which bar is smaller?' with the option 'Circle (•)' selected. To the right of these dropdowns is a note: 'Please randomly select a chart from your kit'. At the bottom left is a 'Next' button. In the center, there is a horizontal slider with a circular track and two tick marks labeled 'Smaller' and 'Larger', with the slider's position between them.

Figure 11: Screen showing the app process when a 3D printed chart was randomly selected

Participants first identified which bar was smaller, and then used a slider with no numerical information to show the ratio of the smaller bar to the larger bar. This differs from the numerical estimation procedure in Cleveland and McGill [6], in that it does not require participants to estimate the number from the size ratio, but this difference was intentional - we wanted to reduce participant cognitive load as much as possible; follow up studies may be necessary to determine how much of an impact this design decision has on the results.

At the conclusion of the experiment, participants were provided with a participation code which could be entered into the learning management system to receive credit for experiment participation. This code was provided regardless of whether participants consented to their data being saved for research purposes.

Results

Demographics

Overall, approximately 118 participants met the inclusion criteria (above the age of majority and a student in the class). This number is approximate because we recorded data anonymously, and can thus only track unique sessions where participants completed the demographic information - this information intentionally cannot be linked to responses for privacy purposes.

Of these students, there were 100 participants who completed at least 10 trials.

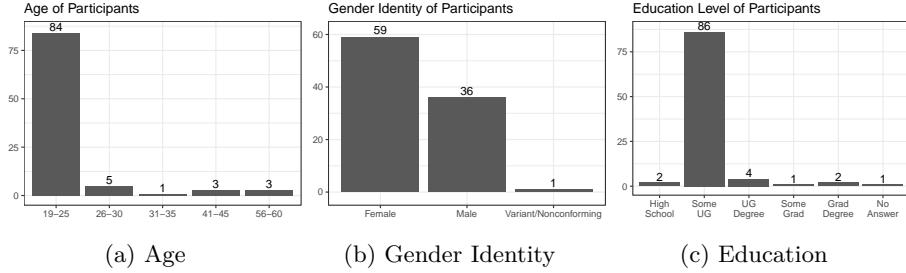


Figure 12: Participant Demographics. As participants were recruited from undergraduate statistics classes, imbalances in age, gender, and education level are to be expected.

Data Cleaning

In studies where participants are asked to perform a task, it is typically important to utilize both attention checks (semi-obvious answers that check whether the participant is paying attention) and to be aware of participants who try to submit the study as quickly as possible without completing the task as directed. In this study, we asked participants to identify the smaller marked bar, as in the original study. Of the 1422 trials completed by the 100 participants with at least 10 trials, 92.28% identified the correct bar. Trials where this attention check was not answered correctly have been excluded from the study with the rationale that the ratio between the smaller and larger bar (which is limited to a range of 0 - 100%) is nonsensical if the smaller bar is not identified correctly.

In addition, we noticed that 15.12% of the trials completed had a response of exactly 50% (the default value of the slider). In particular, 13 participants completed at least 50% of trials with a response of exactly 50%; these participants have been excluded from the study on the grounds that they were clearly not engaging with the purpose of the experiment.

After applying these basic criteria for inclusion in the data analysis, we have 1276 trials completed by 87 participants remaining for further analysis.

Summary Statistics

There are far fewer trials of 3D printed charts, largely because only online sections were offered during the summer, and relatively few in-person sections participated in this experiment during the fall (Figure 13). As a result, we will exclude the 3D printed charts from further analysis in this study.

Examining participant responses in Figure 14, it is clear why Cleveland and McGill [6] worked with the midmeans of the responses - there is quite a bit of variability in the estimates created by participants, sometimes in ways that do not make much sense.

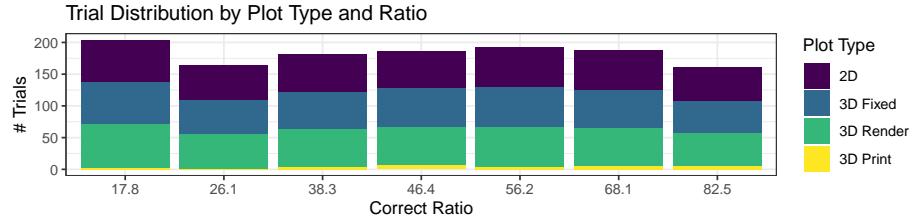


Figure 13: Number of trials across ratio and plot display type.

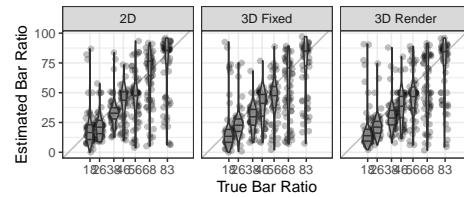


Figure 14: Violin plots of responses relative to true ratio values. It is clear that some participants misunderstood the estimation task, while others simply did not move the slider from 50%. Nonetheless, there is a general relationship between the true ratio and the central values of the distribution of estimates. Note that 3D printed plots have been removed from this chart because there were too few responses to estimate a distribution.

Midmeans analysis

If we repeat the analysis performed in Cleveland and McGill [6], examining a 25% trimmed mean of the log absolute error (with a correction),

$$\log_2 (|\text{Estimated Percent} - \text{True Percent}| + 1/8),$$

we find that there are very few differences across plot types. Comparing to the actual values reported in Cleveland & McGill, however, we find that errors are much higher in this population under the web-based protocol we are using for data collection than similar midmeans and intervals reported in Cleveland and McGill [6]. Our errors are also larger than those reported in Heer and Bostock [9], which used an online sample but otherwise followed essentially the same procedures using similar stimuli to Cleveland and McGill [6]. It is possible that introductory statistics students do not estimate as accurately as academics and their wives [6] or paid participants through Amazon Mechanical Turk [9]; certainly, the number of participants removed for answering 50% for all trials suggests that at least some participants did not take the task seriously. Another potential explanation is that some of these issues stem from the measures we took to minimize cognitive load while avoiding rounding and clustering of responses around benchmark values. In this study, we used a slider with endpoints marked 0 and 100, but no other numerical feedback was provided - no tick marks, no value of the current estimate. While our goal was to remove rounding tendencies, it is entirely possible that we instead introduced higher error values because participants could not do the spatial mapping operation without going through numeric values; then, participants had to invert this process and map back onto a spatial dimension without any visual aids. Further studies will be necessary to distinguish between these two issues. It may also be helpful to provide feedback on a few demo trials before participating in the experiment in order to ensure that everyone is comfortable with the input mechanisms; the current demo may not provide enough active feedback to really get participants familiar with the interface.

Student Responses

Part of the goal of using this experiment as an experiential learning activity was to introduce the idea that not all charts are equally effective to introductory statistics students. In addition, we hoped to reinforce concepts taught in class, such as randomization, experimental control, blocking, and interpretation of results, using experiential learning to help students make the connection between theoretical concepts and how these concepts play out in real life.

In Fall 2023, this project was offered to students in a 75-person section of online introductory statistics as extra credit. About 40 students both participated and consented to having their responses shared across the 6 different parts of the experiment; only 4 of these components have meaningful responses beyond the question of providing informed consent or a completion code for the experiment, and of these, we will briefly consider questions from the post-experiment

reflection, abstract presentation, and presentation. The pre-experiment reflection, which asked students to think about how scientific experimentation works, is less specific to this experiment and will thus be omitted.

In the next 3 subsections, we will provide some brief excerpts from student responses which provide some insight into student learning and engagement with the experiment. Text files with all student responses for each question are available on github.

Post-experiment reflection Students were asked to complete a reflection activity 1-2 weeks after completing the experiment, with questions designed to encourage them to assess how material from the course applied to their experience.

What hypotheses might the experimenter have been testing?

- “Students will get progressively less accurate as questions were asked”
- “Do students change their answers when asked the same question over and over?”
- “3D printed bar charts will lead to more accurate ratio judgments compared to 2D or 3D digital charts.”
- “That 2d is preferred over 3d. It cleans up the data presentation.”
- “The public can more accurately understand data when it is provided to them in a 2-D graph format.”

While some of these hypotheses are not correct (and even amusing), over half of the students made some mention of the use of different types or different dimensionality of graph presentations in their answers, and several more provided reasonable hypotheses about e.g. the use of adjacent bars vs. separated bars in comparisons.

What sources of error are involved in this experiment?

- “Fatigue effect over the course of making many judgments, learning patterns from seeing the same ratios multiple times, possibly difference in eyesight among participants.”
- “There are no line values to help measure it when there is a small difference between the graphs.”
- “People that are guessing”
- “People in the sample misunderstanding directions.”

Here, it is clear that students were capable of identifying many of the same sources of error that we have identified when considering the large variability in our results relative to previous studies.

When asked which variables the experimenter examined and whether these variables were quantitative or categorical, students overwhelmingly (37/41) indicated at least some understanding of the response variables (smaller/larger, %

of smaller to larger), and many participants also identified manipulated variables (chart type) and demographic variables (age, gender identity, education level) that may have also been of interest.

What elements of experimental design, such as randomization or the use of a control group, do you think were present in the experiment? Why?

- “I believe every graph was randomized for every student. I also believe the practice was meant to be a bit of the control group.”
- “Randomization was used as participants all received different sets of graphs to examine. A person wasn’t assigned to a certain set of graphs and it was up to random chance on which set of graphs they received.”
- “I think that there is randomization but not a control group in my opinion, because there isn’t one group that is left alone or not studied....”
- “Randomization was not used because it was offered as an extra credit assignment in class.”

These responses indicate that participants were actively considering how their experience of the experimental design matched terms used in class. While the final excerpt represents a misunderstanding of the difference between randomization and random sampling, it is clear from these comments that students are using their experience and considering the terms they’ve learned in class based on those experiences.

Abstract reflection A few weeks after the post-experiment reflection, students were provided with a 2-page extended abstract that described the experiment in a style which was consistent with submission to a conference. Students were asked only a single question, which was **What components of the experiment are clearer now than they were as a participant? What questions do you still have for the experimenter?**

- “I believed that one of the components was the dimension of the graph. However I also thought that the color was the main component and that was not true. The angle was an obvious component I felt, but then again I wondered if it looked that way because I was using my phone.”¹
- “The exam was about perceptual judgement, using the difference between 2D and 3D graphics. This is a different approach than just deciding how much bigger or smaller something is as the participant. A question I have is why we think 3D graphs are harder to perceive than a 2D graph. This seems a bit confusing to me, because they seem to be about the same for me. I also would like to know about the difference between 2D rendered charts

¹ Note that students were explicitly instructed to use a laptop (and one was available for their use); it isn’t surprising that this student had a hard time using a device with a much smaller screen.

compared to a 3D printed chart. Perhaps this is because I took this course online.”

- “The scientific question is more clear after reading the extended abstract. I now understand that they wanted to compare differences between 2-dimension, 3-dimension, and printed 3-dimension. They were testing not the correctness, but the perceptual judgment. There was also a formula that they provided for judging how the participant analyzed the bar graphs, and if they were correct provided the formula. The random distribution of ratios also makes sense in that there were 21 different combinations of bar graphs amongst different participants.”
- “After reading on the study, I can better understand the reasoning behind it and the purpose of the experiment. I enjoyed that they tried using similar tactics as that of Cleveland and McGill. I thought it was unique that they had strategically planned out the distance between the two bars that were being assessed throughout the study, as I didn’t think it was possible to be that in depth and in such detail. Overall, I am impressed by the experiment.”
- “After reading the abstract, I was surprised to learn that the subject of the study wasn’t the hypothesis I thought it was. Now it’s very clear that there’s a discrepancy between interpreting 3D and 2D graphs/visuals. I am still curious after reading this what the results of the study are based on students feedback. I also want to know if the student results were different than what was expected based on Cleveland/ McGill’s study.”

Generalizing beyond the excerpts included here, almost all of the students seemed to enjoy finding out what the experiment was about, and came up with reasonable and cogent questions about the experiment beyond what was in the abstract.

Presentation reflection As a final component of this experiment, participants were asked to watch a 15 minute conference-style presentation of the results and reflect on the experiment and information present in the abstract vs. the presentation.

If you had to hear about this study using only the extended abstract or only the presentation, which one would you prefer? Which one would be better for determining whether the experiment was well designed?

- “Again I like the presentation better mostly because it adds a more personal touch! The abstract is probably really the best way to understand the design of the experiment. However I struggle reading that kind of material. So for a participant, the video presentation was the best.”
- “I would prefer the presentation. I think that maybe the abstract would be better for determining whether the design of the experiment was better because of the fact that it strictly lays out the experiment and some of what math was involved, whereas even though the presentation did that, it went more in depth about the results as well instead of just the design.”

- “I would prefer hearing about the study using the abstract. I believe it provides more detail on the setup of the experiment, which is better for determining if it was well designed.”
- “If I had to hear about this study using only one source, I would prefer the video presentation. This may be because I am a visual and auditory learner, but I also had a hard time understanding what the researchers wanted us to get out of the abstract because it was so complex. With the presentation, I was able to understand step by step how the study was conducted.”

While participants were decidedly mixed on their preferred information transfer method, most agreed that the extended abstract was preferable for understanding design details, while the presentation was more engaging.

One goal of the introductory statistics class at UNL is to create informed consumers of statistical information. As part of that goal, we asked participants to reflect on what information was available to them at each stage of this project.

How did the information you gained from the components of this project (participation, post-study reflection, extended abstract, presentation) differ?

- “Participation gathers real-time, subjective feedback. Post-study reflection provides deeper insights. The extended abstract offers a formal summary, while the presentation conveys findings to a broader audience. Each component serves a unique role in understanding perceptual judgments on 3D printed bars.”
- “The experiment itself didn’t make it obvious that 2D presentation of a graph distorts the data, which is an interesting perspective to carry when reading different charts, especially bar graphs. I learned this through the extended abstract and presentation, which drastically changed my thought process when reflecting on why each type of graph led me to believe it had that specific ratio on the slider tool.”
- “I think that with each module, we gained more and more insight into the study and its purpose. It was almost like this video was the last part of a scavenger hunt to find the purpose and idea behind the study and the other components were like little puzzle pieces.”
- “As a participant in the study, having no idea what the purpose was at first, I truly enjoyed the experiment. I felt like I was doing a self-challenge to try and accurately determine how much smaller the smaller graph was. Next, I read the extended abstract and appreciated the purpose of the experiment, its history behind it, and the strategies used within the experiment. When doing the post-study reflection, I feel like I got to tie everything together that I had learned so far. Finishing off with the presentation, I feel like everything became full circle and I found interest in the additional information that was given that wasn’t in the extended abstract.”
- “I did not realize the depth of thought that goes into experimental design. As a participant, I had no idea of the depth of the research for this data. Also

as I moved through this process it gave me a clearer understanding of the study and its implications. This experiment also helped give me experience in understanding the experiment design process.”

Many participants expressed a feeling that information was gradually uncovered over time; the sequential unveiling of information seems to have provided an ongoing engagement and even investment in the study’s results, for those who responded. Interestingly, several participants mentioned that the post-study reflection was key for their understanding of the experiment - as no additional information was provided in this reflection, this suggests that the explicit direction to consider how concepts learned in class related to the experiment was a useful exercise for students.

Discussion

While this experiment lacked the precision necessary to provide useful insight into visualization design, the process of incorporating these experiments into introductory statistics classes seems to be a valuable tool for motivating student learning. It is possible that we may be able to reduce response variance in future iterations of this experiment by providing numerical feedback, strictly numerical estimation methods, or otherwise manipulating how students interact with the study. One of the potential explanations for differences between our study and Cleveland and McGill [6] is that we used numerical sliders; however, another explanation is that students did not estimate ratios with the same amount of care as participants in previous studies. Certainly, it is possible to read some of the student reflections and come to the conclusion that some students simply did not read the instructions or participate in good faith.

A much more valuable outcome of this experiment is that participants seemed to enjoy the overall process of participation in the study and reflection upon the experience during the course of their introductory statistics class. While we did not collect information which allows us to assess whether participation increased student learning, we can see from their reflections that most students were able to make connections between participation in the study and concepts in class when prompted to think about these topics. Moreover, students seem to enjoy the “reveal” moments when reading the abstract and watching the presentation. The sense of completing a puzzle was evident in many of the written responses, and it seems likely that the experience of questioning, forming a hypothesis, and having the hypothesis either supported or rejected through new information may stick with them after the concepts in the course are forgotten. In that sense, this experiment was a success, and embedding basic research and experiential learning in statistics courses may prove to be a valuable pedagogical tool.

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