Various Misleading Visual Features in Misleading Graphs: Do they truly deceive us?

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Abstract

Following the increasing use of graphs to communicate statistical information in social media and news platforms, the occurrence of poorly designed misleading graphs has also risen. Thus, previous research has identified common misleading visual features of such graphs. Our study extends this research by empirically comparing the deceptive impact of 14 distinct misleading graph types on viewers' understanding of the depicted data. We investigated the deceptive nature of these misleading graph types to identify those with the biggest potential to mislead viewers. Our findings indicate that misleading graphs significantly decreased viewers' accuracy in interpreting data. While certain misleading graphs (e.g., graphs with inverted y-axis or manipulated time intervals) significantly impeded viewers' accurate graph comprehension, other graphs (e.g., graphs using pictorial bars or graphs with compressed y-axis) had little misleading impact. By identifying misleading graphs that strongly affect viewers' understanding about depicted data, we suggest that these misleading graphs should be the focus of educational interventions.

Keywords: misleading graphs; misleading visual features; graph comprehension.

Introduction

Graphs are ubiquitous in articles, social media, and news outlets, serving as vital tools for conveying statistical information. When designed effectively, graphs can provide valuable insights (Nothelfer et al., 2017). However, flawed designs can distort reality and mislead the audience (Lauer & O'Brien, 2020; Pandey et al., 2015). For instance, a line graph with an inverted y-axis can give the impression that firearm murders decreased after the enactment of Florida's "stand-your-ground" law, as illustrated in Figure 1. This is an example of a misleading graph that manipulates visual features, leading to misconceptions about the presented statistical information.

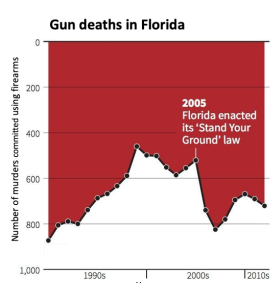

Figure 1: Reproduction of a misleading graph. The original graph was published by Reuters (2014)

Formally, we consider such graph to be misleading. Misleading graphs are a graph or chart that manipulates visual features counter to the conventional design, in a way that interferes with the viewer's ability to accurately comprehend the statistical information being presented (Cairo, 2019; Tufte, 1986). In today's data-centric media environment, misleading graphs have become common. Indeed, a study of medical advertisements revealed that nearly one-third of the graphs used conveyed information misleadingly (Cooper et al., 2003). The COVID-19 pandemic further highlighted this issue, with a significant increase in the use of misleading graphs, sparking extensive social media discussions (Engledowl & Weiland, 2021; Lisnic et al., 2023). This trend underscores the urgency for research to examine the impact of misleading graphs.

Therefore, the existing research on misleading graphs has provided the thorough analyses and in-depth explanations of their deceptive impacts for several well-known types (Fan et al., 2022; Pandey et al., 2015; Yang et al., 2021), such as bar graphs with truncated y-axes or line graphs with inverted y-axes. However, the relative deceptive impact among the various types of misleading graphs remains unaddressed. This leaves a gap in our understanding of the potential for graphs to mislead. As a result, there is limited understanding of which specific types of misleading graphs are most likely to deceive viewers. The goal of this paper is to close this gap by evaluating the deceptive impact of various potentially misleading graphs.

Related Research

Cognitive theories of graph comprehension typically distinguish perceptual and conceptual processing (Cleveland & McGill, 1984; Curcio, 1987; Kosslyn, 1989; Trickett & Trafton, 2006). Perceptual processing occurs automatically and quickly, often without conscious awareness (Ciccione et al., 2023; Kellman & Massey, 2013; Rensink, 2021). It enables viewers to create an initial mental representation of a graph using basic visual features such as color, length, position, or angles. In contrast, conceptual processing is a deliberate and effortful activity that demands substantial cognitive resources and active engagement with the graph (Carpenter & Shah, 1998). It enables viewers to apply their knowledge about graph design and its context to refine their initial mental representation of the graph. Perceptual and conceptual processing interact with each other as viewers seek to understand the quantitative information depicted in a

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graph (Carpenter & Shah, 1998). Consequently, errors that occur during perceptual or conceptual processing can negatively affect overall graph comprehension.

In perceptual processing, errors can occur when viewers fail to detect misleading visual features while encoding a given graph into visual chunks. Viewers use these chunks to construct a mental representation of a given graph. In conceptual processing, errors can arise when viewers use irrelevant knowledge as guidance for building mental representations (Pinker, 1990). Consequently, viewers create an inaccurate mental representation that ultimately results in extracting an incorrect conceptual message from the graph, which leads to misinterpretation (Pandey et al., 2015).

Prior research has identified a range of misleading visual features characterized by poor design choices, based on real-world examples. For instance, Cairo (2019) and Jones (1995) illustrate how manipulating axes, applying logarithmic scales, including dual axes, altering the axis range to conceal or reveal fluctuations, modifying axes orientation, or adding 3D effects can mislead viewers and provoke errors in graph interpretation. Building upon these findings, Lo et al. (2022) developed a detailed taxonomy of 12 categories of misleading visual features, derived from an analysis of 1,143 charts labeled as misleading, which were collected from search engines and social media platforms. Using a grounded theory approach, they iteratively tagged and discussed those collected misleading graphs, ultimately identifying 74 distinct misleading visual features. These 74 features were then grouped into 12 categories. Within these 12 categories, 'choice of axis' emerged as the most prevalent, accounting for approximately 28.6% of the misleading graphs collected. This category includes misleading visual features related to axis distortion, such as truncated, dual, or inappropriately scaled axis. Additionally, in alignment with the findings by Cairo (2019) and Jones (1995), Lo et al. (2022) highlighted 'visual illusion' as one of the prevalent misleading visual features, which includes the use of 3D effects. While these studies have identified a comprehensive list of misleading features, they build on theoretical analysis of the graphs.

Extant empirical research on misleading graphs has primarily concentrated on analyzing a narrow range of misleading visual features, such as truncated y-axes in bar graphs, inverted y-axis, rate of inclination/declination in line graphs, or potentially confusing area depictions in area-based charts (Pandey et al., 2015; Yang et al., 2021). While each study offers an in-depth explanation of these features' deceptive effects, they collectively fall short of evaluating the relative deceptive impact of each feature. Consequently, determining which specific types of misleading features have the greatest deceptive impact remains an open question. To address this question, our study first tests the assumption that those documented misleading features genuinely deceive viewers (Research Question [RQ] 1) and then identifies which types of misleading visual features have the greatest deceptive impact (Research Question 2).

Method

Participants

Participants were 78 undergraduate students (50% were female and 28% were male, and the rest preferred not to answer) at a midwestern university in the U.S. All participants for this study were recruited through email.

Materials

To identify common types of graphs (Battle et al., 2018), we pinpointed prevalent misleading visual features that have been documented in theoretical research (Cairo, 2019; Jones, 1995; Lo et al., 2022). From this preliminary investigation, we defined a misleading graph type as a type of graph (i.e., line graph, bar graph, or pie chart) that includes a misleading visual feature (e.g., truncated y-axis). It is important to note that certain misleading visual features are applicable to multiple types of graphs (e.g., truncated y-axis can be applied to both line graphs and bar graphs).

For each misleading graph type, we crafted four pairs of graphs, so that each pair depicted the same data. One graph in a pair contained the misleading visual feature and the other did not. As a result, for the 14 misleading graph types (Figure 2), we developed four unique misleading/non-misleading pairs, culminating in 112 graphs (14 misleading graph types multiplied by four pairs of misleading/non-misleading graphs). Table 1 shows a brief description of all 14 misleading graph types.

For each pair of graphs, we created a question asking for a value that can be estimated by extracting specific information from the given graph. Questions were identical for each misleading/non-misleading pair. The answer formats varied according to the type of graphs and questions. Text entry answers (Figure 2a) were used for bar or line graphs where participants had to estimate a value by comparing data points of two bars or line points. Text entry answers were also used for line graphs with a truncated y-axis, line graphs with compressed y-axis, bar graphs with truncated y-axis, and bar graphs with compressed y-axis. Ranking answers (Figure 2k) were used for pie charts where participants need to sort the slices according to their sizes. Multiple-choice answers (Figure 2d) were used for the remaining misleading graph types, for example, such as where participants had to estimate trends of the depicted data or find a certain point in the data. Each multiple-choice answer includes three to six choices. In designing these choices, we included one correct (best) answer and one incorrect choice matching to the misleading visual feature, along with other obviously incorrect choices that were unrelated to the misleading visual features. All questions were intentionally designed, aiming to mimic common judgments that people make when encountering graphs in social media or mass media, such as estimating a trend from a line graph, comparing the height of bars from a bar graph, or finding the biggest slice in a pie chart.

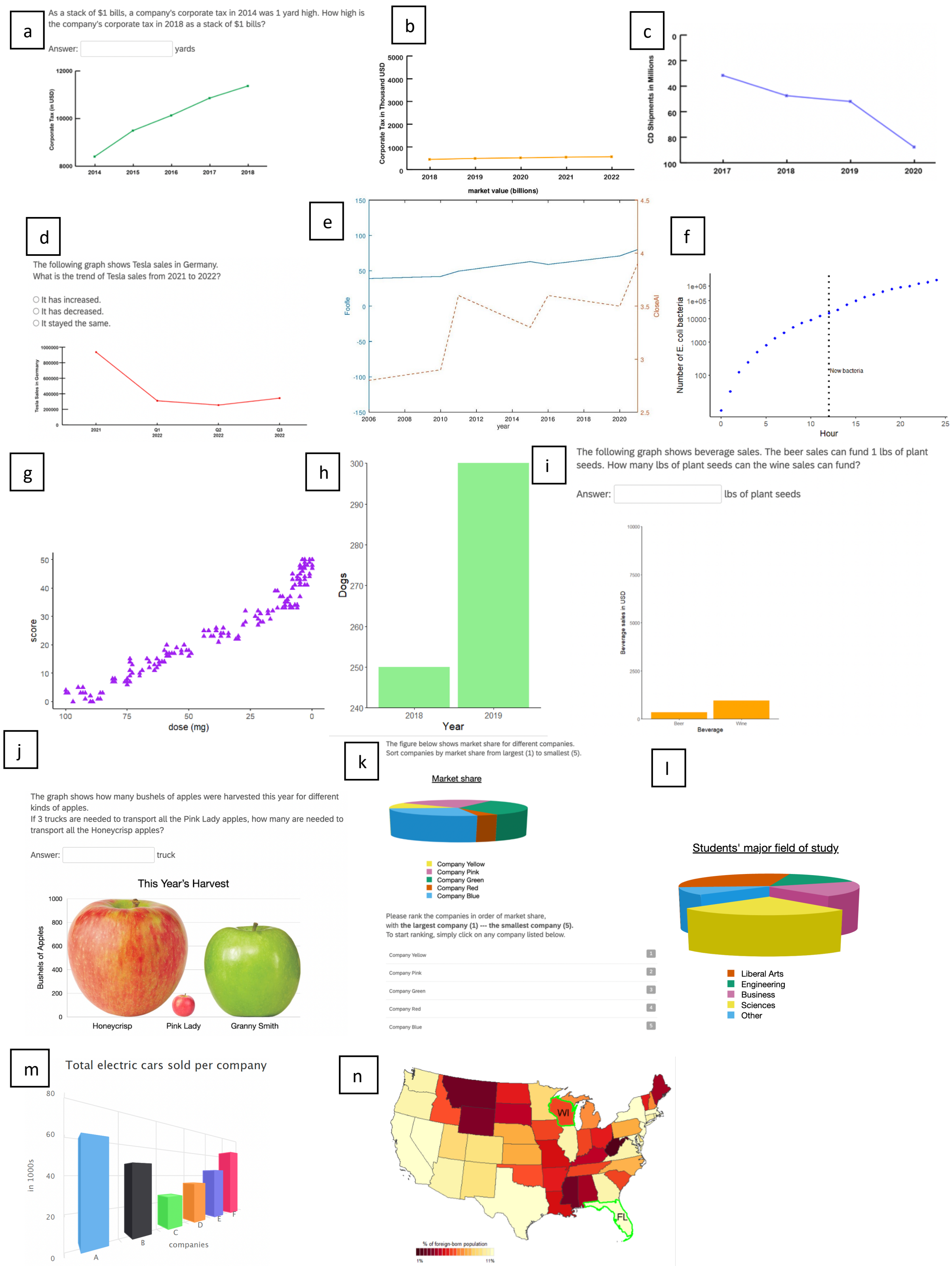

Figure 2: Examples of misleading graphs used in the experiment. (a) Line graph with truncated y-axis, (b) line graph with compressed y-axis, (c) line graph with inverted y-axis, (d) line graph with a manipulated x-axis, (e) line graph with dual axes, (f) scatter plot with logarithmic scale, (g) scatter plot with flipped x-axis, (h) bar graph with truncated y-axis, (i) bar graph with compressed y-axis, (j) bar graph with pictorial bar, (k) pie chart with 3D effect, (l) pie chart with 3D pop-out effect, (m) bar graph with 3D effect, and (n) map chart with inverted color scale

Determining the accuracy of participants' responses required different criteria depending on the type of answer. In the case of multiple-choice answers, participants received a score when selecting the correct answer. For ranking-type answers, participants received a score when they correctly arranged all the given pie chart's slices. For text entry answers, participants received a score when their inputs fell within the correct range. To establish this range, we consulted with two graduate students in educational psychology and identified potential strategies participants might use. This yielded three potential strategies: the correct strategy, the misleading strategy, and the skimming strategy. For instance, for estimating the value with the given bar graph in Figure 2h, the correct strategy involves calculating the accurate answer using the true ratio of the y-axis values between two bars. The misleading strategy involves comparing the bars' heights instead of their true y-axis values. The skimming strategy involves reading only the second bar's y-axis value without performing any calculations. We then established the correct answer range by finding the geometric mean between answers derived from each strategy, as illustrated in Figure 3.

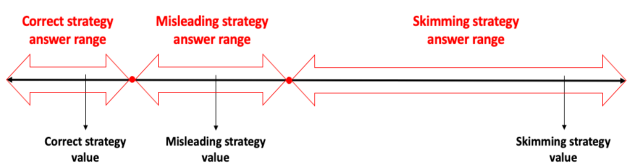

Figure 3: Estimated answer range for each strategy, with the red dots indicating the geometric mean between the values of the adjacent left and right strategies

Moreover, to filter out participants who might answer questions randomly, we incorporated six sanity-check items into the study. These items featured a graph accompanied by a straightforward question, designed to be answerable by anyone who reads the question and looks the graph as shown in Figure 4.

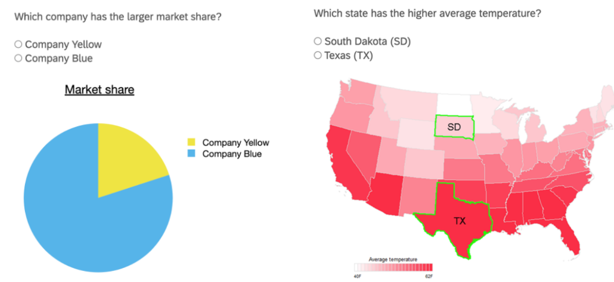

Figure 4: Examples of sanity-check questions

Experimental Design

Our experiment used a within-subject manipulation, where each participant was exposed to a set of 112 graphs, comprising 56 non-misleading graphs and 56 misleading graphs. We randomly assigned one of each misleading/non-misleading graph pairs to appear in the first or second half of the experiment. Within each half, we randomized the order of the graphs. This approach ensured that the misleading and non-misleading pairs were sufficiently spaced out. Further, the six sanity-check items were interspersed randomly among the 112 graph items.

Procedure

Participants began the study by providing informed consent and watching an instructional video that outlined the process. The instructional video informed participants that they would see a series of graphs and answer questions about the information presented in each graph. The video also emphasized the need for participants to quickly extract information from the graphs, simulating a real-world scenario like encountering graphs on social media where viewers swiftly scroll through information. Then they began the main task of answering questions about the graphs. They viewed each graph individually, proceeding at their own pace. Alongside each graph, they received a question that required

Table 1: List of 14 misleading graph types. Non-misleading version didn't contain misleading visual features.

Misleading graph types	Description
Line graph + truncated y-axis (Figure 2a)	The line graph has the y-axis starting at a value above zero.
Line graph + compressed y-axis (Figure 2b)	The line graph has the y-axis ending at an unreasonably high value.
Line graph + inverted y-axis (Figure 2c)	The line graph has the y-axis reversed, so higher values appear lower.
Line graph + manipulated x-axis (Figure 2d)	The line graph has the x-axis with irregular spacing of time intervals.
Line graph + dual axes (Figure 2e)	The line graph has two distinct y-axes with different scales.
Scatter plot + logarithmic y-axis (Figure 2f)	The scatter plot has the y-axis using a logarithmic scale.
Scatter plot + flipped x-axis (Figure 2g)	The scatter plot has the x-axis reversed, so higher values appear on left.
Bar graph + truncated y-axis (Figure 2h)	The bar graph has the y-axis starting at a value above zero.
Bar graph + compressed y-axis (Figure 2i)	The bar graph has the y-axis ending at an illogically high value.
Bar graph + pictorial bars (Figure 2j)	The bar graph has images or icons in place of bars.
Bar graph + 3D effect (Figure 2k)	The bar graph has bars drawn in a three-dimensional effect.
Pie chart + 3D effect (Figure 2l)	The pie chart has a three-dimensional effect.
Pie chart + 3D effect + pop-out (Figure 2m)	The pie chart has a three-dimensional effect and a certain slice popping out.
Map chart + inverted color scale (Figure 2n)	The map chart has an inverted traditional color scale.

estimating specific values based on the information derived from the graph. The study concluded with participants providing demographic information, such as their gender and age.

Statistical Analysis

Our study employed a logistic mixed model, part of the generalized linear mixed models (GLMM) family, to handle the binary nature (correct/incorrect) of responses to each question. This model was designed to predict scores based on 14 different misleading graph types and their counterparts, referred to as '*version*'. Because the main factor of interest in this study is the effect of each misleading graph on viewers' accuracy, we also included the interaction between *version* and 14 misleading graph types in the fitted model (*version* x *graph type*). Additionally, we treated participants and four distinct pairs within each misleading graph type as multiple random effects. We used AIC model selection to distinguish among a set of possible models describing only random effects (AIC = 8305.12), only main effects (AIC = 5868.45), or both main effects and random effects (AIC = 5359.28). The best-fitting model is a full model with main effects and random effects, which showed the lowest AIC score. We estimated Odds Ratios (OR) for an interpretation of the results, aiming to discern a 'significant differences in accuracy' between a misleading graph and its non-misleading counterpart (*version*). This was evaluated by testing the null hypothesis (H_0: $OR = 1$) against the alternative (H_1: $OR > 1$). Following Cohen's *d*, we evaluated the size of *OR* that is in the range of 1.68 to 3.47 as small, 3.47 to 6.71 as medium, and larger than 6.71 as large (Chen et al., 2010).

Results

Data cleaning

We excluded 10 participants who answered more than two of the six sanity check questions incorrectly, and 68 participants were included in data analysis. On average, participants spent 25.04 minutes to complete the study, with a standard deviation of 7.86 minutes. Table 2 summarizes the accuracy of participants' answers.

Misleading effect of misleading graphs

First, we investigated whether misleading graphs genuinely deceive viewers (RQ1). The comparison of odds ratios for overall misleading graphs versus non-misleading graphs (*version*) yielded an OR of 1.85, significantly different from 1 (H_1: $OR > 1$, $p < 0.001$). This suggests that when encountering misleading graphs, participants were 1.85 times less likely to produce an accurate response, compared to interpreting non-misleading graphs.

Second, we evaluated the deceptive impact of each misleading graph type to determine which type has the greatest capacity to deceive viewers (RQ2). This evaluation involved comparing each misleading graph type's OR to the corresponding non-misleading counterpart (*version* x *graph type*). Our analysis revealed that certain misleading graph types, such as line graphs with compressed y-axis, bar graphs with compressed y-axis, and bar graphs with pictorial bars, showed no significant difference in accuracy compared to the non-misleading counterpart (*ps* > 0.1). In contrast, other misleading graph types demonstrated significant differences compared to the non-misleading counterpart (H_1: $OR > 1$, $ps < 0.001$). Following Chen et al. (2010), we categorized the size of these differences into groups corresponding to large, medium, and small effects. Misleading graph types with large effects were line graphs with manipulated x-axes ($OR \approx 15.419$) and line graphs with inverted y-axes ($OR \approx 7.144$). When participants received these misleading graph types, they were significantly less likely to provide accurate responses, compared to receiving the non-misleading counterpart. Misleading graph types with medium effects were pie charts with 3D effects ($OR \approx 4.228$), scatter plots with flipped x-axis ($OR \approx 4.133$), pie charts with 3D effects and pop-out ($OR \approx 3.970$), and line graphs with dual axes ($OR \approx 6.262$). When participants received these misleading graph types, their answers were also significantly less likely to be accurate compared to receiving the non-misleading counterpart. Misleading graph types with small effects were scatter plots with logarithmic y-axes ($OR \approx 2.865$) and bar graphs with 3D effects ($OR \approx 1.757$).

Additionally, when participants received a line graph with truncated y-axis ($OR \approx 1.508$), a bar graph with a truncated y-axis ($OR \approx 1.439$), or a map graph with an inverted color scale ($OR \approx 1.122$), their answers were also less likely to be accurate than receiving the non-misleading counterpart, although the size of deceptive impact was negligible compared to other misleading graph types in other large, medium, and small groups (Chen et al., 2010). Figure 5 summarizes these findings by sorting the misleading graph types, from the most misleading (top) to the least (right).

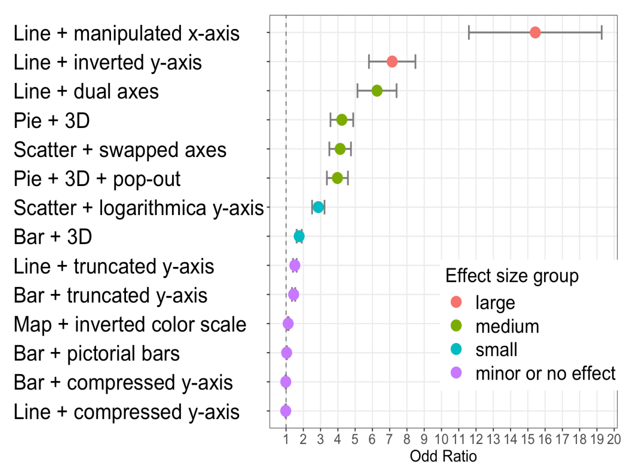

Figure 5: Odd ratio of answering correct with 14 misleading graph types, colors represent effect size groups

Table 2: Average accuracy by graph types, values in parentheses are standard deviations.

	Average accuracy (std)	
Misleading graph types	non-misleading	misleading
Line + truncated y-axis	0.878 (0.327)	0.591 (0.492)
Line + compressed y-axis	0.904 (0.294)	0.926 (0.261)
Line + inverted y-axis	0.970 (0.169)	0.165 (0.372)
Line + manipulated x-axis	0.952 (0.213)	0.080 (0.273)
Line + dual axes	0.808 (0.393)	0.161 (0.368)
Scatter + logarithmic y-axis	0.981 (0.134)	0.367 (0.483)
Scatter + flipped x-axis	0.977 (0.147)	0.268 (0.443)
Bar + truncated y-axis	0.867 (0.339)	0.610 (0.488)
Bar + compressed y-axis	0.904 (0.294)	0.922 (0.267)
Bar + pictorial bars	0.955 (0.205)	0.915 (0.278)
Bar + 3d effect	0.899 (0.313)	0.522 (0.500)
Pie + 3d effect	0.746 (0.435)	0.213 (0.410)
Pie + 3d effect + pop-out	0.702 (0.458)	0.213 (0.41)
Map + inverted color scale	0.977 (0.147)	0.849 (0.358)

Discussion and Conclusion

The goal of this study was to evaluate and compare the deceptive impact of various potentially misleading graph types and to categorize them based on their capacity to deceive viewers. In response to RQ1, we found that misleading graphs resulted in less accurate answers than the corresponding non-misleading graphs. This indicates the deceptive impact of misleading graphs. Furthermore, in response to RQ2, we identified which misleading graph types were particularly misleading by examining the difference in the predicted accuracy of answers between the given non-misleading and misleading graphs. The results indicate that the deceptive impact of misleading graphs varied according to the type of misleading graph. We classified misleading graph types into three groups (i.e., large, medium, and small) based on the size of their deceptive impact. Misleading graph types in the large group significantly decreased accuracy, with answers to these misleading graph types being six to 15 times less accurate compared to answers to the corresponding non-misleading graphs. Those features in the medium group reduced viewers' accuracy by a factor of three to four. Similarly, features in the small group decreased viewers' accuracy by a factor of two. Conversely, a line or bar graph with a compressed y-axis or truncated y-axis, or a bar graph with pictorial bars, had little or no significant deceptive impact.

Our findings expand prior research in two ways. First, this study adds to existing theory-based claims regarding 14 misleading graph types by supplementing them with comprehensive empirical evidence. Second, our study extends prior research on misleading graphs by assessing the relative deceptive impact of various misleading graph types that have not been compared before. Specifically, we found that the most misleading graphs (i.e., irregular time intervals on the x-axis, an inverted y-axis, or dual axes) typically display axis-related distortions. Interestingly, the least misleading graphs (i.e., truncated or compressed y-axis, or pictorial bars) also include axis-related distortions. The key difference between the most and the least misleading graphs lies in the specific nature of the axis distortion. When the values on axes deviate from the conventional pattern of incrementally increasing from bottom to top or left to right, the deceptive impact becomes more noticeable. Conversely, when the value order on the axes follows this standard pattern, with the lowest value at the bottom or on the left, any additional misleading visual features, such as a truncated or compressed y-axis, tend to have a negligible or insignificant deceptive impact. This observation suggests that viewers may heavily rely on standard increment patterns on axes, which leads to the selective processing of certain visual features when interpreting a graph. Our results indicate that viewers' reliance on standard increment patterns is so strong that any deviation can lead to a significantly deceptive impact, potentially surpassing the impact of 3D effects.

Our results should be interpreted in light of the following limitations. First, our participants were undergraduate students. Future research should examine the generalizability of our findings in the broader population of media consumers. Second, we used a variety of question types that differed between graph types. This choice might have introduced noise in our data. Future research should investigate similar question types to each graph type. Finally, deviating from conventional graph features can be advantageous in certain contexts (Ciccione et al., 2022; Correll et al., 2020), further research should explore effective methods for educating viewers about these scenarios.

Despite these limitations, our study provides empirical evidence about the deceptive impacts of various misleading graphs. Further, our study revealed that viewers susceptibility to misleading graphs depends on the type of misleading graphs. Thus, our findings can pave the way for focused interventions aimed at decreasing viewers' susceptibility to the most severe misleading graphs.

Acknowledgement

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